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A Model-Centered Approach

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With a foreword by Norbert Seel

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I dedicate this book to my beloved Ruth and to my son, Lorenzo, whose love made this work possible

Foreword

Since some decades, computer simulations have become a part and parcel of advanced learning environments. This book addresses the nature of simulation from multiple perspectives and within a variety of contexts in order to provide a foundation for its effective integration into education and learning.

Actually, while much has been written about models and simulations, little has been written about the underlying theoretical and epistemological foundations. In addition, there are also several shortcomings with regard to the instructional design principles and the varieties of ways for effective use of models and simulations in learning and instruction. This book provides a theoretically sound and practical guide for designing and using models and simulations to support learning in formal instructional contexts. Furthermore, it provides a comprehensive framework for conducting research on educational uses of models and simulations. This will be illustrated by examples of different types of simulations, including agent-based and system dynamics simulations in various contexts. The author provides the reader with a rationale and methodology for the design of interactive models and simulations along with a variety of applications ranging from the natural to the social sciences. Franco Landriscina makes clear that operating with simulations presupposes the application of mental models that provide the user with both a model of the system to be simulated and a model for reasoning in order to simulate the transformations of the system. Then, a simulation can be used to show the possible real effects of alternative conditions and courses of action. Consequently, the theory of mental models becomes a cornerstone of the theoretical argumentation which covers the broad range of theories and research on mental models—starting with the neopragmatic approach (e.g., Stachowiak) across cognitive-constructivist approaches (e.g., Johnson-Laird) up to the conception of model-centered learning and problem solving (e.g., my own work) that operate with computer-based simulations.

Thus, this book provides a state-of-the-art review of modeling for learning and problem solving in complex domains. Topics covered include the foundations of knowledge structures and mental model development, modeling for understanding, dynamic systems modeling, simulation-based learning, and simulations for thinking. The thread tying these chapters together is an emphasis on what the learner is doing and specifically on having learners engaged in modeling and simulation construction rather than merely interacting with preconstructed simulations. Actually, very often learners use simulations as mere applications that have been designed by programmers and instructors. The learners often do not get insights into the design of the tools itself, and therefore, they do not understand the functions of modeling the world. Such simulations can be called black box models. In contrast, Franco Landriscina is pleading to engage learners in processes of understanding the models underlying the simulations. Such models can be called glass box models. They presuppose that the learners can check the conceptual and mathematical models that are used to run a simulation. Clearly, this part of the book is another cornerstone of the argumentation.

This book deals with these focal points from the perspective called Model-Centered Learning and provides an extension to the glass-box approaches: The author explores the learning impact of students when constructing models of complex systems in various subject matter domains. The act of modeling in this vein needs to include reflection upon the thinking processes and the function of the tools which the learner may apply for modeling. Human learning either yields to manage new situations or improve efficacy of known behavior. This dual approach of human learning is described as the interplay between schemas and mental models. Based on these cognitive tools the human mind is able to create new and artificial models of the world aiming at the simulation of what would happen if the world is manipulated in a certain way. This means a "mental simulation runs" to imagine the events that would take place in the world if a particular action were to be performed. Thus, mental models allow one to perform entire actions internally and to judge the consequences of actions, interpret them, and draw appropriate conclusions. From the perspective of mental model research, Franco Landriscina moves in his book from the notion of models as a particular mode of internal representation mediating between images and propositions to the understanding of mental models as tools of embodied simulation (by means of cognitive linguistics). This is a great extension of mental model theory that could serve as a fundamental basis for future research in this special field of interest.

Humans are probably the only creatures who can simulate complex scenarios in mind in order to anticipate changes in the real world. The theory of mental model takes most of those assumptions into account, when asking how individuals operate successfully with the world and its demands for intelligent behavior. Modeling and simulations are means that make humans smart.

It is of great importance to see all the chapters in this book as contributions to the questions of how people think, how they learn, and how instruction can support those phenomena. Consistently, the book's focus is on the particular relevance of simulations and their unique roles to play in learning. This has to do with creating learning environments, whether simulated or virtual, which students can explore freely or within varying constraints required by guidance in order to construct knowledge on their own. The key to the success of this application of simulations is not so much in how the "message" itself is presented, but in the degree to which students can work out for themselves ways to reduce the dissonance between what the environment presents to the user and the knowledge and experience the user brings in when he or she enters the environment. An extended use of computer-based simulations as a tool to expedite the processes of problem solving may help shift the focus from the end product and from the pure acquisition of facts to cognitive processes like manipulation and understanding which then encourages curiosity and creativity. In this sense, various features of simulation technologies may help students become better problem solvers.

Recent developments in interactive software, and the emergence of systems thinking provide a unique opportunity to create interactive model-based simulations that address student learning. Computer simulation programs encourage students to explore complex and realistic systems. The interactive environment and graphic capability of these programs provides instant feedback to the students. In addition to dynamic simulation capabilities, many of these programs allow the user to incorporate animation into the simulation.

Clearly, simulations are computer programs aiming at modeling complex systems' behaviors. They allow a learner to explore a system in a controlled way in order to better understand how the system components interact, and how alternate decisions can affect desired outcomes. In the future, these types of simulations might merge to create even more intelligent instructional simulation systems. Such simulations could provide a rich level of fidelity along with sufficient instructional support, and include some degree of artificial intelligence that can adapt the fidelity, difficulty, and support to an individual learner's needs.

This book provides a unique and truly comprehensive perspective on the intelligent use of simulations in various fields of learning and education. The book explores the learning impact of students when constructing models of complex systems and using simulations in the context of complex problem solving. According to Landriscina's theory, students should be involved increasingly in building their own models and engaging at a deep conceptual level of understanding of the content, processes, and problem solving of the tasks to be accomplished. Indeed, a simulation is nothing else than a computer program that attempts to simulate the reality by operating with an abstract model of a particular physical or social system and its characteristics in order to gain insight into the functioning of the system. Every model is constructed in accordance with specific intentions in order to simplify its original in several respects as well as to create subjective plausibility with regard to the world.

The core of each computer simulation consists of a (conceptual) model of the system to be modeled and no simulation can be better than the underlying model. In addition to the model of the system, a simulation program must also include a model for reasoning in order to simulate the transformations of the system. Then, a simulation can be used to show the possible real effects of alternative conditions and courses of action. In other words: A simulation is a computerized version of the model of a system that runs over time and is iterative by nature with regard to the underlying model: A model of the system must be constructed, then the computer program simulates the model, learns from the simulation, revises the model, and continues the iterations until an adequate level of understanding is developed. The conceptual model is the focal point of each simulation. All activities either converge upon or emanate from the conceptual model. All structures, through mappings either into or out of the conceptual model, must be to some extent compatible with it. This book describes all these processes in detail and on a solid theoretical foundation.

Simulations and models are increasingly considered to be innovative learning environments which are consistent with how people learn: Variables can be limited to a manageable level and structure and direction for learning can be provided, real-world problems can be addressed, and students can take control and responsibility for their own learning progress.

Instructional researchers apply computer simulations in order to create "synthetic learning environments" for instructional purposes. That is to say, a particular task simulation has been designed to model some specific domain of reality with which students can interact. From an instructional point of view, it is necessary to state that the particular model of the reality that constitutes the core and scope of the simulation represents both the subject matter as well as the "conceptual models" of a subject. A simulation is a method of teaching/learning or evaluating learning of curricular content that is based on an actual situation. The simulation, designed to replicate a real-life situation as closely as desired, has students assume roles as they analyze data, make decisions, and solve the problems inherent in the situation. As the simulation proceeds, students respond to the changes within the situation by studying the consequences of their decisions and subsequent actions and predicting future problems/solutions. During the simulation, students perform tasks that enable them to learn or have their learning evaluated. A well-designed simulation simplifies a real-world system, while heightening awareness of the complexity of that system. Students can participate in the simplified system and learn how the real system operates without spending the days, weeks, or years it would take to undergo this experience in the real world.

Thus, a learning environment which contains computer simulation facilities may support knowledge acquisition as well as problem solving. Actually, learning initiated by computer simulation involves explorative thinking, inductive, and analogical reasoning. These skills put high cognitive and metacognitive demands on students, who must generate hypotheses and test them by accomplishing learning tasks actively as well as performing experiments in the simulated environment. Accordingly, simulations of complex environments often require complex problem solving, which can be trained systematically by situating simulations and model-centered learning into the various field of instruction. Actually, this book is a great contribution to the infusion of simulations into the field of learning—it is a milestone of educational technology research and development.

September 2012 Norbert M. Seel

Preface

This is a book about "Simulation and Learning". It is written for educators, teachers, and instructional scientists, but also for instructional designers, and anyone else involved in designing or using simulation-based learning environments. I argue herein that, to comprehend the instructional potential of simulation and to design effective simulation-based learning environments, what occurs inside the computer and inside the students' minds *must receive equal consideration*.

The framework I adopt to do so is *Model-Centered Learning*, in which simulation is viewed as being particularly effective when learning requires a restructuring of students' individual mental models, as ideally occurs when they learn scientific concepts. I focus on mental simulation as a fundamental capacity of the human brain, which allows us the flexibility of shifting from static to dynamic mental models, in function of a given situation.

I also formulate the hypothesis that simulation models can extend our own biological capacity for carrying out simulative reasoning. I therefore examine recent approaches in cognitive science such as Embodied Cognition and the Extended Mind Hypothesis. Lastly, I propose a conceptual model, the "Epistemic Cycle", as a blueprint for understanding the cognitive activities that are involved in simulation-based learning and for designing and planning instructionally effective simulation-based instructional activities.

This book is intended to promote the increased use of simulation in educational institutions, and the examples presented herein range from those that are appropriate for middle school to higher education levels. Most of the examples are drawn from the natural and applied sciences, but the accompanying considerations and guidelines are equally valid for other branches of science. The book is also intended to provide teachers with insights into making simulation-based activities more meaningful for students.

My choice of basing the book on the cognitive approach to simulation does not, of course, intend to minimize the importance of other approaches to this topic, such as the social, cultural, and historical, which I consider equally valuable, as they are beyond the scope of my own field of investigation.

As illustrated throughout the book, given the appropriate instructional planning and conditions, a circular, student-simulation interaction can arise, in which mind and program modify each other in real time. My own aim in writing this book was to engage the reader in a similar interaction.

I would therefore be very grateful to receive the Reader's comments, suggestions, and/or critiques on the ideas presented herein, so as to adapt my conceptual models to better reflect the complex nature of the simulation-learning relation.

Trieste, Italy, September 2012

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I am particularly grateful to Hans Fuchs, of Zurich University of Applied Sciences at Winterthur, for his helpful criticism of earlier versions of materials in this book and for getting me to think more deeply about science education.

Antonio Calvani, of Florence University, has likewise been a source of intellectual stimulation, and to him I owe my academic interest in instructional science. This is an appropriate place for me to express my gratitude to him.

I thank the numerous researchers and philosophers who are cited in this book, and I hope that my ideas might serve as a stimulus for their further theorizing and research.

My thanks go out to all those many people who gave me permission to utilize the illustrations in this book. Some of the diagrams are my own, which I drew, however, with the generous help of graphic artists at Alta Formazione.

I would like to thank Melissa James, of Springer International, for believing in the project in the first place, and for her patience in awaiting delivery of the final version of the manuscript.

I am particularly grateful to Melinda Tucker-Furlan for her accurate translation. This is my first book in English, and I was surprised to learn the extent to which a translator can contribute to the quality of the final work.

Contents

Chapter 1
An Introduction to Simulation for Learning

Reality is that which, when you stop believing in it, doesn't go away.
Philip K. Dick, How To Build A Universe That Doesn't Fall Apart Two Days Later (1978)

1.1 The Simulation Paradox

Simulation is all around us. Indeed, most of the objects in our everyday lives have been carefully simulated before being physically produced. Young people spend hours playing video games that vividly reproduce sports or imaginary worlds; doctors practice on virtual patients; molecular process simulations allow pharmaceutical companies to invent new medicines; and realistic simulation models render weather forecasting more precise than ever before. Moreover, managers in multinational companies use simulations to analyze future market scenarios, and simulation is also a recurrent theme in many movies and science fiction novels.

The field of scientific research, however, most heavily relies on simulation and uses it for nearly all topics of inquiry, for example, from those of the birth of the universe to the neural underpinnings of consciousness and intelligence. Science is therefore the realm that pushes the technological limits of simulation to their extremes. In fact, simulations of galaxy formations, molecular dynamics, protein unfolding, ocean currents, and aerodynamic design require the use of advanced numerical algorithms and parallel computers located in powerful data processing centers. Furthermore, simulation is not only transforming scientific practice, but it is also leading scientists and philosophers of science to re-examine relations between models, theories, and experiments. According to Winsberg (2010), "the last part of the twentieth century has been, and the twenty-first century is likely to continue to be, the age of computer simulation" (p. 9).

One of the aims of simulation, both in science and in industry, is that of learning: Through simulation of a real or imaginary system, one can better understand its inner workings and how to intervene when necessary. Simulation-based training typically aims to help trainees acquire specific operative skills, as in the case of aircraft pilots, anesthesiologists, or power plant workers. In business contexts, learning simulations usually operate on a company's organizational level, with the goal of improving its overall market competitiveness.

Given the above considerations, one might easily imagine simulation being used as a teaching method in schools and universities, in adjunct to more traditional methods, such as classes and laboratories. One might also legitimately

F. Landriscina, *Simulation and Learning*, DOI: 10.1007/978-1-4614-1954-9_1,

expect that its teaching potential has been both theoretically and experimentally investigated to develop applicative simulation guidelines for diverse educational contexts. Strangely, however, these suppositions are far from true in current educational scenarios.

Although the last few years have witnessed an increase in the use of simulations as a teaching tool, their actual penetration into school programs is still quite scarce. According to the National Research Council (2011) report entitled *Learning Science Through Computer Games and Simulations*, "several barriers slow large-scale development and use of games and simulations for science learning in K-12 and higher education" (p. 175).

This dearth of educational applications parallels a delay in research programs. The same report states, "there is moderate evidence that simulations motivate students' interest in science and science learning, and less evidence about whether they support other science learning goals" (p. 2). One of the report's conclusions stated that "The many gaps and weaknesses in the body of research on the use of simulations and games for science learning make it difficult to build a coherent base of evidence that could demonstrate their effectiveness and inform future improvements. The field needs a process that will allow research evidence to accumulate across the variety of simulations and games and in the face of the constant innovation that characterizes them" (p. 55).

We are therefore faced with the paradox of an instructional method receiving positive, even enthusiastic comments, which lacks momentum, however, to be translated into sound school practice. Wherein lie the reasons for this aspiration-reality divide? The above-mentioned report identified a series of practical hurdles to be surmounted, such as the need for a closer alignment with school curricula, teacher's professional support needs, and school policies that actually do allocate funds for hardware and software purchases. Although these issues are important, they concerns difficulties in introducing not only simulation, but also other technology-enhanced teaching methods into classrooms, such as hypermedia learning and computer-based scenarios (not discussed in the present book). With respect to simulation, specifically, cultural and conceptual factors linked to its specific features as a knowledge method and to its role in educational practices can also significantly delay this instructional updating and integration process. The remaining part of this chapter will therefore more closely examine three of these aspects:

- the epistemic status of simulation;
- different meanings of the word "simulation";
- differences between simulations and games.

1.2 The Epistemic Status of Simulation

Etymology shows that the verb "to simulate" (lat. "simulō," *imitate*) can also mean *pretend* and can take on a negative connotation thereby. In fact, up to the post-war period and the consequent development of computer simulations in military and scientific contexts, the word simulation was considered to exclusively mean the intentional distortion of an event. This negative connotation actually harks back to Plato's idea of "μίμησις" (*mimesis*, the Greek term for *simulation*) intended as an imperfect copy or fictitious replica of reality (as opposed to Aristotle, who conversely viewed *mimesis* as a means to know nature through potentially valid and acceptable representations). For example, Ulysses, the symbol of human capacity to solve problems through cunning and intelligence, pretended to be insane to avoid participating in the Trojan War, but his "simulation" was discovered. In more modern times, a simulation foul in soccer is a player's attempt to gain an unfair advantage by pretending to be injured through harmless or even no physical contact with a rival, and is therefore misconduct punishable by a yellow card. Simulation is therefore frequently considered to be a "fake" representation of the real world. In fact, many Sci-Fi film protagonists find themselves lost in a simulated world created to conceal the real world. In other words, simulation has a certain ambiguity due to its epistemic status, as something existing halfway between fiction and reality.

This ambiguity can therefore underlie some even unconsciously pessimistic ideas about simulation. For example, teachers view the method with suspicion, believing that it risks showing students a poor or distorted representation of reality. The concern is not entirely unjustified; students can easily confuse simulation with reality, especially if their knowledge of the simulated system is not yet fully developed. This is the "seductive power" of simulation, described by Starr (1994) in his analysis of the game *SimCity*. Turkle (1997) drew the same conclusion by maintaining that people react differently to the seduction of simulation: "One can accept simulations on their own terms […]. This might be called simulation resignation. Or one can reject simulations to whatever degree possible […]. This might be called simulation denial. But one can imagine a third response. This would take the cultural pervasiveness of simulation as a challenge to develop a new social criticism. This new criticism would discriminate between simulations. It would take as its goal the development of simulations that help their users understand and challenge their model's built-in assumptions." (Turkle 1997, p. 82).

Thus, the idea of simulation as imitation or reproduction of an objective reality makes up part of the epistemic beliefs with which students and teachers approach it as a learning method. As shown by research on personal epistemologies, these types of beliefs significantly influence different aspects of the learning process; some epistemic features of simulation will therefore be more closely examined here below.

1.3 Not All Simulations are Created Equal

The online *Merriam-Webster's* dictionary defines simulation as "the imitative representation of the functioning of one system or process by means of the functioning of another."[1] Hence, a fundamental feature of simulation is the reproduction, in form or content, of some aspects of a system—although, as described above, "fake reality" is another feature frequently attributed to the concept.

In practice, however, the word "simulation" implies many meanings, which vary in function of specific contexts and aims; the most commonly used ones are as follows:

- *understanding*, to gain knowledge of theories, models, and structures;
- *prediction*, to obtain a currently reliable imagine of a future occurrence;
- *decision support*, to support individual or team decision-making skills;
- *design and modeling*, to explore various design options, verify the quality of a product's performance before production, and to refine production processes;
- *training*, to teach operational and technical skills and work methods;
- *entertainment*, for curiosity, fun, and competition.

Each of these aims is linked to a specific type of simulation that varies per application area, knowledge required, modeling methods, and software tools. Overall, however, we can distinguish between two main types of simulation:

- *model-based simulations*, based on the construction of the theoretical model of a system (also known as "theoretical simulations");
- *experiential simulations*, based on the creation of a virtual event to be experienced by one or more participants.

Experiential simulation, of course, has broad application in training and games, for example, for interacting with real or imaginary people (role-play), driving a vehicle, manipulating a device, or moving through a virtual world. Experiential simulation environments are quite popular with the general public, due to the advanced technologies that are currently being used to create virtual worlds, immersive environments, and augmented reality devices. The present book, however, will exclusively examine model-based simulation, henceforth termed "simulation."[2]

1.4 Differences Between Simulation and Games

The terms "simulation" and "games" are frequently used interchangeably. The main reason for this phenomenon lies in the massive presence of simulation in commercial video games. Simulation games are designed to simulate some aspects of an imaginary or real situation, and this is achieved by using a wealth of details, stories, and special effects. Popular sub-genres are city building, life simulation games, social simulation games, sports games, and vehicle simulation games. Some well-known examples are *SimCity*, where the player acts as a city planner,

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[1] The Chap. 2 will propose a definition more specific to the instructional use of simulation.

[2] Even this type of simulation allows for the use of technologies such as virtual reality, but they are more frequently run as traditional computer programs.

and *The Sims*, a simulation of the daily activities of virtual people. Moreover, the expression "business simulation" is sometimes used as synonym for the business games used in manager training programs.

Recent years have also witnessed a growing interest in simulations in the field of e-learning, where the term "simulation" is frequently associated with terms such as "serious games" and "game-based learning" (Aldrich 2003; Prensky 2007; Quinn 2005). Typical examples are simulated co-worker consultancy, meetings, and sales negotiations. These are experiential simulations and thus essentially role-play, which generally progress along decision tree lines.[3]

Although technical or cultural simulation versus game lines are blurring, they present key differences from an instructional perspective. It is therefore important to distinguish between these two methods.

By definition, a simulation is based on the imitation of a system or a situation, whereas a game is not bound by this constraint, but exclusively follows its own rules. As Kant wrote in his *Critique of Judgment*, game playing is an "occupation that is pleasant in itself" (in Bernard 1914, p. 184). In addition to this basic difference, games are competitive in nature. Thus, whereas game players usually want to win (even against themselves, to improve their score), simulation is oriented toward the acquisition of knowledge or achievement of practical goals. Furthermore, although games are played spontaneously, for fun and/or for socializing, students generally interact with simulation in educational and therefore more structured contexts.

The instructional effectiveness of games, in general, and video games, in particular, remains a debated topic. Researchers investigating the issue have mostly focused on examining motivational and psychosocial development aspects. According to the National Research Council (2011), "Evidence about the effectiveness of games in supporting science learning is only beginning to emerge, and the body of evidence is much smaller and weaker than the body of evidence related to the effectiveness of simulations" (p. 37).

Having clarified these differences, it is also important to note that games and simulation do overlap to some degree; for example, both simulation games and instructional simulations have explicit goals, rules, and scores; they may both also present elements of inter-participant competition (Fig. 1.1).

1.5 What is Simulation?

As described above, the main feature of a simulation is the reproduction of a particular aspect of an observed or possible reality. It is not, however, a static reproduction, but an active, or rather, an "interactive" one. Parisi (1997)

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[3] Each tree node represents a situation and branches into potential decisions concerning that specific situation. Numerical weights can be incorporated into the nodes, but the simulation flow will ultimately depend on the player's qualitative decisions.

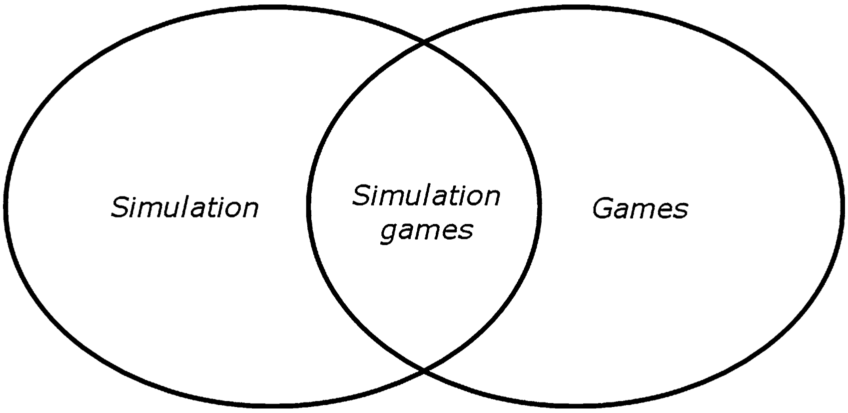

Fig. 1.1 The relation between simulation and games

distinguishes interactivity "between images" from interactivity "with images." The first type of interactivity is hypertextual, in which the user moves from one image to another by clicking on the links indicated. The second type of interactivity is based on simulation, in which an image conceals its own underlying model. Specifically, the image changes in function of the action the user performs indirectly on the model by interacting directly with the image (via key-press, mouse-click, screen-touch, etc.). These considerations therefore lead to the following definition:

- *A simulation is an interactive representation of the system to be studied, based on a model of the system.*

The aim of this definition is to limit the meaning of the term *simulation* to situations more easily encountered in scientific and educational contexts, and to couple it with the terms *model* and *system*, which appear elsewhere herein and can be defined as follows:

- *A model is a simplified representation of a real or imagined system.*
- *A system is a collection of different elements whose combination yields results that are unobtainable by the elements alone.*

These definitions allow us to imagine a series of epistemic transitions, from a reality or an idea to a system, from the system to a model, and from the model to a simulation. Although these entities are conceptual in nature, during the construction process of a simulation, they become cognitive artifacts, such as physical models, data files, written descriptions, visual representations, mathematical formulas, formal specifications, and computer programs. Moreover, the above definition's emphasis on the interactive nature of simulation distinguishes it from other forms of knowledge representation and focuses on its potential for creating a relation of interpenetration and synergy between a human mind and a computer. For example, when a student uses a simulation, students using a simulation do not typically interact directly with a given model, but exclusively via mediation of the simulation program's user interface, and with the goal of gaining a better understanding of the modeled system (Fig. 1.2).

When attempting to define the relation between simulation and learning, a useful approach is to list the advantages of actions implemented in a simulated system versus a real system, and specifically

- *independence from spatial dimensions*, that is, the opportunity to examine extremely large or small systems and related processes, which would otherwise be difficult or impossible to analyze (e.g., galaxy formation or alpha particle emission from an atomic nucleus);
- *time compression* (*or expansion*), that is, being able to observe either real-world phenomena requiring very long time spans in a few minutes only (such as continent formation) or which occur too quickly for observation by the human eye (such as molecular vibration or action potential propagation in the axon of a neuron);
- *feasibility of the impossible*, that is, the opportunity to perform actions that are impossible in reality (e.g., eliminating friction on a flat surface, causing an earthquake, shifting the planets' positions in the solar system);
- *safety*, that is, being able to interact safely with potentially dangerous systems (e.g., an erupting volcano) and to carry out actions that would cause considerable damage in the real world (e.g., releasing a pollutant into a lake, to analyze the ecosystem impact);
- *cost-effectiveness*, because acquiring data from a simulation costs much less than doing so from a real system.

Thus, simulation allows us to practice without time or space constraints and, therefore, to proceed by trial and error safely and cost-effectively, to verify alternative hypotheses, and to reflect on the structure of the system itself and our own decisional processes concerning it. In suitable conditions, this approach can also enhance cognitive processes that are crucial to learning, such as

- selecting key information;
- organizing this information into a cognitive structure;
- integrating this new information with previous knowledge;

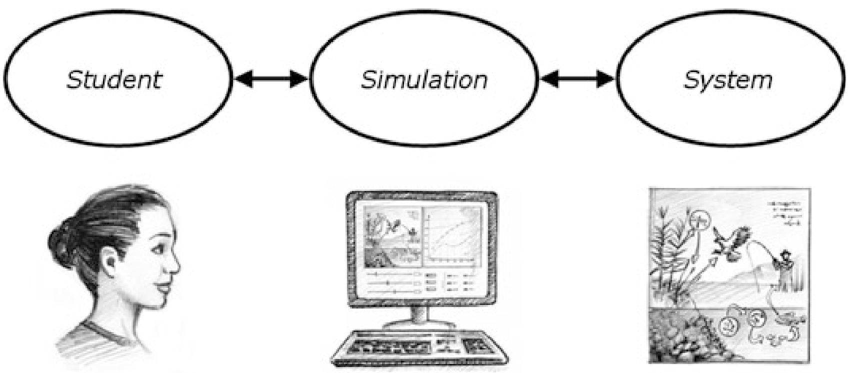

Fig. 1.2 Computer-based simulation as mediator between student and system

- accessing and creating appropriate analogies and metaphors;
- generating inferences;
- reorganizing cognitive structures.

Overall, these steps can facilitate the construction of new cognitive structures or the modification, or even replacement of preexisting ones, favoring complex learning processes thereby (Chi and Ohlsson 2005; Mayer 2005; Seel 1991, 2003).

1.6 The Need for a Multidisciplinary Approach

Scientists and educators wanting to investigate the learning potential of simulation must first deal with the problem of a knowledge scattered among many disciplines. Thus, in addition to the variety of meanings of the term simulation, important differences along three key dimensions—that is, simulation paradigm, learning goals, and curricular development—must be kept in mind.

1.6.1 Simulation Paradigm

Simulation paradigms are the theoretical frameworks that guide the modeling practices of simulation experts. They therefore guide decisions as to the selection of phenomena to be modeled, modeling methods, software tools, validation criteria, and the ways in which the simulation results will be interpreted. The present book focuses on the paradigms and methods that are most frequently encountered in educational contexts, and specifically

- Equation-based modeling;
- Molecular Dynamics;
- Agent-based modeling;
- System Dynamics;
- Cellular Modeling and Simulation.

(Other simulation paradigms used predominantly in the fields of applied mathematics or systems engineering, such as Monte Carlo Simulation (Rubinstein and Kroese 2008) and Discrete-event Simulation (Banks et al. 2009), are not examined herein).

The above-mentioned issue of knowledge fragmentation is due to the fact that each paradigm listed above has its own individual or organizational supporters, who tend to underscore the benefits and strengths of their chosen paradigms. Yet, the variety of phenomena to be modeled does not allow for the exclusive use of a single paradigm; nor is there a single modeling method or tool that suitable for all instructional situations. In fact, different educational contexts call for different approaches. A useful perspective is therefore that of applying and comparing many approaches. Moreover, in doing so, it is important to remember that one's choice of a simulation paradigm is not just a technical matter: Every paradigm comes with its own set of assumptions about the types of phenomena that can be modeled, the model characteristics required, and potential simulation uses in that context.

1.6.2 Learning Goals

Many studies do not thoroughly investigate the instructional effectiveness of simulation, and specific learning goals have therefore not been clearly defined, nor have they been expressed in terms of measurable learning outcomes. For example, implicit learning goals can be those of developing general thinking skills (e.g., critical thinking skills, higher-order thinking skills, problem-solving skills) or acquiring more specific subject matter knowledge (e.g., physics, biology, economics). Adding to the confusion is the frequently unstated motivational purpose of a proposed simulation, that is, to increase student's overall interest in science, with no reference, however, to specific learning goals. The above-cited National Research Council (2011) report on *Learning Science Through Computer Games and Simulations* states, somewhat cautiously, that "There is moderate evidence that simulations motivate student's interest in science and science learning. Less evidence is available about whether simulations support development of science process skills and other science learning goals" (National Research Council 2011, p. 54).

1.6.3 Curricular Development

In curricular development, the development and application of modeling and simulation skills are not easily encountered among courses offered by schools or universities. A distinctive feature of simulation is that a relatively small number of models can be applied to a wide range of phenomena in different fields. This fact entails, however, a systemic view of science, which focuses on similarities rather than differences between phenomena. It also does not harmonize well with the distinction-among-discipline view, which still represents the main criterion for designing curricula at any level of education. One way to overcome this obstacle is to develop science education programs by focusing on a small number of unifying concepts and processes, as indicated, for example, in the Benchmarks for Science Literacy (American Association for the Advancement of Science 1993), the National Science Education Standards (National Research Council 1996), the Science College Board Standards for College Success (College Board 2009), and the Framework for K-12 Science Education (National Research Council 2012). Some ways in which the instructional use of simulation could support this endeavor are illustrated throughout this book.

The integration of simulation into curricular development requires a *multidisciplinary approach*, that is, an approach that continuously takes the various contributions of diverse disciplines into due account. The aim thereby is to acquire sufficiently broad-based knowledge of the general aspects of simulation and their implications for learning, so as to make informed decisions about how simulation can be used in instructionally effective ways. The reader might wonder whether this type of a multidisciplinary approach is actually possible and whether the various contributions of such a multidisciplinary approach could be integrated in a unitary framework. The answer, of course, is affirmative. Indeed, an in-depth look at the instructional uses of simulation reveals some recurring themes an examination of which provides great potential for increasing the effectiveness of simulation-based learning, and namely

- cognitive processes involved in simulation-based learning;
- teacher's and student's epistemic beliefs about simulation;
- a simulation project's activities and outputs;
- instructional strategies informing the design and use of simulation-based learning environments.

1.6.4 Cognitive Processes

The cognitive processes involved in simulation-based learning can be analyzed in light of the concepts of mental model and mental simulation, which have been extensively studied in many areas of Cognitive Science (Johnson-Laird 1983; Goldman 2006; Gibbs 2006a; Barsalou 2008a). As described in the next chapter, a large body of cognitive science research evidence provides support for the idea that mental simulation is a fundamental capacity of the human brain, as it allows us to move from static to dynamic mental representations. This process, in fact, helps us imagine events that could happen in the world as a consequence of our own actions. Furthermore, the mental simulation system is linked closely with the linguistic system and, therefore, has wide-ranging implications for learning.

1.6.5 Epistemic Beliefs

The teacher's and student's epistemic beliefs about simulation are related to the ways in which simulation can yield knowledge about the world to us. For example, a simulation might be viewed as an imperfect copy of reality and, therefore, as an only partially reliable source of knowledge. A related issue is that of the comparison between simulation and laboratory experiments—that is, whether, and if so to what extent, a simulation can be considered a sort of "numerical experiment," which is analogous to a physical experiment. These and other similar issues are studied in Philosophy of Science under the more general category of scientific models (Knuuttila 2005; Frigg and Hartmann 2009). Philosophers of science have also shown growing interest in the distinctive features of simulation models and in the uses of simulation for representation, prediction, explanation, and policy decisions (Grüne-Yanoff and Weirich 2010; Winsberg 2010).

1.6.6 Activities and Outputs

The activities and outputs of various simulation projects have been described in detail by researchers and experts in the field of modeling and simulation (M&S). M&S developed in the context of systems science, and its main fields of applications are industry, defense, and health care (Birta and Arbez 2007; Robinson 2004; Sokolowski and Banks 2010). Interestingly, M&S experts have analyzed general simulation project aspects that are common to different application areas and simulation paradigms. Thus, the conceptual and methodological contributions of M&S could also be usefully applied in educational contexts, and particularly in situations requiring learners to build their own simulation models or to evaluate a model constructed by someone else.

1.6.7 Instructional Strategies

A useful theoretical framework for analyzing the best suited instructional strategies for simulation-based learning is that of model-based learning and teaching (Buckley 2012a, b). The framework views learning as a series of mental models successively progressing from an initial state to a final desired one. Simulation (both mental and computer based) is seen as a tool that can facilitate this progression process and is particularly effective when learning goals require the restructuring of student's mental models, as in the instance of conceptual change. Cognitive load theory (Sweller 2010) has also made an important contribution to this field of inquiry. This instructional theory focuses on the role of working memory in learning processes and provides a set of principles and guidelines for the design of efficient simulation-based learning environments.

The disciplines illustrated in Fig. 1.3 can serve to more accurately define the relation between simulation and learning. These contributions, of course, must be meaningfully integrated to obviate the risk of finding ourselves in the ancient Indian story of the blind wise men and the elephant: although each man touched the same animal, his understanding of "the elephant" pertained to only a part of the elephant (trunk, ear, tail, leg, etc.) and, indeed, the story warns us of the difficulty in achieving a full understanding of "elephant" in its entirety.

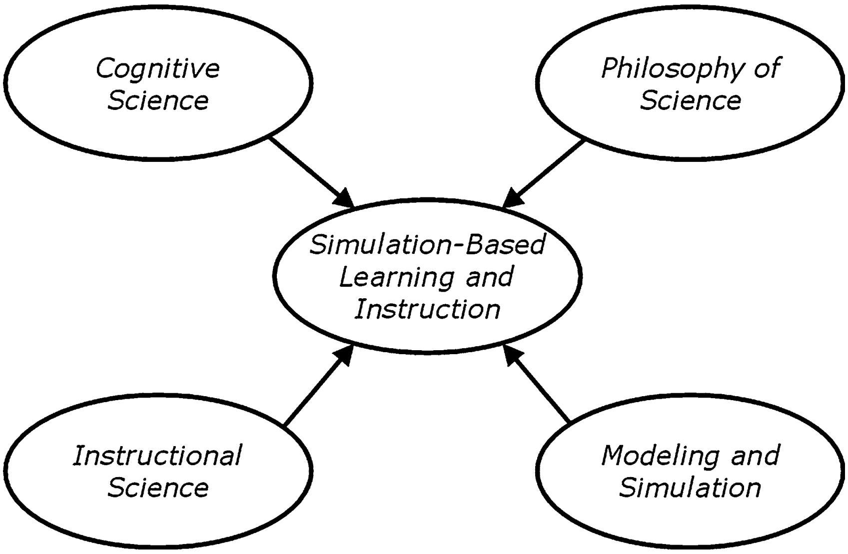

Fig. 1.3 Other discipline's contributions to simulation-based learning and instruction

It is therefore proposed herein that one fruitful way to integrate the above contributions into a unitary framework is to carefully consider the link between processes ongoing in the student's mind and those occurring in the computer, as well as the technical and cultural interfaces, that make this connection possible.

The following chapters are, respectively, dedicated to examining the topics of mental models and mental simulation (Chap. 2), models in general (Chap. 3), their relation to simulation (Chap. 4), simulation-based learning (Chap. 5), and the relation between mental and computer simulation (Chap. 6).

Chapter 2
Simulation and Cognition

Music is a horizontal force that unfolds in time.
Leon Fleisher (American pianist and conductor)

2.1 Mental Models

What if mental simulation is not just a way to discuss and to solve problems, but also an essential aspect of brain functioning? Indeed, what if this process lies at the very foundation of our ability to understand other peoples' intentions and emotions, to remember past events, to create new ideas, and to imagine the future? A growing body of cognitive science literature on human "mental simulation" capacity points to the cogency of this view. The present chapter begins by examining a particular kind of model, i.e. "mental models", to more closely investigate the relation between simulation and cognition.

Mental models are internal representations people commonly use to comprehend, reason about, and predict events in the world. In his 1894 work "Principles of Mechanics", Heinrich Rudolf Hertz clearly expressed the idea that our thought processes are based on internal representations that allow us to simulate the external world: "We make for ourselves internal images or symbols of external objects, and we make them in such a way that the consequences of the images that are necessary in thought are always images of the consequences of the depicted objects that are necessary in nature… Once we have succeeded in deriving from accumulated previous experience images with the required property, we can quickly develop from them, as if from models, the consequences that in the external world will occur only over an extended period or as a result of our own intervention" (in Niehans 1990).

As early as 1943, the English psychologist Kenneth Craik laid the foundations for more recent mental models theories (in his book entitled "The Nature of Explanation") by stating that the mind develops "small-scale models of reality" on the basis of experience and uses these models to think, to predict future events, and to provide explanations: "If the organism carries a 'small-scale' model of external reality and of its own possible actions within its head, it is able to try out various alternatives, conclude which is the best of them, react to future situations before they arise, utilize the knowledge of past events in dealing with the present and the future, and in every way to react in a much fuller, safer, and more competent manner to the emergencies which face it" (Craik 1943, p. 61).

F. Landriscina, *Simulation and Learning*, DOI: 10.1007/978-1-4614-1954-9_2,

Interestingly, he prophetically viewed this predictive power as not pertaining exclusively to the human mind. The word “simulation” never actually appears in Craik’s book, given that the computer, as we know it, had not yet been invented. He did use, however, the example of Kelvin’s tide predictor—a mechanical calculator that is also an analog computer. Moreover, by stating that a thought process can be divided in three steps: (1) representation by symbols, (2) calculation, and (3) retranslation into events, he was implicitly referring to a form of mental simulation.

Craik’s ideas subsequently lay fallow for many decades, one of the causes being the growing behavioral psychology movement’s rejection of all forms of “mentalism”. Yet, later on, during the 1970s, in the newly consolidated field of cognitive psychology, Shepard and Metzler’s experiments on the mental rotation of images brought researchers’ attention back to the subject of mental representation (Shepard and Metzler 1971). Shortly thereafter, Kosslyn and his collaborators found interesting experimental evidence for the mental scanning of images (Kosslyn 1973, 1980). In Shepard and Kosslyn’s “pictorialist” approach, thought was considered to operate through some process of visual imagery and therefore, to be capable of representing information analogically, i.e., by maintaining the visuospatial features of visual perception. Pylyshin’s (1973) “computational” approach conversely considered mental images to be akin every other kind of thought, and therefore based on linguistic representations, with none of the visuospatial features of images. An analogy can be made with the images on a computer screen, which are actually based on a binary language decoded by the software. In any event, regardless of whether images are analogical or propositional in nature, these experiments demonstrated that they can be analyzed, rotated, and/or scanned, as occurs with perceptual images and that they “behave” like the physical objects they represent.[1]

The concept of mental models came to the forefront in 1983, when two books with the same title “Mental Models” (but representing two different approaches) were respectively published by Gentner and Stevens (1983) and by Johnson-Laird (1983). The first approach originated in the field of Artificial Intelligence and conceived mental models as being knowledge structures people use to understand specific knowledge domains (Gentner and Stevens 1983). The domains analyzed were simple physical systems or artificial devices, and participants tended to rely on “naïve theories” to describe and explain them. These theories are similar to scientific ones, as they have axioms and rules, but are “naive” because they are not formalized and are occasionally wrong. The knowledge representation formalisms used in this approach were those of Artificial Intelligence. The second approach focused on mental models viewed as a special kind of mental representation supporting speech comprehension and logical reasoning (Johnson-Laird 1983).

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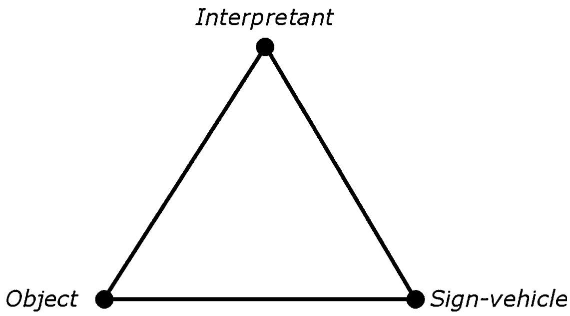
[1] Auditory, olfactory, and tactile mental models have also been studied. In particular, Halpern (1988) used experiments similar to those of Kosslyn to investigate the mental scanning of auditory images produces by familiar songs. Visual mental models, however, have been the most widely studied.

According to Johnson-Laird, mental models are structural analogues of the world: "they are analogies because structural relations between their elements correspond to the perceptible relations between the elements of the corresponding real-world objects" (1983, p. 147). These kinds of mental models are *iconic representations*; that is, they have a relation of similarity with the corresponding real-world situation, as opposed to *propositional representations*, in which the relation is of a purely conventional nature. This similarity relation has a spatial nature, because the disposition of the elements ("tokens") in the mental model is isomorphic with that of corresponding real-world elements. Based on the analogical relation between their supposed structure and the situation they represent, Johnson-Laird (2004) compared mental models to architects' and molecular biologists' models and to scientific diagrams. Moreover, he formulated the hypothesis that mental models can also contain abstract symbols that allow for the representation of propositional connectives, such as negation and disjunction, used in logical reasoning. According to Johnson-Laird's "triple code" hypothesis, mental models are a type of representation that differs from both propositional representations and mental images.

Johnson-Laird also saw the most important forerunner of mental model theory in the American philosopher Charles Sanders Peirce, the father of pragmatism. Peirce considered himself mostly a logician and made many important contributions to the domain of logic. In particular, he invented two kinds of logical notation: one symbolic, as currently used in mathematical logic, and the other, graphic—i.e., "existential graphs" or "logical diagrams". In an existential graph, logical relations are represented by spatial relations among different types of signs, as in Venn diagrams. Existential graphs support a type of reasoning Peirce termed "diagrammatic reasoning", consisting in the manipulation of relations among the diagram's signs, by following specific rules to obtain other relations among them. These diagrams therefore constitute a deductive system in which the signs and the rules for manipulating them represent the diagram's syntactical aspect, and the relations among the signs and objects make up the semantic aspect. With regard to semantics, the problem is to understand how a graphic sign in a diagram can represent something else other than itself. Pierce's response lay in the triadic model of the sign, which he began to illustrate in 1897, in his work titled "On a New List of Categories" and further developed in his later works. In this model, which is currently used in *semiotics*, a sign is defined by the relation among a *sign-vehicle* (or "representamen"), an *object*, and an *interpretant*, and this relation can be represented as a triangle (Fig. 2.1).

The sign-vehicle is commonly called "sign", and as Peirce stated, it is "something which stands to somebody for something in some respect or capacity" (1897, p. 228). The object is what the sign refers to—i.e., a real-world thing or another representation. The most difficult concept to grasp, however, is that of the interpretant. It refers to a further kind of a sign, created *in the mind* of a subject *as the effect* of a material sign. In his various works, Peirce specifically addressed the mental nature of the interpretant: "A representation is that character of a thing by virtue of which, for the production of a certain mental effect, it may stand in place

Fig. 2.1 Peirce's triadic sign theory



of another thing. The thing having this character I term a *representamen*, the mental effect, or thought, its *interpretant*, the thing for which it stands, its *object*." (1899, p. 1564). "A *Sign* is a Representamen of which some Interpretant is a cognition of a mind" (1903, p. 291). Peirce argued that thoughts are signs, too, and it is this position that reveals a clear analogy between Pierce's existential graphs and Johnson-Laird's mental models. Pierce moreover classified signs into the three categories of icons, indexes and symbols (Table 2.1), according to the type of relation that exists between the sign and the corresponding real-world object.

Both the mental models in Johnson-Laird's theory and Peirce's existential graphs are *multimodal* or *heterogeneous* information representation systems, because they can contain different types of signs, and specifically iconic elements, spatial elements, and symbols (Shin 2002).

In this parallelism between internal and external representation, some confusion arose as to the different formats Peirce assigned to icons. In fact, at times he compared them to pictures, as in the instance of a portrait or statue of a person, and other times, to diagrams. He actually meant, however, both meanings: In the first case (icons as pictures), the element in common with the object is a visual feature (e.g., a statue partakes its shape with the original), and thus the relation between sign and object is a similarity relation. In the second case (icons as diagrams), sign and object share a spatial feature (e.g., a diagram partakes the spatial structure of an object's elements), and the sign-object relation is one of analogy. Moreover, although it was not possible for Pierce to foresee it, the difference between these two kinds of iconic representations can also shed some light on the difference between mental images and mental models (Table 2.2).

Table 2.1 Kinds of signs in Peirce's semiotics

Kind of sign	Relation between sign-vehicle and object	Example of sign-vehicles
Icon	Features partaking	A picture with a cat
	Similarity or analogy	A subway map
Index	Direct connection	The mercury level in a thermometer
		A hand pointing an object
Symbol	Convention or habit	The letters of the alphabet
		A dove as the symbol of peace

Table 2.2 Difference between mental images and mental models

Representation type	Representation relation	Features
Mental images	Similarity	Varyingly vivid visual representations of persons, objects, shapes, and colors (auditory, olfactory, and tactile mental images are also possible)
Mental models	Isomorphism	Spatial representation, of an abstract and schematic nature

It is important to note that the above-mentioned knowledge-based (Gentner and Stevens 1983) and speech comprehension and logical reasoning-based (Johnson-Laird 1983) accounts for mental models also differ at the neuropsychological level. In the first instance, mental models are considered to be structures in long-term memory, and in the second, they are thought to be temporary representations (i.e., "constructed at the moment") in working memory, to make inferences or to solve problems.

The concept of a mental model as being a relatively stable cognitive structure at times overlapped with that of "schema". Head and Holmes (1911) introduced the latter concept in the terms of neurology to explain control body posture and movement control mechanisms. They defined the term "body schema" as an "organized model of ourselves". In psychology, the schema concept was applied by the German psychologists Otto Selz (1913) and Karl Bühler in the field of productive thinking and cognitive development. British psychologist Frederic Bartlett (1932) used the concept of schema to account for the constructive nature of the act of remembering. Bartlett viewed schemas (also called "schemata") as organized mental structures, which provide a framework for understanding and remembering information. Thus, the schema concept was characterized early on in two different ways: one linked to sensorimotor experience and the other to abstract knowledge representation. Schemas also play a key role in the psychology and epistemology of Jean Piaget (1954), who considered them to be the mental structures children form to adapt to their physical and social environment. Piaget achieved a synthesis of the neurological and psychological approaches, by pinpointing the foundations of language and of abstract thought in young children's eye-hand coordination schemas. Moreover, he proposed that this type of adaptation occurs via the two complementary processes of *assimilation* and *accommodation*, which refer, respectively, to the incorporation of new knowledge into a previously existing schema and to modification of the schema itself. During the 1970s and 1980s, the schema concept was popular in many theories of cognition. For example, in Neisser's (1976) approach to visual perception, "anticipatory schemas" were viewed as being plans for perceptual action and readiness for particular kinds of sensory structures. They were therefore considered to make up part of the perceptual cycle we use to explore our environment, and are in turn modified by information picked up from the environment. The concept's most important influence on cognitive psychology, however, occurred in Artificial Intelligence, which developed schema-like constructs—such as "frames"

(Minsky 1977) and "scripts" (Schank and Abelson 1977)—as ways to represent the generic knowledge people have about objects, situations, and actions in a computer program. For example, Mandler (1984) developed a schema theory based on findings from her research on the ways in which young children recall stories read to them. The theory proposed that a schema is an abstract knowledge framework for interpreting and constructing stories and that when children listen to a story, they implicitly place the story's specific details into a schema's categories, and then reconstruct the story based on these categories.

Rumelhart and Norman (1978) further developed the concept of schema in the psychology of learning, by viewing schemas as "active data structures", which control and direct the comprehension process. These authors also proposed three qualitatively different mechanisms of learning, which were respectively based on:

- *schema accretion*, i.e., adding new information to an existing schema;
- *schema tuning*; i.e., modifying a schema by "fine tuning" its structure;
- *schema restructuring*; i.e., reorganizing an existing schema or creating a new one.

The reader might note that the schema accretion mechanism clearly corresponds to Piaget's assimilation process and that schema tuning and restructuring correspond to his concept of accommodation.

This body of research also impacted educational psychology and instructional theories—e.g., in Anderson's (1978) and Spiro's (1980) theories on the role of schemas in text comprehension and recall.

Over the years, various authors have used the term "schema" in different ways and to different purposes. In its broadest sense, the term now denotes all forms of complex knowledge representation, although its narrower meaning refers to a form of mental representation pertaining only to generic and abstract knowledge. In fact, the limitations of the concept of schema for representing all form of knowledge led to the introduction of other cognitive structures, such as mental models and naive theories, to represent specific (i.e., non-schematic) aspects of knowledge.

Seel (2003, 2012b) recently investigated the relation between mental models and schemas in the context of his approach to model-based learning, which will be examined in Chap. 5.

2.2 Mental Models as Simulations

The previously described analogy with molecular models and diagrams at times connoted mental models as static structures to be visually inspected, as occurs with a physical model or a picture. Yet, a mental model can represent causal or time relations among events, and is capable of making this information available to other cognitive subsystems by way of mental simulation. Indeed, this meaning underlies Hertz and Craik's idea of mental model. Similarly, Norman (1983) noticed that "it should be possible for people to 'run' their models mentally"

(p. 12), and Gentner stated that “mental models often permit *mental simulation*: the sense of being able to run a mental model internally, so that one can observe how it will behave and what the outcome of the process will be” (2002, p. 9684). Johnson-Laird recently stated that “reasoning is a simulation of the world fleshed out with our knowledge, not a formal rearrangement of the logical skeletons of sentences” (2010, p. 18243).

Rumelhart et al. (1986) provided a very germane analysis of the relation between mental models and simulation by describing a view of mental models and sequential thought based on the parallel distributed processing (PDP) paradigm. In this approach, the cognitive system consists of two types of processing units:

1. an *interpretative system,* which obtains input from the world and produces action;
2. a *model of the world*, which obtains the actions produced by the interpretative system as input and predicts the way the input should consequently change (Fig. 2.2).

As the authors stated: “Now, suppose that the world events did not happen. It would be possible to take the output of the mental model and replace the stimulus input from the world with input from our model of the world. In this case, we could expect that we could ‘run a mental simulation’ and imagine the events that would take place in the world when we performed a particular action. This mental model would allow us to perform actions entirely internally and to judge the consequences of our actions, interpret them, and draw conclusions based on them” (p. 42). As shown in Fig. 2.2, this is a cybernetic model, because it structurally represents an internal control system, consisting of two units interacting through a feedback circuit. This characterization of mental models underscores the role of mental simulation and its adaptive value from an evolutionary perspective. For instance, one need only reflect on the need for prehistoric humans to mentally simulate a hunting strategy or to predict their group members’ social behavior.

The term “mental model” is also recurrently used in the branch of research examining the mental representations people form to understand the functioning of simple mechanical systems starting from their description in the form of texts and diagrams. For example, Hegarty and Just (1993) investigated participants’ thought processes concerning gears, pulley systems, and hydraulic devices. They consequently proposed a dynamic view in which people “run” a mental model of the

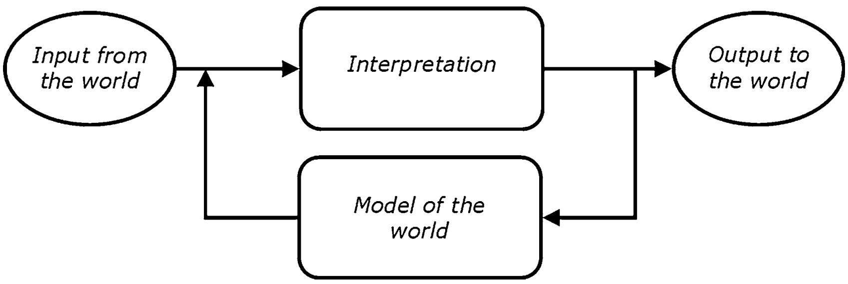


Fig. 2.2 A simplified representation of the PDP model of mental models (Rumelhart et al. 1986)

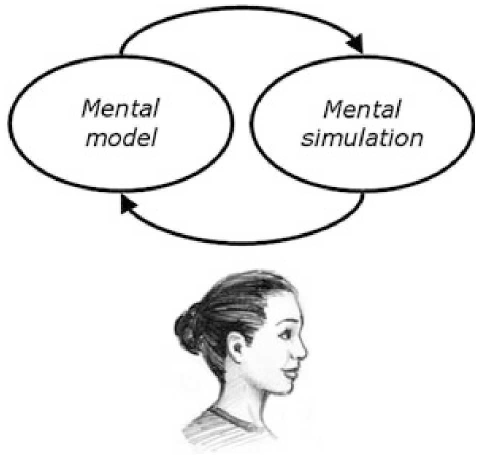


Fig. 2.3 The interaction between mental model and mental simulation

system in their heads to understand the working of these systems. Hegarty (2004) reviewed the evidence and concluded that mental simulation is a strategy available to humans to reason about mechanical systems. She also underscored a key difference between visual imagination and mental simulation, by stating that visual imagination is based on the holistic inspection of a mental image of the moving system, and that mental simulation is conversely based on:

- the piecemeal simulation of the events;
- some information, both visual or otherwise (e.g., force or density);
- the representation of the associated motor actions.

It is also important to note Schwartz and Black's (1996) findings, however, that participants knowing verbal rules to infer a movement rely on these rather than on simulation, so as to solve the problem more quickly. Figure 2.3 summarizes the interaction between mental model and mental simulation according to these ideas.

2.3 Simulating Other Minds

Mental simulation is one of the mechanisms that possibly underlies "theory of mind" (ToM), i.e., people's ordinary capacity to refer to specific mental states, in particular beliefs and desires, to understand and predict other peoples' thoughts, intentions, and emotions. Two conflicting arguments have been proposed to account for this capacity (known as "mindreading" or "mentalization"). In the "theory-theory" (TT) perspective, ToM is seen as a naïve theory (a "folk psychology" known by tacit agreement) with posits, axioms, and rules of inference (Stich and Nichols 1992). Developmental psychologists offer two different explanations for the origin of this theory during childhood. In one version, children are thought to acquire it through the same kind of empirical methods scientists use to test their scientific theories (Gopnik and Wellman 1994). This point of view, also known as the "child-scientist" perspective, is a part of a more general approach that aims to explain children's cognitive development in terms of analogy with change in scientific theories. In the second version of TT Theory, the basic elements of the theory are innate modules, which are progressively activated during children's early years in a process of biological maturation (Leslie 2000).

The "simulation theory" (ST) (Gordon 1986; Harris 1994) conversely states that human beings use their mental resources to simulate the psychological causes of other people's behavior, with no need for an internal body of knowledge structured as a theory. Two theories have been proposed to account for the ways in which this process might occur: In the *role-taking* approach (Gordon 1995), people pretend to be the person in a specific situation and simulate the thoughts of that person, by imagining what they might be (as in the metaphor "putting yourself in someone else's shoes"). For instance, to understand how John feels when he goes to school in the morning, we can imagine that we are John walking along the path he takes to school; we can also simulate the way he feels. Conversely, the *introspection* approach (Goldman 2006) holds that people take specific beliefs and desires as mental input and simulate possible and consequential mind states thereby. They then use analogy to infer from those states how another person might be thinking and/or feeling. For example, to understand the way Mary feels when she gets a good grade, we can simulate the way we might feel getting the same grade, and infer Mary's feelings from our own. These examples also indicate that simulation-based mindreading can be inaccurate at times: By mentally simulating the way John feels while walking to school, we risk counting too much on our own past experiences and feelings, and thereby attributing an emotional state to John that is not really his own. These kinds of errors, resulting from the projection of our mental states onto those of another person, are called "egocentric biases".

ST obtained a great deal of support with the discovery of "mirror neurons". These are a special kind of neurons found in the human and primate brains, which activate in individuals both when making specific movements and when they see others do the same movements (Rizzolati et al. 2006). Mirror neurons activate not only when viewing an action, but also in comprehending the movement's goal and, therefore the intentions of other individuals making the same movement. Generally in cognitive neuroscience, the term "mirroring" (or "resonance") refers to a process of neural imitation of the behavior observed in another person which under normal conditions, is similar to the neural process underlying this behavior. For instance, neuroscientists have observed neuron populations that activate both when people report experiencing an emotion and when they observe someone showing the same emotion in a video. Gallese and Goldman (1998) therefore suggested that mirror neurons might represent the substratum of the human brain's simulation capacities. More recently Goldman (2006) introduced a distinction between two kinds of mental reading and two respectively corresponding types of simulation:

- *"low-level"* mental reading—i.e., simple ways to assign mental states to another person, such as attributing emotions to people based on their facial expressions; the associated simulation is based on automatic, unconscious mirroring responses such as the mimicking of facial expressions and body movements;

- "*high-level*" mental reading, involving imaginative reasoning, such as that involved in predicting someone else's decision in a complex situation; in this instance, the associated simulation requires at times conscious effort and is guided by information in long term memory.

High-level simulation is similar to scientific simulation, because task-specific knowledge is used as a model to predict and anticipate behavior. Moreover, Shanton and Goldman (2010) outlined some similarities between mental reading and other cognitive skills, such as episodic memory (the capacity to consciously remember personally experienced events and situations with the accompanying feeling of mentally reliving them and prospection (predicting what will happen). They considered these similarities as indirect evidence that memory and mental reading actually tap the same kind of simulation mechanism.

2.4 Grounding Cognition in Simulation

Independently of ToM, the idea that many different cognitive abilities depend on the basic mechanism of simulation has developed in other areas of cognitive science, particularly in theories of "embodied cognition" (Gibbs 2006a; Shapiro 2010) and "grounded cognition" (Barsalou 2008a). The core idea of the embodied view is that cognition arises from the interaction of the brain with the body and with the rest of the world. In other words, the body and the social and physical world shape the very nature of our cognitive processes and thus, the ways in which we perceive and conceive the world. This embodied view runs counter to the neo-Cartesian stance, which is founded on an ontological separation between mind and body. This latter view is reflected in the separation between mental states and physical substratum in the functionalist philosophy of mind, between the algorithmic and implementation levels in artificial intelligence, and between cognitive and sensorimotor processes in psychology. We can find the origins of the embodied cognition account in many fields of cognitive science, and particularly, in:

- the cognitive linguistics literature on conceptual metaphor (Lakoff and Johnson 1980);
- the construction of robots based on biological principles (Brooks 1991; Pfeifer and Bongard 2006);
- the field of active perception in human and computer vision (Ballard 1991; Noë 2004);
- the dynamical approach to developmental psychology (Thelen and Smith 1994);
- studies on the role of action in cognition and meaning (Glenberg and Kaschak 2002).

Barsalou (2008a) summarized a large body of research supporting the existence of modal representations and simulations in all aspects of cognition—e.g., in perception and action, memory, knowledge and conceptual elaboration, language comprehension, reasoning, social cognition, and developmental psychology. All of these different branches of research are critical towards the traditional cognitive science view, which is based on formal logic and computer science. In this latter approach, human cognition is considered to be the result of a "physical symbol system", i.e., a set of symbol structures manipulated by processes to produce other symbol structures (Newell and Simon 1976). Specifically, a symbol structure is made up of a certain number of fixed instances (or tokens) and of processes acting on the symbol structures in concert with syntactic rules, similar to those of a formal language. Newell (1980) considers this kind of system as equivalent to a universal Turing machine (an early, abstract model of what later became the digital computer). It is the cognition-computation analogy established thereby (and similarly between mind and software) that informed the classic cognitive approach in psychology (Pylyshyn 1980).

Embodied cognition diverges from classical cognitive science on the issue of the nature of mental representations and of processes operating on them. In particular, symbols are not viewed as fixed entities to be manipulated from formal rules, but neural activity elements that are analogically coupled with perceptual and motor states.[2] According to the "dynamical hypothesis" (van Gelder 1999), cognitive processes are best described not in the language of formal systems, but in the language of dynamical systems theory, i.e., as "a set of quantitative variables changing continually, concurrently, and interdependently, over quantitative time in accordance with dynamic laws described by some set of equations" (ibid., p. 245). A further difference from traditional cognitive science concerns the semantics of mental representations. In the traditional approach, the meaning of a symbol has a conventional nature, as occurs with the words of a language or with the *zero* and *one* sequences of a computer's binary code. Searle (1980), however, criticized the idea that a system can be intelligent if the meaning of its symbols originates only out of its internal relations with other symbols, as in a dictionary or in a semantic network. According to Harnad (1990), symbols must be somehow based on direct relations with their external referents, and the issue of specifying the nature of this relation has been called the "symbol-grounding problem". These ideas were further developed in embodied cognition theory, which states that a symbol takes on meaning through perception and action, i.e. through the causal pairing with external objects or environmental features. What happens, however, when this sensorimotor pairing is not possible, because the external object is unavailable, as occurs, e.g., when we recall a past event, attempt to grasp an abstract concept, or to make future plans? As illustrated below, in this instance, the symbol-grounding problem solution might lie in the concept of mental simulation.

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[2] A radical version of the embodied cognition view, influenced by dynamical systems theory and by ecological psychology, actually denies the existence of mental representations (Chemero 2009). Most proponents of embodied cognition, however, continue to view representational states as being fundamental to a theory of cognition.

Barsalou (1999, 2008a), in fact, examined the idea of mental simulation as a solution for the grounding of conceptual and abstract mental representations. In his "grounded cognition" approach, simulation is considered a fundamental form of computation in the brain, and this simulation ability is thought to underlie many cognitive skills such as perception, memory, language, and problem-solving.[3] In Barsalou's definition: "Simulation is the re-enactment of perceptual, motor, and introspective states acquired during experience with the world, body, and mind" (2008a, p. 618). At the basis of cognition there are "perceptual symbols", i.e., subsets of perceptual states extracted from the above-mentioned states to serve as symbols and to support superior cognitive functioning. These symbols are called "modals" because they preserve the modality-specific information of the perceptual states from which they derive, as opposed to the "amodal" symbols of computational theories, which are arbitrary transductions of perceptual states. Some examples of modal symbols in the human brain are mental images and feature detectors. The different modalities' information is combined in neuron populations called *convergence zones* (Damasio 1989). Representations of conceptual knowledge are conversely multimodal, as they integrate visual, auditory, motor, tactile, gustatory/olfactory, emotional, and motivational information. Barsalou explains how mental simulation works thereby "As an experience occurs (e.g., easing into a chair), the brain captures states across the modalities and integrates them with a multimodal representation stored in memory (e.g., how a chair looks and feels, the action of sitting, introspections of comfort and relaxation). Later, when knowledge is needed to represent a category (e.g., chair), multimodal representations captured during experiences with its instances are reactivated to simulate how the brain represented perception, action, and introspection associated with it." (2008a, p. 618). Barsalou also suggested the possible neuronal architecture of these processes: during the storage phase, the superior associative areas in the temporal, parietal, and frontal lobes capture the modality-specific sensory, motor, and introspective activation patterns, and integrate them in a multi-modal mental representation. In the simulation phase, the same associative neurons reactivate the original patterns, allowing for simulation to begin thereby. It is important to note, however, that simulations:

- never completely recreate the original experience, but are always partial recreations and can therefore contain biases and errors;
- can be unconscious, as most frequently is the case, or conscious (as in mental imagination).

Barsalou proposed a "simulator" mechanism—essentially, a distributed multimodal system—to account for how simulations can represent not only individual instances, but also categories. In this view, a "simulator" forms after several

[3] Barsalou calls his approach *grounded cognition*, as he believes that the term *embodied cognition* places too much emphasis on the role of the body in cognition, and that cognition can be grounded in many ways, including through simulation and situated actions, not only through body states.

experiences with individual instances of a category, and corresponds to the *concepts* or *types* of traditional cognitive theories. Importantly, once a simulator is formed, it can reactivate its perceptual symbol subsets as specific simulations and can create an infinite number of simulations depending on the situation. For instance, as described above, a simulator for the concept of "chair" forms after several experiences with this type of object; it can then create simulations of events, such as those of standing on a chair, sitting in the armchair of a cinema, lifting a chair and taking it to another room, etc… . It is the context that determines which simulation will be activated. Simulators for abstract concepts form in the same way, but tend to capture even more multimodal simulations of events extended over time and their corresponding introspective states. For example, a simulator for the concept of "success" can create the simulation of a sports race, including the start, race, and finish line phases, as well as internal perceptions, such as motivation to continue the race, the belief you can win, and the emotion of winning.

2.5 Simulation and Metaphor

Simulation has also been gaining ground in another area of cognitive science—Cognitive Linguistics—which analyzes natural language through the lens of the conceptual and experiential bases of linguistic categories (Evans and Green 2006). The fundamental assumption of cognitive linguistics is that language reflects the organization of thought and is therefore a window on cognitive functioning. The most well-known cognitive linguistics studies were conducted by George Lakoff and Mark Johnson during the 1980s (Lakoff and Johnson 1980; Lakoff 1987) and investigated the topic of conceptual metaphor. These authors found that metaphor is not only a figure of speech, but also the way in which the conceptual system organizes abstract concepts in terms of concrete experiences. In conceptual metaphor, a conceptual domain (target) is understood in terms of another conceptual domain (source), which is typically less abstract or complex than the target domain. This process is achieved through a series of systematic correspondences, or "mappings", between elements and relations in a source domain and those in its target domain. For example, in the conceptual metaphor of LIFE IS A JOURNEY, the domain "life" is comprehended in terms of the domain "journey", as the latter is less abstract and complex than the former.[4] According to Lakoff and Johnson (1980), metaphorical relations between conceptual domains do not emerge from their intrinsic similarities but from recurring physical experiences that provide the bases for correlations between specific domains. For instance, in the metaphor MORE IS UP, which is inherent in phrase such as "the temperature rose" or "high

[4] In cognitive linguistics, conceptual metaphors are usually written in capital letters to distinguish them from corresponding expressions in everyday language.

energy particles", the abstract conceptual domain of "amount" (target) is based on the domain of "level" (source). This latter domain is more concrete because it is grounded on the common experience of pouring a liquid into a container and watching the level rise, or of placing an object on a pile and watching the pile grow as more objects are piled on. In this example, the experiential basis is that of the behavior of physical objects, but in other cases, it can be of a bodily nature, as in DESIRE IS HUNGER, or of a social and cultural nature, as in LIFE IS A GAMBLING GAME.

According to a theory developed by Grady (1997), more complex metaphors can be broken down into elementary structures called "primary metaphors". For instance, the metaphor THEORIES ARE BUILDINGS depends on expressions such as "the foundation of a theory", "facts solid enough to support the hypotheses" or "a shaky argument". It can result from two primary metaphors: ABSTRACT ORGANIZATION IS PHYSICAL STRUCTURE and VIABILITY IS ERECTNESS. In a primary metaphor, the source domain is always made up of a body experience having a sensorimotor or interoceptive nature, whereas the target domain does not consist of an abstract concept, as generally occurs, but of a subjective one. For example, in the metaphor AFFECTION IS WARMTH, both concepts are linked to direct experiences, but the former is more personal and subjective than the latter. Their role of linking mind and body allow primary metaphors to be considered a solution offered by cognitive linguistics to the symbol-grounding problem. Another solution has been suggested by image-schema theorists.

In 1987, in his book "The Body in the Mind", Mark Johnson described image-schemas as being abstract structures emerging from sensorimotor experiences, such as a movement in space and the handling of objects, or from introspective experiences, such as sensations and emotions. For instance, the image-schema PATH results from the physical experience of following a movement with your eyes or of moving from one place to another. The image-schema CONTAINER results from several experiences with physical objects, such as glasses, boxes or closets, and from interoceptive body experiences, for example, sensations linked to the consumption of drink and food. Some image-schemas have a complex structure, such as CONTAINER (once again), as it can be considered to be made up of the elementary image-schemas of INSIDE, OUTSIDE, BOUNDARY. Table 2.3 lists our most basic image-schemas.

In language comprehension, a word describing spatial relations, such as "in", activates an instance of the schema CONTAINER and of its elements. Thus, when we hear the phrase "in the bottle", we naturally associate the parts of the bottle with the elements of the schema. The reader should note that image-schemas are non-propositional representations and are therefore non-linguistic in nature. At the same time, however, they are also not mental images, as they represent knowledge at a more general and abstract level than that of a specific image. Moreover, they are analogical, because they maintain a relation of similarity with the same type of sensorial experience that creates them. In cognitive linguistics, image-schemas are commonly illustrated via diagrams (Fig. 2.4) with the accompanying caution to

Table 2.3 List of image-schemas (from Evans and Green 2006, p. 190)

Space	Up–down, front–back, left–right, near–far, centre–periphery, contact, straight, verticality
Containment	Container, in–out, surface, full, empty, content
Locomotion	Momentum, source-path-goal
Balance	Axis balance, twin-pan balance, point balance, equilibrium
Force	Compulsion, blockage, counterforce, diversion, removal of restraint, enablement, attraction, resistance
Unity/ multiplicity	Merging, collection, splitting, iteration, part–whole, count–mass, link (age)
Identity	Matching, superimposition
Existence	Removal, bounded space, cycle, object, process

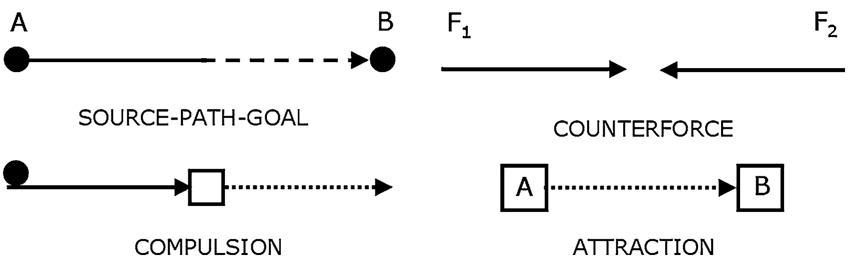


Fig. 2.4 Examples of graphic representation of image-schemas

consider them simple visual aids. In fact, image-schemas are not directly available for conscious introspection, and should therefore not be confused with any type of image.

The importance of image-schemas lies in the fact that, in addition to organizing the experience and comprehension of concrete events, they are also the foundation of abstract thought, given that they serve as source domains for many conceptual metaphors. For example, the image-schema SOURCE-PATH-GOAL is the source domain of the metaphor PURPOSES ARE DESTINATIONS, linked to phrases such as "going ahead with our plans" and "working our way around obstacles". The dynamic and knowledge-organizing nature of image-schemas leads us once more to the topic of simulation.

In cognitive linguistics, mental simulation has been proposed as a comprehension mechanism for figurative language and conceptual metaphors.[5] Matlock (2004) experimentally studied the comprehension of fictive motion sentences such as "the road runs through the valley" or "the trail goes from El Portal to Yosemite". These kinds of sentences use a motion verb in a non-literal way, to communicate the idea of a situation in which nothing is actually moving. To understand these metaphors, the listener assumes a perspective in the scene and

[5] Several psycholinguistics studies (see Fischer and Zwaan 2008, for a review) have examined the role of perceptual and motor simulation in the comprehension of literal, and thus non-metaphorical, language.

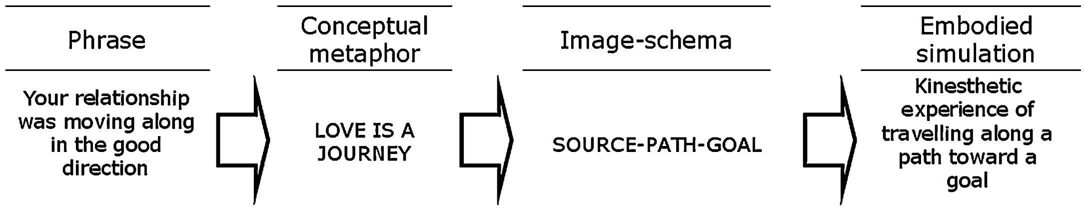


Fig. 2.5 The comprehension of a metaphorical sentence based on embodied simulation

unconsciously simulates moving through it or scanning it. According to Gibbs (2006b), when people encounter abstract conceptual metaphors or metaphors concerning physically impossible actions, they create mental simulations of their bodies performing the actions described in the metaphor. For example, in the context of a romance, understanding the sentence "Your relationship was moving along in the right direction" induces listeners to imagine they are physically moving along a path to a destination. The image-schema SOURCE-PATH-GOAL constitutes the model underlying the simulation (Fig. 2.5).

Embodied simulations such as these allow us to understand abstract entities as if they were concrete objects and to mentally act on them thereby, as for example, in phrases such as "grasping a concept", "chewing on an idea", "swallowing one's pride", "coughing up a secret", or "breaking off the relationship" (Gibbs 2006b, p. 444). Also in this case, simulation presumably involves the automatic recruitment of the brains' perceptual and motor areas corresponding to the execution of real action. It is underscored, however, that these research findings do not suggest that people necessarily use embodied simulations every time they hear metaphorical phrases. The conventional nature of these phrases suggests that in ordinary discourse, people rely on lexical (and thus more automatic) comprehension mechanisms. Simulation processes are most probably marshaled, conversely, when reasoning and problem solving tasks require that a given metaphor phrase be used to make inferences.

Lastly, Ritchie (2008) proposed a mechanism for the interpretation of conceptual metaphors based on Barsalou's perceptual symbol theory. In this account, global actions described in the metaphor are not simulated, but the partial simulations of perceptual experiences, moods and emotions are, and remain uncoupled from any particular experience. The simulation of a specific perceptual symbol depends on its importance in a given context. Thus, "the perceptual simulations activated by a metaphor such as *depths of a dark cave* or *filled with discoveries* are complex and subtle; they will be experienced differently by each reader, and they defy simple labels" (ibid.). Ritchie moreover maintains that three processing levels can be identified, in function of whether the construction of meaning is based on:

1. linguistic relations among lexical elements;
2. the partial activation of perceptual simulations;
3. the complete activation of the body action simulations.

The first level is considered more “superficial”, and the other two, of respectively increasing depth.[6]

In the 1970s, Newell and Simon concluded their presentation of the Physical Symbol System Hypothesis, by stating that, “the principal body of evidence for the symbol system hypothesis that we haven’t considered is negative evidence: the absence of specific competing hypotheses as to how intelligent activity might be accomplished whether by man or machine” (1976, p. 120). Nowadays, however, embodied cognition has indeed become a competing hypothesis by attributing simulation with a key role as a form of computation that is a plausible alternative to the one traditionally conceptualized in classical cognitive science.

[6] The difference between superficial and deep processing is crucial in instructional contexts and will be examined in reference to simulation, in Chap. 7.

Chapter 3
Models Everywhere

The original is unfaithful to the translation.
Jorge Luis Borges, Sobre el Vathek de William Beckford (1943)

3.1 A Concept at the Crossroads of Different Disciplines

In early human history, the main function of mental models was most probably that of fostering human environmental adaptation. Mental simulation capacity made it possible to predict the behavior of other humans and to plan and organize complex action sequences, such as large animal hunts. Yet, if the models available to those early humans had remained only mental models, we likely would not have progressed much from prehistoric to modern times! At one point during human evolution, humans began to externalize their own mental models and share them with their companions, launching the "cognitive revolution" of the upper Paleolithic period (40,000–10,000 years ago) thereby. Some anthropologists believe that this change was due to enhanced working-memory capacity (Coolidge and Wynn, 2005), which allowed for the growing use of spoken language and tool construction as well as the beginnings of new forms of language, such as rituals, visual arts, and music. Several millennia later, humans began to wonder about the relations that might exist between their symbolic creations and reality. For example, Plato described the cognitive role of models or "paradeigmata" ("παραδείγματι") in his dialog "Politicus" (the Statesman). One of the characters therein referred to the model of the weaver to illustrate the nature of the statesman and compared his method to that of weaving various fibers to create a single fabric. More generally, Plato described the usefulness of models in terms of a process that involves identifying similarities and differences. When examining the conceptual similarities and differences between a model and a phenomenon under examination, people transform their initially confused and approximate ideas into more precise and rigorous comprehension. As described in the following chapters, this is also what occurs when students compare their own mental models of a system to a simulation model.

Currently, models are a topic of interest for philosophers of science who are particularly interested in the relation that exists between models, scientific theories, and experiments. Yet, the epistemic role of models was initially investigated, and the first working models of the human nervous system were constructed, shortly after World War II in the field of cybernetics.

F. Landriscina, *Simulation and Learning*, DOI: 10.1007/978-1-4614-1954-9_3,

3.2 From Logic to Representation

For many years, the prevailing view in philosophy of science was that of logical empiricism, according to which knowledge is based on logical inferences derived from observable facts. In this view, a scientific theory is made up of axioms (the "laws of nature") and of correspondence rules that connect theoretical terms to observational ones (Carnap 1956; Nagel 1961). A theory can therefore be described in a formal language, such as that of logic. To assign a meaning to symbols of a formal language, one must resort to a form of interpretation that renders a particular statement true (or false), and indeed, this interpretation is called a "model." In other words, a model is a function that connects a predicate with a series of values, making it *true* or *false*. Since the 1960s, this linguistic approach to theories has presented many problems, linked both to difficulty in discerning the theoretical from the observational parts of a language and to its limited applicability to theories other than those of physics. Moreover, in the latter part of the twentieth century, philosophy of science increasingly focused on the historical process of changes in scientific theories—a view influenced by Khun's 1962 publication of "The Structure of Scientific Revolutions." As a result of these studies, the conceptual picture of empiricism was increasingly perceived as being detached from true scientific practice, and several alternative conceptions developed over the intervening years.

One such conception is the "semantic view" of scientific theories: It conversely places models at the very center of scientific activity and affirms that a theory is a "family of models" (Suppes 1960; Suppe 1977; van Fraassen 1980). In this context, the term "model" indicates an abstract structure that can be described, not linguistically, but through set-theoretical methods, that is, as a set of objects with properties and relations defined in that set. The semantic view holds that a model's epistemic value does not lie in its provision of a way to interpret a formal system, but in its representation of a part of the world and in its allowing for true deductions about it. The solution proposed to account for this representational capacity is the existence of a relation R connecting a target system S and a model M, as shown in Fig 3.1

The arrow indicates that the relation is asymmetric: M represents S, but S does not represent M. To ensure the accuracy of this representation, van Fraassen (1980) proposed the existence of a relation of isomorphism between the target system and a substructure of the model. This type of relation is based on the presence of correspondences between the S and M elements and relations, such that each S element corresponds to an M element, and the correspondence maintains binary relations between the respective elements. Thus, when a pair of S

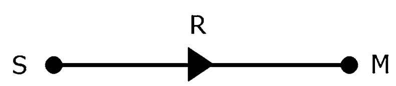


Fig. 3.1 Dyadic relation between target and model system

elements is linked by a certain relation, the two corresponding M elements are connected by an analog relation. More simply put, two entities are isomorphic if they have the same structure, even if differing in substance or appearance. For example, two cubes can be isomorphic due to the number and spatial disposition similarity of their faces, even when made of different materials, colors, or sizes. Isomorphism, however, turned out to be too restrictive a criterion to account for the models used in scientific practice, which are idealized structures that can seldom be isomorphic with the system they represent. Moreover, scientists typically use even partial or inexact models. Thus, as an alternative to isomorphism, Giere (1999) proposed the criterion of similarity, according to which even an idealized model may be compared with a real system in terms of its degree of similarity with it.

In his book "Languages of Art" (1968), the philosopher Nelson Goodman outlined a general characterization of the representation relation based on the concept of "denotation." Goodman maintained that resemblance is not a necessary and sufficient criterion for one object to represent another. The resemblance relation is symmetrical, contrarily to that of representation: "while a painting may represent the Duke of Wellington, the Duke doesn't represent the painting" (ibid. p. 4). An object X can be similar to an object Y but that does not necessarily mean that it is a representation of Y: "none of the automobiles off an assembly line is a picture of any of the rest; and a man is not normally a representation of another man, even his twin brother" (ibid.). Moreover, resemblance is not a necessary criterion, given that an object can refer to another one, via even symbolic convention and thus with no resemblance to it.

So, what then might be the general feature of representation? Goodman sees it in the denotation relation, which means that, to represent an object, a picture "must be a symbol for it, stand for it, refer to it" (ibid., p. 5). At the same point, he states that resemblance is the feature of a particular kind of denotation, in addition to other kinds of denotation, such as verbal and diagrammatic forms. By considering models in this light, isomorphism and resemblance become just two of many ways for a model to refer to a system. We can say that a model M denotes a system S if it is isomorphic to S, but also if it is similar to S; it describes S; it symbolizes S; and so on. These different kinds of denotation are not mutually exclusive, and in a scientific model, they rather frequently appear together. For example, in a three-dimensional model of DNA, the shape of the spiral coils is similar to the DNA double helix; the pairing between nucleotide couples is isomorphic to that of the molecule, and its chemical elements are symbolized by different-colored materials (Fig. 3.2).

3.3 Models and Problem Solving

With respect to the different ways a system can be represented, and the role of these in different forms of reasoning, several general considerations can be derived from the historical mathematical problem of the "Seven Bridges of Königsberg."

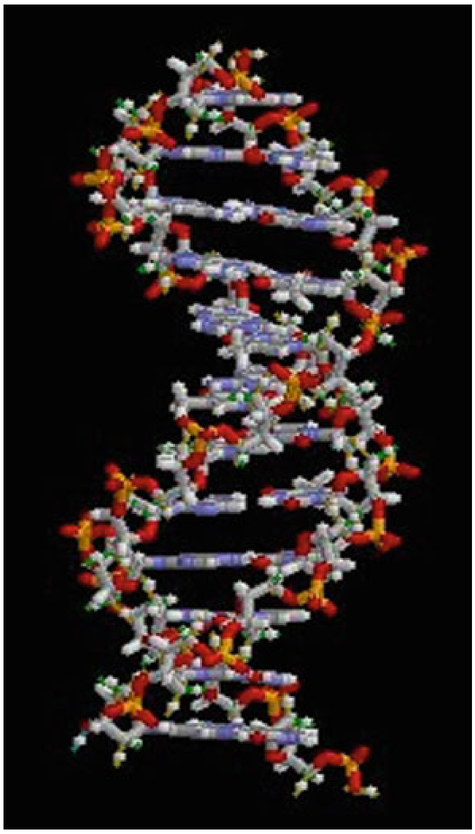


Fig. 3.2 Three-dimensional model of DNA molecule (from Wikipedia)

Specifically, the city of Königsberg (currently Kaliningrad, in Russia) once straddled the two banks of the Pregel River with an island in the middle and the river forking off into two branches downstream of it. In the city's earlier days, the island and the land areas were connected by seven bridges (Fig. 3.3, left). The problem, solved in 1735 by Leonhard Euler, had been posed in terms of how one might stroll through the city by crossing each bridge only once.

Euler's solved the problem by imagining (and drawing) the bridges in a simplified map (Fig. 3.3, right) and by marking the different land areas separated by the river, respectively, with a capital letter (A, B, C, D) and each bridge with a small letter (a, b, c, d, e, f, g). He wrote: "My entire method rests on the

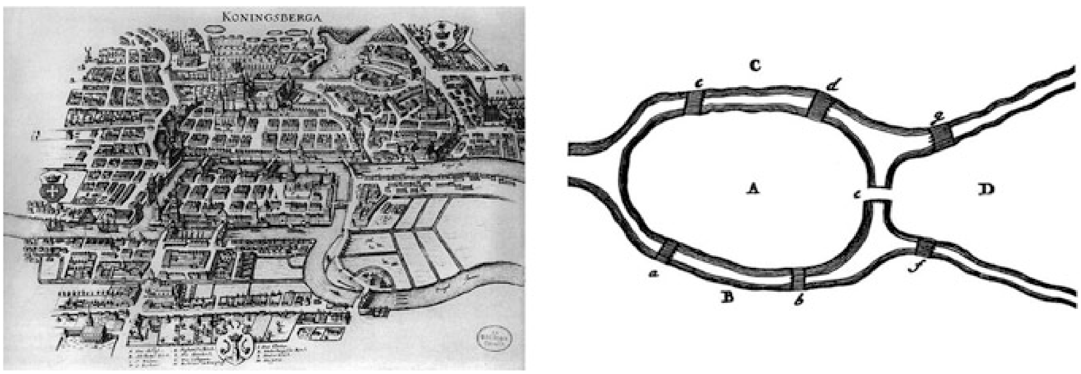
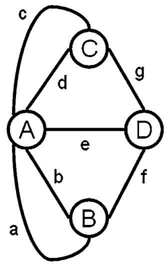


Fig. 3.3 An inkprint of Königsberg in seventeenth century and Euler's map of the city bridges



$$A=\begin{pmatrix} 0 & 2 & 2 & 1 \\ 2 & 0 & 0 & 1 \\ 2 & 0 & 0 & 1 \\ 1 & 1 & 1 & 0 \end{pmatrix}$$

Fig. 3.4 The bridges of Königsberg represented as a graph and as an adjacency matrix

appropriate and convenient way in which I denote the crossing of bridges" (1741, Newman 1956, p. 574). Thus, each bridge crossing was assigned two letters, the first indicating the departure point and the second, the point of arrival (for example, AB denoted the path from A to B). Each path conversely was assigned a series of letters. The type of representation Euler chose allowed him to rapidly demonstrate that it was impossible to cross each bridge only once. His reasoning was based both on the aforementioned graphical representation and on combinatorial methods. Euler also found a general solution for the problem, by developing some simple rules to determine whether the task was possible, given any river branch pattern and number of bridges.

Hence, Euler essentially used an abstract structure that was characterized by a relation of isomorphism with the city's bridges. Today, this type of structure is called a "graph" and can be visually represented with a set of points (vertices) connected by lines (edges).[1] In this representation, the land areas correspond to the vertices and the bridges, to the edges (Fig. 3.4, left). Moreover, the same structure can be represented as an "adjacency matrix," that is, a matrix in which the element in line j and column k equals the number of edges linking the nodes j and k (Fig. 3.4, right).

Thus, the system of the city's bridges can be represented via different models characterized by increasing level of abstraction:

- a pictorial model (the inkprint of Königsberg in seventeenth century) linked to his original by a relation of resemblance;
- a schematic visual model (Euler's map of the city bridges), which preserves the spatial relations among represented elements;
- a diagrammatic visual model, which preserves only the topology of links among elements;
- a mathematical model (the matrix) consisting of numbers and symbols combined according to the rules of matrix algebra.

All of the above-listed models are isomorphic with the represented system and with each other—that is, they all represent the same abstract topological structure. As described in Sect. 2.1, isomorphism was also a property that Johnson-Laird

[1] Although Euler's work is historically considered to be the origin of graph theory, both the term "graph" and its visual representation appeared more than a century later. The English mathematician Arthur Cayley, inspired by the molecular structures of organic chemistry, was the first to represent a graph as we know it today.

assigned to mental models, which he moreover compared to scientific diagrams and graphs. It is interesting to note that Euler's original map can play a cognitive intermediation role between the realistic and more abstract types of representation. In fact, the schematic representation and letters he used rendered the respective correspondences between the picture's elements and those of the graph much more salient and, consequently, the meaning of the graph itself. This example brings us back to the topic of the role of models in reasoning, which the next section will examine in the context of scientific practice.

3.4 Types of Models

Research on the role of models in scientific practice reveals that they are neither linguistic statements nor abstract structures, as maintained by logical empiricism and by the semantic view of theories, respectively, but are objects constructed and used in many different ways (Black 1962; Hesse 1966; Cartwright 1983; Morgan and Morrison 1999). Models can differ in terms of their denotation relation, representation format, media used, and information representation standards. Table 3.1 shows a taxonomy proposed by Gilbert and Boulter (1998) in the context of a model-based approach to learning and instruction. Here, the classification criterion is the mode of representation, that is, the way in which a model can be expressed by a person through action, speech, written description, and other material depictions.

Table 3.1 Main types of models based on the mode of representation (Gilbert and Boulter 1998). (descriptions and examples provided by Author)

Mode	Description	Examples
Concrete	Plastic, wood, or metal objects; laboratory equipment	The sticks-and-balls model of a molecule. The scale model of a building or of a plane
Verbal	The written or spoken description of a system	The text explaining a scientific picture in a book. A teacher's verbal explanation of a physical phenomenon
Mathematical	Mathematical equations and formulas	The equation of motion of a body. A system of differential equations describing a population model in biology. A statistical formula
Visual	Pictures, animations, maps, graphs, and diagrams	The picture of a cell in a biology book. The animation of oceanic currents. The diagram of a mechanical system
Symbolic	Chemical formula and symbols, circuits, technical schemas	A chemical equation. An electronic circuit. A musical score
Gestural	Gestures and body movements	The movement of the hands made by someone to support his/her explanation of a concept

Another way to classify models is based on the distinction between *propositional* and *diagrammatic* representations, mentioned in the previous chapter. Larkin and Simon (1987) used this distinction to highlight the ways in which two formats can convey different kinds of information and allow for different actions. In particular, propositional and diagrammatic models can contain the same information, but differ in terms of *computational efficiency*. Specifically, whereas a diagram explicitly preserves spatial relations among the system's components, spatial relations remain implicit in a propositional model (e.g., a verbal description or a computer program). Conversely, a propositional model can preserve other kinds of relations, such as temporal or logical sequences. Differences among representational formats can also be interpreted in terms of a model's specific "cognitive affordances," that is, the ways in which it supports and facilitates thought and knowledge (Zhang 1997). For instance, whereas a 3D model "invites" the manipulation and spatial exploration of the object represented, a simulation program invites the observer to modify the parameters of a curve to view a corresponding change in the curve's shape. Knuuttila (2005) discussed the characterization of a model in terms of affordances and constraints in her conception of models as "epistemic artefacts," that is, material objects constructed via a specific medium and used in different ways to produce new knowledge.

Another distinction is that of static versus dynamic models, given that static models are structural representations of a system and dynamic models show the time-related change in a system. In a static model, such as a molecular structure model or an architectural model, the time variable is not rendered explicit, whereas in a dynamic model, time takes on a primary role, as in the case of educational animations. Yet, if we include the person using the model, the distinction between static and dynamic models is not as clear-cut as it seems. Hegarty's experiments (1992) on the comprehension of simple mechanical systems' diagrams showed that even a static picture can be interpreted dynamically and can be mentally animated. Specifically, if a picture contains arrows or other symbolic elements suggesting movement, people tend to interpret it as a functional description of the system, making inferences as to the movement of its parts thereby (Heiser and Tversky, 2006).[2] Thus, these inferences essentially employ the "tool" of mental simulation (Hegarty 2004). Movement is not simulated continuously, but is broken down into small steps, which are animated in a sequence that corresponds to a causal chain of events. Similarly, when people observe a continuous process in an animation, they tend to interpret it and remember it part by part, probably due to the human mind's general tendency to structure experience by segmenting it into meaningful units (Tversky et al. 2008). A similar phenomenon was observed by Bogacz and Trafton (2002) in studies with experienced weather forecasters, who were found to mentally animate static meteorological visualizations. In particular, the forecasters

[2] Many scientific images contain extrapictorial elements, such as arrows and other conventional graphic signs, to represent, for example, the lines of force of a magnetic field in a conductor and facilitate comprehension thereby.

examined very few dynamic visualizations, although animations were available. Based on the forecaster's talking aloud descriptions, the authors concluded that they preferred mentally animating their own weather models over viewing explicit animations.

The models presented in the context of the Königsberg bridge problem were all static, given that a structural description sufficed to solve the problem. One way to untangle the problem, however, would have been to mentally simulate walking over the bridges and through the town. Yet, simulating all possible walks would have been tedious and difficult, due to the high number of possible combinations, and thus, formal reasoning was more appropriate to solving the problem. In the final analysis, a model may be interpreted as being static or dynamic, but this outcome will ultimately depend on the user's goals and mental models. This is therefore another instance of the subtle interaction between models and thought processes.

3.5 The Pragmatic Perspective

The semantic view of theories, which holds that a model is an abstract structure, has been called into doubt by more recent studies on the history of science, which highlight both the variety of models used in scientific research and the importance of their material dimension. Even the idea that the epistemic value of a model consists in the accurate representation of a part of the world has run counter to a series of objections, due to the fact that representation is merely one of a model's possible uses. This situation has led philosophers of science to develop new conceptions about the nature of scientific models. Their point of departure is the observation that the simplification of reality accompanying the construction of a new scientific model always entails unrealistic assumptions, which can take on the following forms:

- *abstractions*: these do not take target system properties thought to be irrelevant into account. For example, the effect of air resistance is disregarded in projectile trajectory calculations, and the ideal gas law similarly does not take the effect of molecular volume and intermolecular forces into account;
- *idealizations*: these models contain elements that do not exist in the target system, such as frictionless planes and point masses in mechanics, isolated populations in biology, or agents with perfect information in economics.

Thus, omissions and distortions are as much a part of a model as its correspondences with the original. Moreover, a model can be created without any links to an actual target system, as in the instance of the Goodwin oscillator. This mathematical model of enzymatic control processes was conceived during the 1960s and linked to a real biologic mechanism only after specific scientific discoveries were made later on, in the 1980s and 1990s (Bechtel and Abrahamsen 2010). In the instance of models that refer to future events (e.g., prediction or prototype models), the systems they represent do not even exist yet. Furthermore, many scientific models do not aim to represent real systems, because they are used as demonstrations or proofs of existence. Noteworthy examples are John Conway's *Game of Life*, which inspired further research on self-organizing systems, and artificial neural networks, invented as an information processing mechanism alternative to those of classic cognitive science. Similarly, the "toy models" of theoretical physics are highly idealized representations with no direct links to observable physical phenomena. They are invented to render complex systems such as quantum fields or black holes mathematically tractable and to yield insights for the development of new theories. Lastly, scientists also use models with errors or which have been superseded by other more accurate models, if they consider them to be useful for practical tasks or teaching purposes. Coll and Lajium (2011) cite two examples from chemistry, that is, the Aufbau principle and the ligand field theory, which are still used in textbooks and in laboratory practice, in spite of their limitations. The economist Milton Friedman (1953) famously defended economic models that contain false assumptions, as long as they yield satisfactory predictions. Thus, if models can contain overt omissions or distortions, not represent a real system, and can be used even if they contain mistakes, their epistemic value is nearly completely independent from their ability to represent reality in an accurate way.

The limitations of the representational view led to new explanations considering the pragmatic aspects of representation, that is, the *intentions* of the model creator and its user. These intentions are indeed an essential aspect for creating the directionality required by the representation relation, because to represent something else, a representation must be constructed or used intentionally. This view requires, however, a shift of attention from the idea of representation to the action of *representing* and thus to the purposes and goals of the person carrying out this activity. Unrealistic assumptions in the construction of a model are not arbitrary, insofar as they satisfy the purpose for which the model was created and the conventions and standards of the community to which it is addressed. Specifically, Giere (2004) proposed the following triadic relation as an alternative to the dyadic relation discussed at the beginning of the present chapter:

- S uses X to represent W for purposes P (p. 743);

where S can be a person, a group or a community, and W is an aspect of the real world. This means then that the choice of a model depends on the problem at hand and on the users' goals. Yet, why should one choose one model over another to represent a given system? Suarez (2004) identified a selection criterion in the model's objectivity, conceived as its ability to convey specific information about the target system. Thus, a model can allow for true, informative, and scientifically appropriate inferences on a target system without necessarily being isomorphic with it or similar to it.

The progressive refining of the concept of model has had a consequent impact on how the model–theory relation itself is conceived. As described in Sect. 3.2, in the linguistic approach of logical empiricism, models had a marginal position as compared to theories, given that the latter were considered the very core of scientific knowledge. Conversely, the structuralist view holds models to be the fulcrum of scientific theorization. Yet, both paradigms define a model in relation to a theory: It is always "the model of" a theory. A more thorough analysis, however, of the ways in which models are actually constructed and of their functions, has shown that a model can be relatively independent from a theory. According to Cartwright (1983), models are a bridge between theory and data: "To explain a phenomenon is to find a model that fits it into the basic framework of the theory and thus allows us to derive analogs for the messy and complicated phenomenological laws which are true of it" (p. 152). To serve this function, a model must include some attributes of the target system but can also possess elements of convenience or imagination. For instance, in London's model of superconductivity, the model's equations cannot automatically be derived from Maxwell's equations of electromagnetism, but are motivated by phenomenological considerations and are the result of intuition and creativity. The effectiveness of the model does not depend on its capacity to verify a theory, but on its capacity to account for the Meissner effect (i.e., that a material crossing the threshold of superconductivity expels all internal magnetic fields[3]). Morgan and Morrison's (1998) *models as mediators* conception also places models somewhere between theory and reality, and indeed, it is their partial autonomy from both that renders them such effective investigation and learning tools. The autonomy of models is to be seen in their ability to mediate not only between theory and data, as in Cartwright's account, but also to mediate among theories and paradigms. For example, the "small-world" and "scale-free" networks proposed in the 1990s (Watts and Strogatz 1998; Barabasi and Albert 1999) are now used in the domain of neuroscience as mediators between the theoretical approaches of computational neuroscience and the anatomic and functional studies of brain networks (Stam and Reijneveld 2007).

Knuuttila's conception of models as epistemic artifacts is very much in line with these pragmatic approaches and holds that models are material objects used in many ways to create knowledge (Knuuttila 2005). In this conception, models are not considered just any type of material objects, but the materialization of theoretical, abstract, or ideal objects through the use of some medium. Thus, their material dimension makes them shared objects of knowledge and therefore able to serve a mediation function among diverse people and practices. Moreover, Knuuttila took a radical step in setting aside the representational view and in stating that models can be independently researched in and of themselves: "Our understanding of modeling should not be restricted to the view that models represent some external target systems accurately. Apart from being representative things, models are typically also productive things whose workability and testability are crucial for their epistemic value. Models can function not only as tools

[3] The Meissner effect can produce the phenomenon of magnetic levitation.

and inference generators, but also as research objects in their own right" (ibid., p. 3). Thus, models do not only represent, but produce new knowledge, during their construction, through experimentation and by allowing alternative uses. As described in Chap. 5, this conception is particularly appropriate for characterizing the epistemic role of simulation models, which, due to their complexity and interactivity, lend themselves well to investigation and experimentation (Knuuttila and Merz 2009; Knuuttila and Loettgers 2010).

3.6 The Cybernetic Perspective

The idea that the epistemic value of models cannot be based on a constant and absolute relationship with reality had already been stated in cybernetics, an interdisciplinary research program conceived in the 1940s, the purpose of which was the study of abstract principles of organization in complex systems.[4] Most cybernetic themes emerged during the Macy Conferences on cybernetics (1946–1953), which aimed to establish the bases of a general science of the human mind. Among many participants, Norbert Wiener, William Ross Ashby, Warren McCulloch, and Arturo Rosenblueth are considered to be the founders of this discipline (Heims 1991). In particular, they employed the mathematical tools of dynamical systems' theory and servomechanism theory to study the brain and the nervous system. A servomechanism is an automatic device, which regulates variation through differences between current and desired value, that is, through a feedback circuit. Cybernetics was the first discipline to recognize the importance of feedback mechanisms in determining the goal-directed behavior and self-organization of all types of complex systems, including biological and social ones.[5] The main cybernetics research method was that of using electronic and electromechanical devices to construct working models. For example, Ashby's homeostat (1952) was the model of an abstract, self-organizing system made up of four reciprocally interacting parts (see Sect. 4.10). A system of differential equations was used to describe the homeostat, and it was physically built as an electronic device. In a similar way, Grey Walter's "turtle robots" (1953) were small roller robots that could move about a room and respond to external stimuli. The cyberneticians' approach consisted in deriving general principles from the analysis of these working models' conduct. Pickering (2010) called this type of approach as "performative epistemology" and described it as "a vision of knowledge as *part of* performance rather than as an external controller of it" (ibid., p. 25).

[4] For a more thorough discussion on the history of this discipline, see Heims (1991) and Pickering (2010). Previous influences from physiology and psychology are described in Cordeschi (2008).

[5] The opening Macy Conference (1946) was entitled "Feedback Mechanisms and Circular Causal Systems in Biological and Social Systems."

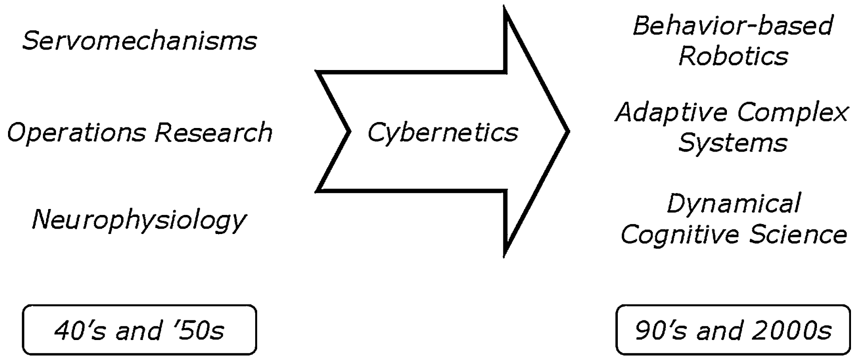


Fig. 3.5 Cybernetics as an intermediary between time-separated approaches

In the 1970s, cybernetics began to rapidly cede ground in university's computer science departments to the new paradigm of artificial intelligence, which prevailed over the following decades. This also occurred in the social sciences, where artificial intelligence methods provided the nascent cognitive revolution with its "mind as software" metaphor. Later, cybernetic electromechanical models came to be considered nearly obsolete with respect to computers and programming languages. Nonetheless, like an underground river occasionally surfacing, the ideas of cybernetics continued to influence subsequent scientific developments in the fields of cognitive science and simulation, such as behavior-based robotics (Brooks 1991), Kaufmann's theory of complex adaptive systems (1995), and dynamical approaches to cognition (van Gelder 1998) (Fig 3.5).

Ashby, one of the founding fathers of cybernetics, analyzed the nature of the relation between models and reality on various occasions through the years. For example, in his "Introduction to Cybernetics" (1957), he explained this relation in terms of isomorphism, by using the example of a dynamic system that can be represented in three ways—that is, via mechanical, electrical, and mathematical models—each of which is isomorphic with the system it represents. In the same work, he proposed the less-restrictive criterion of *homomorphism*, which preserves the binary relations between the elements of two systems, but, differently from isomorphism, does not require a one-to-one correspondence between the elements of each system. This criterion makes it possible to consider only certain aspects of a system and its model: "the model is itself seldom regarded in all its practical detail: usually it is only some aspect of the model that is related to the biological system; thus the tin mouse may be a satisfactory model of a living mouse—provided one ignores the tininess of the one and the proteinness of the other" (ibid., p. 109). A few years later, Ashby (1967) described his own homeostat theory with a structuralist approach similar to the one used many years later by proponents of the semantic view of scientific theories. In 1970, Conant and Ashby demonstrated a theorem by which any "good regulator" of a system is also a part of that system, and concluded that modeling is a necessary part of the regulation of a complex system and, therefore, also of the human brain. In 1972, Ashby's previous structuralist considerations yielded to a more pragmatic approach: "Nothing can exceed, or even equal, the truth and accuracy of the real system itself. Every model is inferior, a distortion

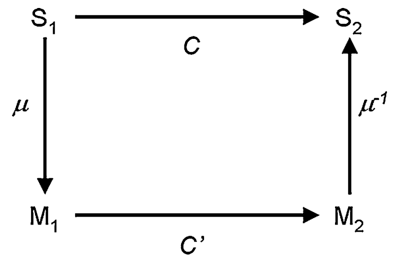


Fig. 3.6 Relations between a dynamic system and its model (adapted from Ashby 1972, p. 96)

and a lie. Why then we bother with models? Ultimately, I propose, we make models for their convenience" (1972, p. 94). Ashby described the relation between a dynamic system and its model as a series of operations that map a succession of system states onto a succession of model states (Fig. 3.6).

Suppose the system S is the orbit of a planet, then the model M gives a description of the planet's coordinates in time to predict its positions. Let us also imagine a change C in S, that is, from an initial position S_1 of the planet to a position S_2 one year later. In model M, a corresponding change C' from an initial coordinate M_1 to a subsequent coordinate M_2 will occur. If the model is to be useful, it must have a correspondence rule, μ, such that if we use μ to translate the real state S_1 to obtain a corresponding M_1, and thereby impose C' to obtain M_2, followed by the inverse rule μ^{-1}, we finally obtain S_2. Thus, three model operations correspond to a single direct operation in real world:

$$\mu^{-1}\, C'\, \mu = C$$

In Ashby's own words: "What science has found is that many cases exist in which the use of the three operations is actually more convenient than the use of one. It seems to me that this purely pragmatic reason for using a model is fundamental, even if it is less pretentious than some of the more 'philosophical' reasons" (p. 96), concluding that: "from here on, then, I shall take as a basis the thesis that the first virtue of a model is to be useful" (ibid.). The idea that a model depends on the goal for which it was conceived, ignores some aspects of the system to be understood, and changes some other aspects is at the root of a later development in cybernetics known as "second-order cybernetics," whose main exponent was Heinz von Foerster. According to von Foerster (2003), most models are not models of an objective reality but of other models (thus second-order models), and it is for this reason that second-order cybernetics focuses on the interaction between an observer and the system.

3.7 A General Theory of Models

Considering the general focus of cybernetics on models, it should come as no surprise that a general theory of models emerged from this discipline in the 1970s. This theory was formulated by Herbert Stachowiak, a German philosopher and mathematician with a cybernetics background. In 1973, Stachowiak published a

Table 3.2 The four-question schema of models

Model	
Of what?	*For whom?*
For what?	*When?*

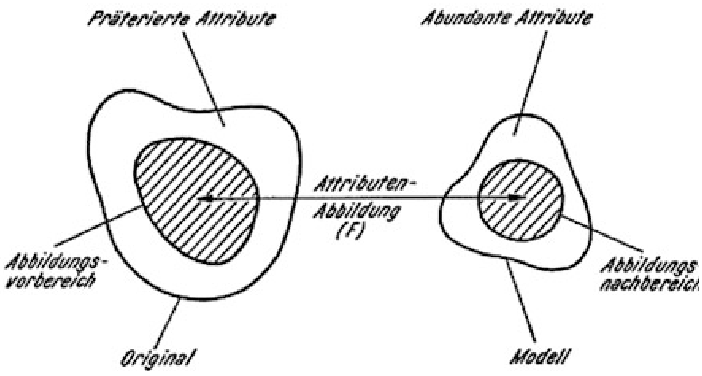


Fig. 3.7 The original-model relation. *Präterierte attribute* ignored attributes. *Abundante attribute* superflous attributes. *Attributen abbildung* attributes image. *Vorbereich* domain. *Nachbereich* codomain. (From Stachowiak 1973, p. 157)

book in German entitled “Allgemeine Modelltheorie” (A General Theory of Models), presenting a model-based conception of knowledge and action. This conception, called “systematic neo-pragmatism,” was based on Peirce’s pragmatics and semiotics, on cybernetics, and on a structuralist view of scientific theories.[6] According to this conception, a model is a limited reproduction of reality, characterized by at least three features:

1. *Representation*. Models are always “models of something,” that is, images, representations of natural or artificial originals, which in turn can be models of something else.
2. *Reduction*. Models generally do not capture all the attributes of the original, but only attributes considered to be important by the model’s creators and users.
3. *Pragmatism*. Models are not copies of their originals. They have a substitution function for (a) specific individuals who must understand and/or act using the model, during (b) specific time intervals, and (c) within the limitations of specific ideal or real operations.

Stachowiak wrote that “models aren’t just models *of something*; they are also models *for someone*, a human or artificial user. They perform their role *in time*, meaning during a time interval. And finally, they are models *for a particular purpose*. A completely pragmatic definition of the concept of model doesn’t have to consider only *the thing represented* by it, but also *for whom, when* and *for what* the model has been built, in relation to its specific function” (ibid., p. 133). A model should always be understood by answering the four questions that made up Stachowiak’s “four-question schema” of models (Table 3.2).

[6] Stachowiak’s neopragmatic epistemology is recognized by Seel (2003) to be an influence on his model-centered approach to learning and instruction, which will be examined in Chap. 5

Table 3.3 Taxonomy of physical models (adapted from Stachowiak 1973)

Physical models			
Graphical models	Pictures		
	Diagrams		
Technical models	Physico-technical	Mechanical	*Static/dynamic*
		Electro-mechanical	
		Electronic	*Analog/digital*
		Electro-chemical	
	Biotechnical		
	Psycho-technical		
	Socio-technical		
Semantic models			
Emotional models	Belief		
Cognitive models	Scientific	Formal	
		Empirical/theoretical	*Formal/non-formal*
		Operative/prospective	
	Metaphysical		
	Poetic		

Stachowiak represented the original–model relation by using a relation of homomorphism (Fig. 3.7), which he characterized very pragmatically, as follows:

1. the relation concerns only a subset of the original's attributes, that is, the one in dashed area, and attributes outside of this area are ignored;
2. the model presents superfluous attributes not included in the relation, but introduced to make the model work;
3. the decision as to which attributes are to be considered depends on a specific person's aims in a given time interval.

An important consequence of these ideas is that to understand a model, we must also know the context in which it was created. Moreover, even the original is relative, as all things that can be modeled can be used as an original for some modeling process, not only a "part of reality," but also another model or a system, object, or entity that does not yet exist, but can be created in the future.

According to the Austrian philosopher Gelbmann (2002), the Allgemeine Modelltheorie of Stachowiak also entails a corresponding non-statement view of the concept of theory. Gelbmann defines a theory as a quintuple:

$$Th = \ <O, M, k, t, Z>$$

where O and M are attribute classes, respectively, of the original and of the model; k indicates the subject defining the model; t a particular moment or time interval; and Z stands for the interests, purposes, targets, calibrating values to be accounted for by the theory. Thus, Z has the role of a pragmatic selection criterion for the attributes of M, considered crucial to the description of O. Moreover, each model is, by its own nature, incomplete and temporary; thus, in science, we frequently witness a progression of models, which in turn lead to change in the theory itself. In Stachowiak's conception, models are classified as:

physical (or external) models, which are of a physical nature;
semantic (or internal) models, which are mental models.

Stachowiak's articulated taxonomy of models (Table 3.3) does not include only physical models but also visual, linguistic, and electronic models (the latter type including analog or digital ones).

Chapter 4
Simulation Modeling

All teems with symbol; the wise man is the man who in any one thing can read another.

Plotinus, The First Ennead (c. 250)

4.1 From Models to Simulation

A fundamental aspect of simulation is the presence of a model, of a real or imagined system. But how does a simulation model differ from other kinds of models; what is its distinctive feature? Firstly, the models we have considered herein are also, in of and themselves, representations of something else. For example, in a picture, small scale model, or chemical formula, model and representation coincide. A simulation model, conversely, must actually be run if it is to render the phenomenon under examination visible. Specifically, it must produce a process that must evolve autonomously, from an initial to a final state, as if it had its own life. Thus a simulation model is:

1. a structure to produce a behavior.

Moreover, simulation users should be able to interpret this process as the representation of the behavior of a real or imagined system. As Hartmann states "a simulation imitates one process by another process" (1996, p. 5). The behavior showed in the simulation should:

2. reproduce some aspects of the time evolution of a system.

Lastly, this process must not be considered final, but users should be able to modify it by changing the simulation's initial conditions or other features. A model is thereby able to:

3. create a variety of behaviors depending on the users' decisions.

These three properties allow a model to become an object that can be explored and manipulated in many different ways; it can also produce behaviors that cannot be predicted by merely examining its structure. The simulation process unfolds in

F. Landriscina, *Simulation and Learning*, DOI: 10.1007/978-1-4614-1954-9_4,

a sequence of states of a physical system that is the "vehicle" of the simulation, and this can be:

- a physical model (physical simulation);
- an analog computer (analog simulation);
- a digital computer (computer-based simulation).

The hypothesis underlying a physical simulation is that the causes acting in the model are of the same type of those acting in the real system. For instance:

- air running over the scale model of an aircraft wing in a wind tunnel acts on it just as wind does on a real aircraft wing;
- electrical discharges in the experiments of Miller and Urey on the origin of life have the same role of lightning in the primordial atmosphere.

In these instances, modeling consists in the construction of an experimental apparatus that should reproduce the real system in the truest way. A different case is that of analog computers, i.e., mechanical, hydraulic, or electronic devices, in which some physical quantities continuously change in a way that mirrors the changes in the systems' variables. Examples of analog computers are:

- Kelvin's tide predictor, a mechanical calculator build by Lord Kelvin in 1876, which uses a system, of pulleys, wires and dials;
- Phillips Hydraulic Computer (also known as MONIAC, Monetary National Income Analogue Computer), created in 1949 by the economist William Phillips to model the United Kingdom's national economic processes;
- Electronic analog computers built with operational amplifiers and used from the 40s to the 70s in science and industry.

The equivalence between model and system is not physical in this instance, but mathematical. The model's creation consists in the configuration of computer elements, such that its internal processes are analogous to those of the represented system, even if they occur over a much shorter time span. For example, an electronic analog computer can simulate a mechanical, biological, or economic system, because its circuits follow the same dynamics of the studied system, i.e., they are regulated by the same type of equations (Small 2001). Although electronic analog computers became obsolete with the advent of the digital computer, analog computation is still of theoretical and practical interest, as an alternative to the symbolic computation represented by the Turing machine, and for building new types of computers (MacLennan 2009). Another interesting feature of analog computation lies in the frequently proposed hypothesis that the human brain is also a particular kind of analog computer (Rubel 1985; Shagrir 2010; Siegelmann 1996; van Gelder 1998).

4.2 Computational Models

The most well-known simulations are digital, which allow for the simulation of any kind of system, regardless of its physical nature and the phenomenon being studied. The model underlying these simulations is a *computational model*, which may be defined as:

- an algorithm created to reproduce some behavioral features of a system in a computer program.[1]

A computational model is not just the translation of a mathematical model into a computer language, but it involves a series of adjustments and changes, which depend on the algorithm and on the hardware and software architecture of the computer that will run the program. It is important, however, to distinguish between simulation and other scientific uses for computers not requiring the construction of a model, for example:

- the manipulation of mathematical expressions in a symbolic versus numerical form;
- the automatic or semi-automatic demonstration of theorems;
- the visualization of scientific data.

The essential elements of a computational model are *variables*, *constants*, and *parameters*, which are interlinked by *relations* in the form of *equations* or *rules*. A variable is a symbol representing a relevant aspect of the studied system, the value of which can change during a simulation run.[2] A constant conversely represents a quantity that does not change. A parameter is a quantity used to define a relation between variables. For example, in the equation of a line, $y = \mathrm{ax} + b$, the a and b parameters define the relation between the variables y and x, and the set of their values determine a family of lines that differ in terms of slope and intercept. Parameters are kept constant during a simulation run but they can be varied from one run to another to explore the model's behavior. There are three types of variables:

- *state variables,* which define the state of the system at a given point in time;
- *input variables*, which reflect the action of external elements influencing the behavior of the studied system and which are user-modifiable;
- *output variables*, which provide information on the model's behavior.

The "time" variable, generally indicated by the symbol t, is a particular one: Although many other variables depend on it, it does not depend on any other variable. The time dependence of a variable x can be indicated by the function $x(t)$,

[1] The terms "computational model" and "simulation model" will be used hereafter interchangeably.

[2] Only the variables that are part of the model of the system are considered here and not all the computer code variables, which do not necessarily pertain to an equation or rule.

the domain of which is the set of t values for which corresponding x values exist. This domain generally coincides with the system's *observation interval*.

In a computer, information is represented by discrete values and in a "memory of finite dimension". A continuous variable must therefore be represented by a finite number of digits. Due to the same limitations, a continuous function can be digitally represented only by its value at a finite number of points of its domain. Thus, approximation errors are introduced and can be reduced, but not completely obviated (Table 4.1). The study of algorithms using numerical approximation for problems of mathematical analysis is the subject of numerical analysis, a field of mathematics that also yields the numerical solution methods used in simulation.

The equations used to describe a system's behavior over time are differential equations, i.e., equations in which the unknown is a function of one variable (ordinary differential equations) or of several variables (partial differential equations), which relates the values of the function itself and its derivatives of various orders. Most nonlinear ordinary differential equations and partial differential equations cannot be solved analytically, i.e., through a series of well-known operations, but only numerically. This implies that they must be transformed into "finite difference equations" and that their solutions must be calculated by way of numerical analysis methods. The use of these methods requires the choice of an appropriate algorithm and the determination of its validity for the current equation.

An appropriate numerical algorithm should be:

- *stable*, i.e., it should not amplify the errors that are necessarily present in data representation and in computation;
- *efficient*, a computer should be able to yield the solution in an acceptable timeframe;
- *precise*, the calculated solution should not differ too greatly from the exact one.

The efficiency and precision criteria cannot always be satisfied at the same time, and in more complex simulations, the former is at times preferred over the latter.

One of the most important aspects of a numerical algorithm is the modeling of time progress. Continuous time must be divided into discrete time-steps. The smaller the steps, the better the approximation will be. Very small time-steps, however, can slow down the execution of the algorithm, because they require relatively more calculations per time unit and therefore have a greater computational cost. Moreover, in the numerical resolution of some differential equations, time-steps that are too small can cause errors that increase in an uncontrolled manner.

Table 4.1 Types of approximation errors

Type of error	Source of error
Round-off errors	A real number is represented with a finite number of digits
Discretization errors	A continuous function is represented by its value at a finite number of points of its domain
Truncation errors	An iterative method is terminated and the approximate solution differs from the exact solution

The results of a numerical simulation must therefore be carefully studied, to verify that they correspond to the workings of the system under study and that no undesired effects due to the chosen algorithm occur.

An important aspect of a computational model is the extent to which it considers uncertainty and variability. We can distinguish two kinds of models in this sense:

- *deterministic*, in which a certain input always produces the same output;
- *stochastic*, which accept random input variables that lead to random outputs.

The main difference between these two kinds of models consists in the fact that in a deterministic simulation model, the same initial situation always leads to the same result, whereas the results of a stochastic simulation are in and of themselves stochastic, and therefore may vary greatly from one simulation run to another. To study the behavior of a stochastic model, one must execute a certain number of simulations and use appropriate statistical techniques to analyze the results.

4.3 The Modeling and Simulation Process

Modeling and simulation process can be described in varying detail, depending on the simulation context and project. Birta and Arbez (2007, p. 41) provided an overview of the essential steps involved in carrying out a modeling and simulation study in the context of system engineering (shown here in Fig. 4.1[3]) The following chapters will be dedicated to explaining how many of these steps must also be considered when building an instructional simulation.

For the sake of simplicity, only the most salient outputs will be examined herein: (1) the project description (2) the conceptual model (3) the computational model, and (4) the simulation program. Figure 4.2 shows the relations among these outputs (as indicated by the backward arrows, it is often necessary to backtrack from one step of the modeling process to the previous one).

4.3.1 Project Description

The project description is a document using a relatively informal language to describe the project goals, the system to be modeled and, if available, real data to use as a reference in validating the model. Clarity of purpose is essential here, as

3 Balci (1998, p. 337) and Robinson (2004, p. 211) developed their own, similar diagrams of the life cycle of a simulation study.

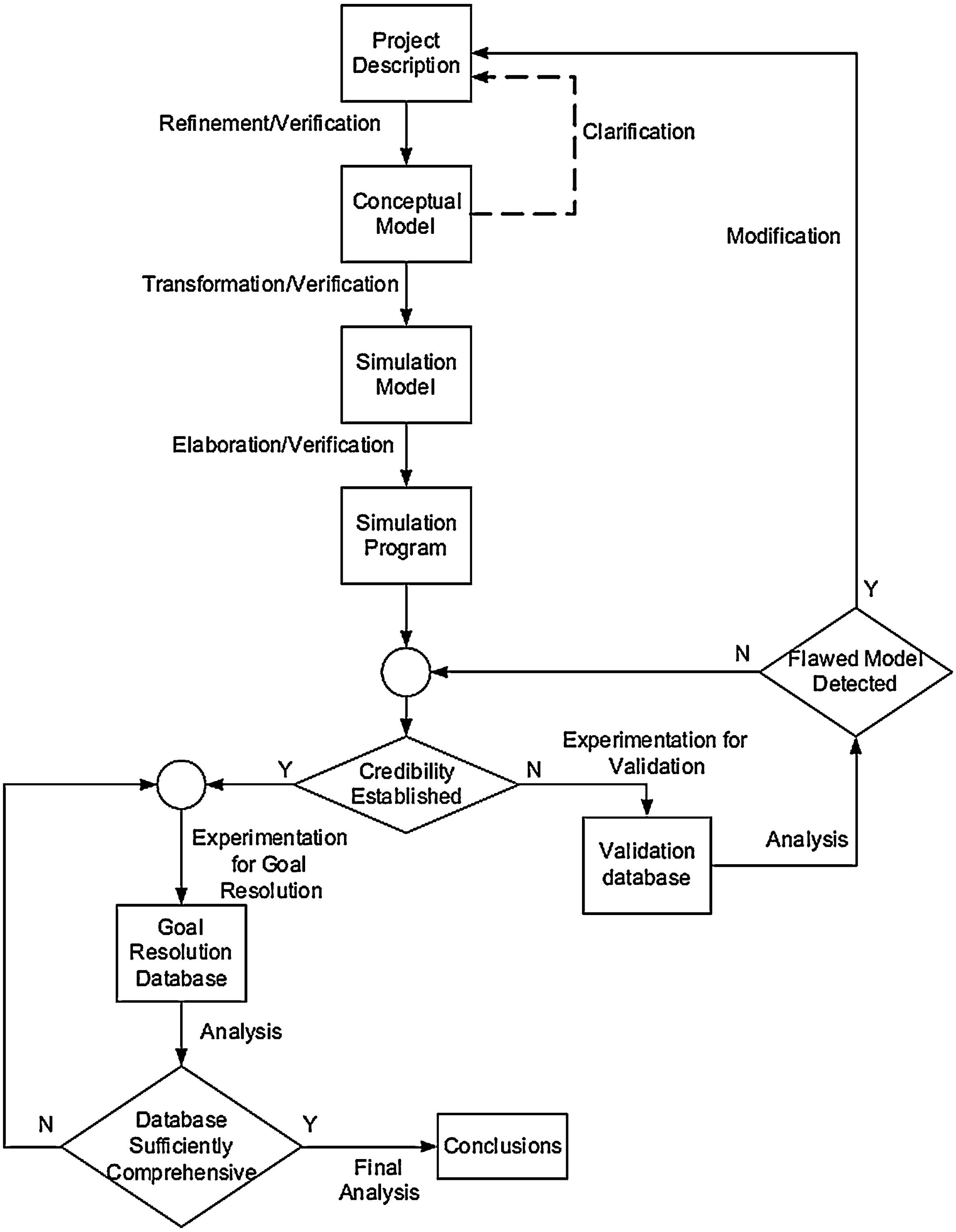


Fig. 4.1 The modeling and simulation process (Birta and Arbez 2007, p.41)

the project description should illustrate not only *what* the model should represent, but also *for whom*, *when,* and *for what purpose*, as suggested in Stachowiak's "four-question schema" (see Sect. 3.6).

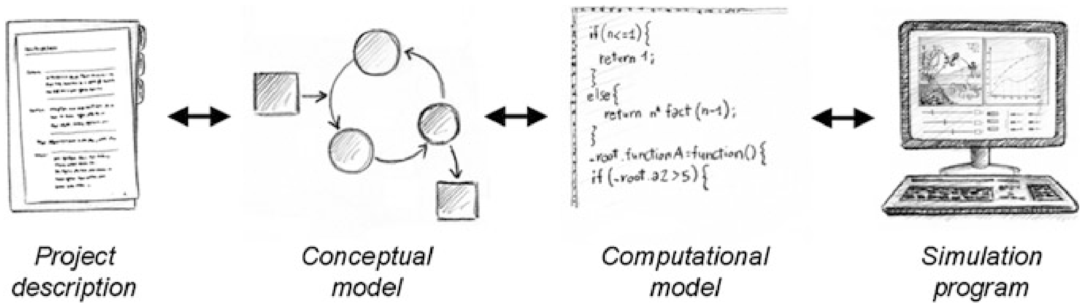


Fig. 4.2 Main outputs of a modeling and simulation process outputs

4.3.2 Conceptual Model

The hypotheses underlying the simulation are specified in the *conceptual model*, which Robinson defines as “a non-software specific description of the simulation model that is to be developed, describing the objectives, input, output, content, assumptions and simplifications of the model” (2004, p. 65). Conceptual model development depends on our amount of knowledge of the studied system. In some cases, one can use a pre-existing mathematical model that allows for system representation through an equation or a system of equations. In other instances, it is necessary to describe the system’s structure as realistically as possible, and to use specific equations or rules to model the interrelations among its elements. The conceptual model can be a collection of partial models each of which captures some specific aspect of the system and which can materialize in cognitive artefacts, such as descriptions, pictures, diagrams, maps, graphs, equations, or rules. The definition of the conceptual model can also lead to a better specification of the project’s goals, including the possibility that a research method other than simulation might be more appropriate to achieving these goals.

4.3.3 Computational Model

The hypotheses and indications yielded by the conceptual model, in turn make up the computational model input. Computational model development can involve a refinement or a revision of the conceptual model. As emphasized by Robinson: “because the processes in a simulation study are performed iteratively, there is an interplay between the computer model, such as it is being coded and the conceptual model, with constant adjustments to both” (ibid., p. 65). A great deal of iteration may be required before the computational model can be considered to satisfactorily represent the conceptual one.

4.3.4 Simulation Program

In and of itself, a computational model cannot provide the interaction mechanisms that simulation users require to explore the model's behavior, advance hypotheses, and analyze the results. These mechanisms are provided by the software's functional components, which allow the user to visualize the simulated processes, decision input, data analysis, report creation, and parameter optimization. Together, the computational model and these functional components make up the *simulation program*: the instrument that allows users to conduct numerical experiments (Fig. 4.3).

The simulation program also allows for the verification and validation of the computational model's accuracy. Verification is the process of ensuring that the computational model is consistent with the specifications of the conceptual model, and validation is the process of ensuring that the computational model is consistent with the project's goals. As suggested by Balci (1994, 1998), verification and validation processes answer the following questions, respectively:

- Did we build the model right?
- Did we build the right model?

Typical verification activities are checking for programming errors and verifying that the numerical algorithm does not produce a greater degree of error than expected. Typical activities of the validation process are submitting the simulation results to the judgment of domain experts and comparing the simulated behavior to that of the real system. One of the most common techniques used to validate a model is that of parameter optimization. Specifically, the parameters are varied continuously to explore the corresponding model behaviors as broadly as possible (a process called "exploring the parameter space"), to bring them as close as possible to the observed or desired ones. The final goal of verification and validation is to ensure the credibility of the simulation program in terms of the project's goals.

As examined in the next chapter, the outputs described in this section are those that students must produce when constructing a simulation as part of a model-based learning activity.

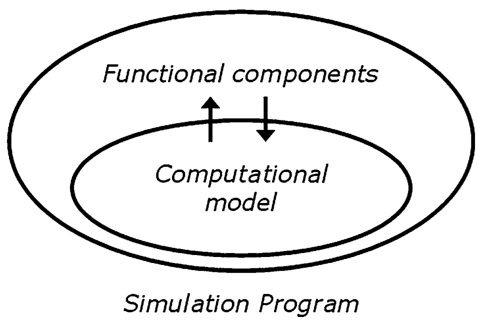


Fig. 4.3 The components of a simulation program

4.4 Modeling and Simulation Paradigms

Over the years, many simulation methods have been developed, each with its particular modeling strategy and with its corresponding modeling and simulation software environments. Some of these methods can be considered paradigms in and of themselves, because they differ from not only a technical perspective, but also in terms of their underlying assumptions about the object to be modeled, how it should be modeled, and how to interpret the simulation results. A modeling and simulation paradigm is characterized by the type of elements and relations that are used in the simulation's conceptual model (Table 4.2).

The equation-based paradigm was the first to be used, and is to date the most frequently employed. It has therefore led to the development of other methods, which in turn differ in terms of the type of elements and relations they use (Table 4.3).

Many simulations in science and industry are based on the approximate solution of partial differential equations or of integral equations. Thus, numerical methods, which essentially evolved into domains of highly specialized theoretical and practical research (Table 4.4), have been developed to this end; these are linked to:

- *computer science*, for the use of parallel algorithms and high-speed supercomputers; and
- *scientific visualization*, for the large amount of data that must be visualized as outputs.

How does one choose one simulation paradigm or method over another? Ideally, every modeling and simulation project should include a phase dedicating to choosing the approach (or combination of approaches) in function of the project's goals. Robinson (2010) emphasized the need to maintain the simulation's conceptual model distinct both from the chosen computational model and from a specific modeling software. In concrete terms, however, the modeling software is frequently a project's starting point, and thus, no consideration is given as to whether the phenomenon or problem under examination might be better approached otherwise. The following Sections of this chapter describe each modeling and simulation paradigm's main features and are of a very technical nature. Readers not interested in the paradigms' details can skip to Sect. 4.13, which illustrates a framework that is helpful for understanding the paradigms' conceptual differences.

Table 4.2 Scientific modeling and simulation paradigms

Paradigm	Elements	Relations
Equation-based modeling	State variables	Differential equations
Molecular dynamics	Particles	Intermolecular forces
Agent-based modeling	Agents and their environment	Local interaction rules
Systems dynamics	Stock and flows	Feedback loops
Cellular modeling and simulation	Cellular components and modules	Structure/function relations

Table 4.3 Equation-based modeling methods

Modeling method	Elements	Relations
Dynamical systems modeling	State variables	Continuous or discrete evolution rules
Continuum physics modeling	Volumes and fields	Balance equations and constitutive equations
Compartmental models	Compartments	Coupled ordinary differential equations

Table 4.4 Methods of partial differential equations approximation

Method	Application field
Finite difference method	Thermal engineering, acoustics, fluid dynamics, financial engineering
Finite volume method	Fluid dynamics, physical oceanography, global climate models
Finite element method	Structural mechanics, prototype design weather prediction

4.5 Dynamical Systems Modeling

As mentioned in the previous section, the most well-known simulation paradigm is the equation-based paradigm. Given that the purpose of a simulation is to reproduce some form of time-related change, the equation's independent variable is generally time. In the simplest case, an equation is a known functional relation of the form $y = f(t)$, in which the value of y can be directly calculated for any given value of t, i.e., through a formula. For example, suppose we want to create a simulation to study the motion of a free falling body. The variable of interest in this instance is the space traveled by the body after a certain time, to be calculated as follows:

$$s(t) = -\frac{1}{2}gt^2 - v_0 t + h$$

where g is the standard gravitational acceleration, h is the height from which the body falls, and v_0 is its initial velocity. Knowing the values of the constant g and of the parameters v_0 and h, we only need to substitute any value of t in the formula to obtain the corresponding value of s.

The change of a system over time is the subject of an area of mathematics known as *dynamical systems theory*. A *dynamical system* is a system in which an *evolution rule* describes a system change over time and predicts the system's future state based on its current state. The system's evolution is represented by an orbit in an n-dimensional space, called *phase space*, where n is the number of the system's degrees of freedom.

A well-known model of elementary physics, the *simple pendulum*, can serve as an example of a dynamical system. This model presents the same type of idealizations and abstractions that typify modeling in general. Specifically, the simple pendulum is made of a point-like mass m, hanging from a massless string of constant length l attached to a frictionless pivot and is subject to the standard gravitational acceleration g (Fig. 4.4).

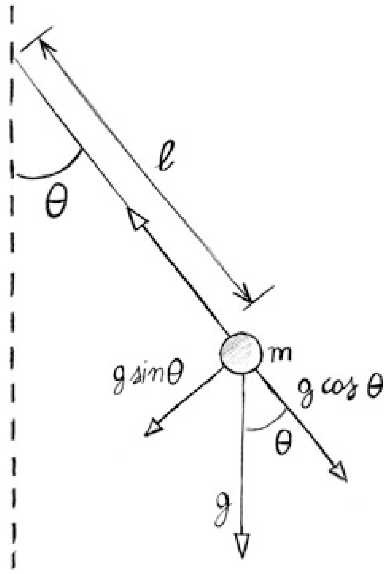


Fig. 4.4 The simple pendulum

If the mass m is pushed only slightly away from its resting position, it oscillates around this position with a constant amplitude and with an oscillation period given by the formula proposed by Huygens in 1658:

$$T = 2\pi\sqrt{\frac{1}{g}}$$

Now, suppose we want to find the mass m position at a certain time t. The quantity we are looking would be the angular displacement $\theta(t)$ between the string and the vertical direction. To find this, we can start from Newton's second law, which is expressed by the equation $\mathbf{F} = m\mathbf{a}$. Humphreys (2004) emphasized that this equation is a *theoretical template*, i.e., a schema describing a general constraint between some quantities (in this instance, force, mass, and acceleration) but which does not allow for the calculation of specific quantities. To achieve an actually computable equation, i.e., a *computational template*, we need to specify a particular function for the force **F**. To do this, we must consider a specific model, such as the free falling body, the inclined plane, or the simple pendulum. In the case of pendulum, it means we should consider only the tangential component of the force, because this is the component that forces the body on its circular path. Thus, the specific function we are seeking is yielded by the formula:

$$F = -\mathrm{mg}\sin\theta$$

Moreover, if we use it as the right hand member of Newton's equation, we obtain:

$$F = \mathrm{ma} = \mathrm{ml}\frac{\mathrm{d}^2\theta}{\mathrm{d}t^2} = -\mathrm{mg}\sin\theta$$

in which $\mathrm{d}^2\theta/\mathrm{d}t^2$ is the angular acceleration. If we then simplify the mass m that is present in both parts, we obtain the following equation of motion:

$$l\frac{\mathrm{d}^2\theta}{\mathrm{d}t^2} = -g\sin\theta$$

This equation is a computational template, as it can be solved and allows for calculation of the angular displacement $\theta(t)$. The presence of the term "sin", however, renders the equation nonlinear, and it is therefore difficult to solve. We can therefore introduce another abstraction (consider only small oscillation angles, for which $\theta << 1$) into the model; approximate the function $\sin\theta$ with the linear term of its development in the Taylor series, $\sin\theta \cong \theta$; and can therefore write:

$$l\frac{\mathrm{d}^2\theta}{\mathrm{d}t^2} = -g\theta$$

which is the "linear" version of the previous equation. The solution of this equation is the formula we were seeking:

$$\theta(t) = \theta_0 \sin(\omega t + \phi_0)$$

which is the well-known harmonic oscillator's formula, describing a periodic motion with angular magnitude θ_0, angular frequency $\omega = 2\pi/T$ and initial phase ϕ_0.

The previous formula can be easily implemented as a program simulating the simple pendulum model. This type of simulation allows a student to use "virtual experiments" to explore some properties of the model—e.g., verifying the oscillation period independence from the mass, or what happens when changing the gravity acceleration value, as if the pendulum were on another planet (Fig. 4.5). We must also remember, however, that the simulation does not show a real pendulum, which physicists call a "material pendulum", but a mathematical model characterized by idealizations and abstractions, such as the hypothesis of small oscillations. Even in Huyghens' time it was understood that if the oscillations become larger, their duration is no longer independent from amplitude, but that larger amplitudes correspond to longer durations—a phenomenon that the simple pendulum simulation cannot reproduce.

How could we calculate the period of a pendulum for any amplitude of oscillation? To do so, we should solve our initial equation of motion, but by abandoning the idea of approximating the function $\sin\theta$ with θ. The equation remains nonlinear thereby, and its solution calls for the evaluation of an *elliptic integral of the first kind*, which can be calculated only by using approximation methods, i.e., an infinite power series:

$$T = 2\pi\sqrt{\frac{L}{g}}\left(1 + \frac{1}{16}\theta^2 + \frac{11}{3072}\theta^4 + \frac{173}{737280}\theta^6 + \dots\right)$$

To complicate matters further, to continue "de-idealizing" the model, we can also consider the effect of friction and obtain the model known as a *nonlinear damped pendulum*. When friction is proportional to angular velocity, the equation of motion becomes:

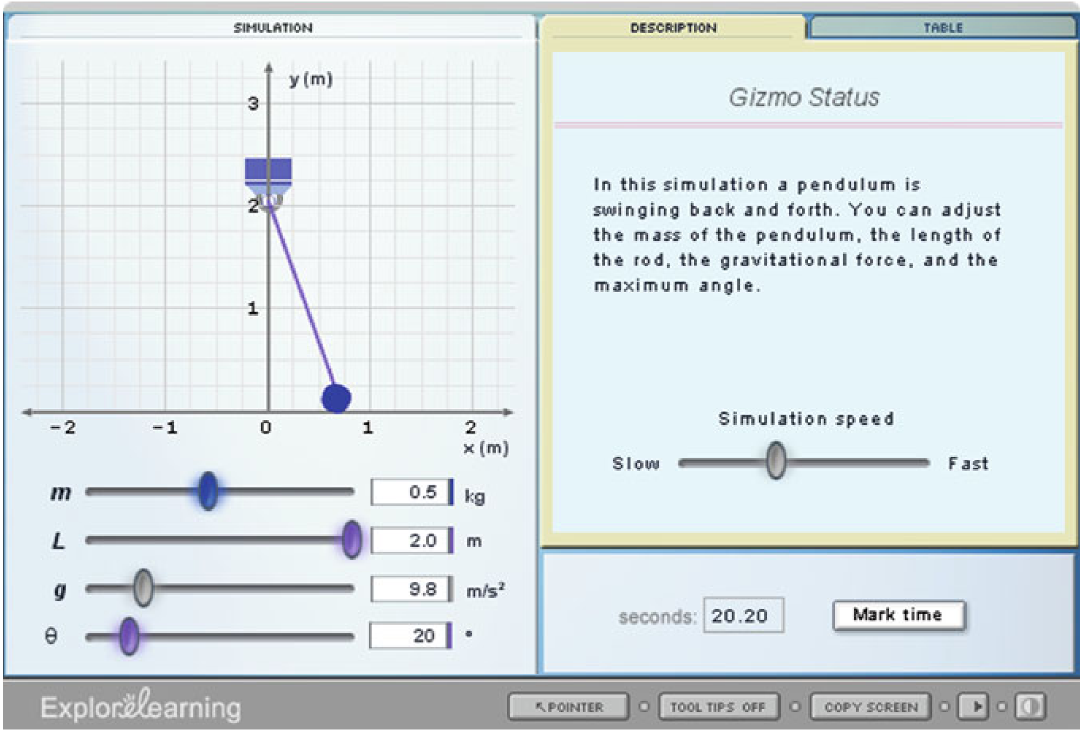


Fig. 4.5 An educational simulation of the simple pendulum. Image courtesy of ExploreLearning Gizmos™. Web site: http://www.ExploreLearning.com

$$l\frac{\mathrm{d}^2\theta}{\mathrm{d}t^2} = -g\sin\theta - c\left(\frac{\mathrm{d}\theta}{\mathrm{d}t}\right)$$

where c is the friction coefficient. Depending on the value of a parameter ζ, called *damping ratio*, the pendulum returns to its resting position by oscillating with an amplitude gradually decreasing to zero ($\zeta < 1$, *underdamping*), or by reducing velocity or stopping without any oscillation ($\zeta > 1$, *overdamping*). In this instance, creating a simulation program is a more complex activity, but also a useful one to explore variety in the model's behavior.

In addition to the standard graphs showing the behavior of the variables over time, the phase space diagram is a further instrument for studying the pendulum. The system has 2 degrees of freedom—the angular displacement θ and the angular velocity $d\theta/dt$—and thus, the phase space in this case is a plane. At any time, the pendulum's condition is represented by a point, and its evolution by an orbit. Whereas the simple pendulum's orbit is an ellipse, the damped pendulum's orbit has a spiral shape (Fig. 4.6). The point representing the system's state moves toward the center of the spiral, as if attracted by it; the center is therefore called an *attractor*. The shape of an orbit can also be interpreted in terms of energy: if the orbit is closed, the system maintains its energy, if it is open, the energy gradually dissipates due to the effect of friction.

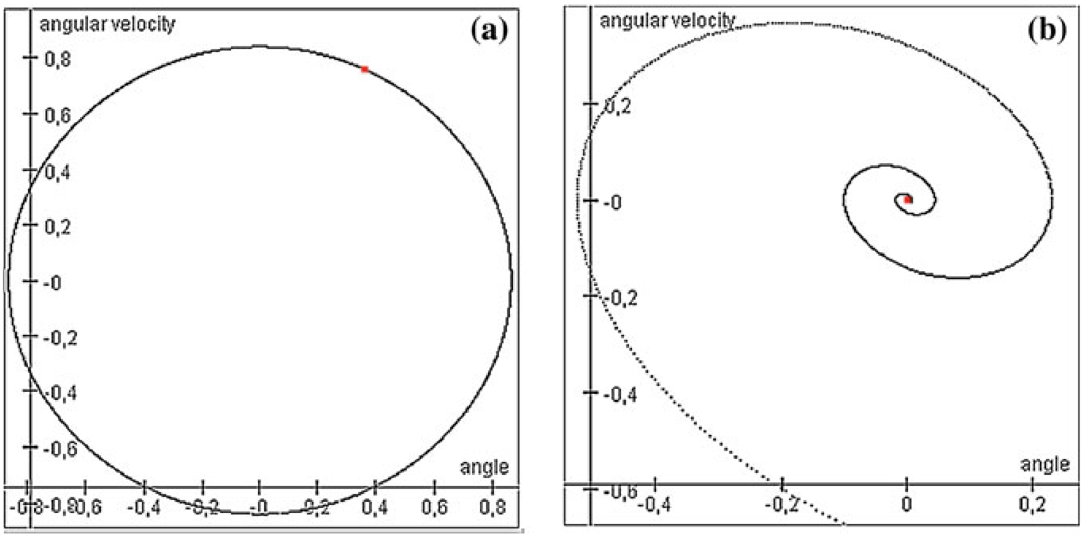


Fig. 4.6 Phase plane diagram **a** Frictionless pendulum. **b** Damped pendulum. Image courtesy of My Physics Lab. Web site: http://www.myphysicslab.com

Many practical applications call for the construction of an artificial system oscillating with a desired frequency even in the presence of friction—e.g., robot leg movement. The only way to maintain a damped pendulum in movement is to apply an external force to it, to balance the energy loss due to damping. In the hypothesis of a periodical external force, the equation of motion becomes:

$$l\frac{d^2\theta}{dt^2} = -g\sin\theta - c\left(\frac{d\theta}{dt}\right) + F\sin\Omega t$$

This differential equation cannot be solved analytically, but only numerically. The system's behavior becomes more and more complex, and simulation is the only way to explore it. If the force is small, the pendulum reaches an equilibrium state, in which the external energy perfectly balances the dissipated energy. Whatever the initial conditions, the orbit in the phase plane is a closed curve, albeit not necessarily an elliptical one, which is called *limit cycle* and also behaves as an attractor.[4] If the external force's amplitude continues increasing, the trajectories become more complex: The point representing the state of the system begins to trace loops, which repeat themselves infinitely, but never identically (Fig. 4.7, left). With a further increase in the amplitude of the external force, we witness a phenomenon called *period doubling* or *bifurcation*, in which the number of loops gradually doubles, such that for particular parameter values, the system becomes *chaotic* (Fig. 4.7, right).

Chaotic systems are deterministic systems that are very sensitive to initial conditions, in which small changes in the initial state lead to significantly different final

[4] For a value of Ω called "resonance frequency", the transfer of energy from the external force to the pendulum reaches its maximum, and the amplitude of the oscillations reaches its maximum value too.

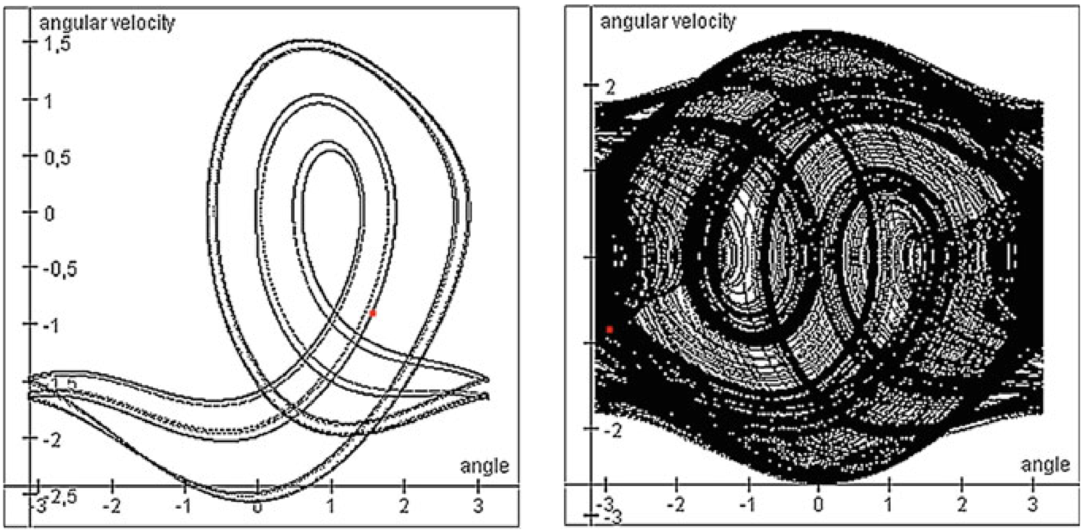


Fig. 4.7 Phase plane diagram. Period doubling (*left*). Chaotic behavior (*right*). Image courtesy of My Physics Lab. Web site: http://www.myphysicslab.com

states (Strogatz 1994). In mathematical terms, uncertainty about the system state increases exponentially with time. The investigation of these systems is the subject of *chaos theory*. Now, reconsidering our nonlinear pendulum, its behavior is represented by a figure called *strange attractor*, made up of countless trajectories that remain enclosed within a finite space. This figure is also a *fractal*, i.e., an irregular geometric curve that has a fine detailed structure, even if observed at arbitrarily small scales, and which is self-similar, i.e., containing copies of itself at different scales. The first strange attractor was discovered in 1963 by the meteorologist Edward Lorenz, who used a digital computer to simulate the behavior of a simple weather variations model made up of a system of three ordinary differential equations.

It should also be noted that many applications do not require the exact or approximate solution of a dynamical system's equation, but only knowledge of some of its qualitative aspects, such as the stability of its equilibrium points. Scientists therefore use the *qualitative theory of differential equations*, a branch of mathematics using geometric techniques developed towards the end of nineteenth century by Henri Poincaré to analyze the stability of the solar system.

4.6 From Mechanics to Everything Else

Although drawn from Newton's mechanics, dynamical systems theory is a mathematical approach that is applicable to any type of system that can be described through a set of time-related variables and an associated evolution rule, and thus by a trajectory in phase space. As stated by Mainzer (2005): "The states (of a dynamical system) can also refer to moving molecules in a gas, excitation of neurons in a neural network, nutrition of organisms in an ecological system, supply and demand of economic markets, or behavior of social groups in human societies" (p. 240). For instance, the system can be an ecosystem, in which two species interact, one of prey and the other of predators (e.g., foxes and rabbits). Alfred Lotka and Vito Volterra studied this type of system in the 1920s as a population biology model. The system can be described by two variables, $x(t)$ and $y(t)$, which respectively represent the prey and predator populations. The evolution rule can take on the form of a system of two ordinary differential equations:

$$\frac{\mathrm{d}x}{\mathrm{d}t} = \mathrm{ax} - \mathrm{bxy}$$

$$\frac{\mathrm{d}y}{\mathrm{d}t} = -\mathrm{cy} + \mathrm{dxy}$$

where a is a parameter representing the difference between the prey's natural birth and death rates, b and d are two constants linked to chance encounters between prey and predators, and c is the natural decay rate of predators when prey are absent. Unlike other nonlinear dynamical systems, Lotka-Volterra equations can be solved analytically. The solutions correspond to periodic oscillations of both populations, in which the prey's growth is followed by the predators' growth, in turn causing a decrease in prey, and so on (Fig. 4.8). The system behavior is represented in the phase plane diagram by a limit cycle. Introducing biologically more realistic features into the model, such as the presence of other species or time delays, can result in complex dynamics, including chaotic phenomena similar to those described in the nonlinear pendulum example. The last part of this chapter will describe how some real ecosystem features cannot be easily modeled via Lotka-Volterra equations, such as spatial effects depending on the position of individual animals in their environment and stochastic effects due to random fluctuations in the prey and predator populations.

In a dynamical system, time can be either continuous, as in the heretofore-described examples, or discrete. In a discrete-time dynamical system, the states of the system are evaluated only after certain discrete intervals and the system's orbit in the phase space is a sequence of points, $x_0, x_1, x_2, \ldots, x_{n.}$[5] The evolution rule of a discrete-time dynamical system is called an *iterative map*, i.e., a function describing the system state in a future time t_{n+1} depending on its state in the present time t_n (in which n is an integer). An example is the *logistic map*, a quadratic map of the form:

$$x_{n+1} = \mathrm{rx}_n(1 - x_n)$$

The logistic map is used in biology as a model of population growth, and in this case x_n is a number between zero and one, which represents the ratio of existing

[5] The concept of discrete time in a dynamical system should not be confused with that of time discretization in a computational model. In the latter case, time is made discrete for computational reasons only, but in the former time is considered a discrete variable already at the mathematical model level.

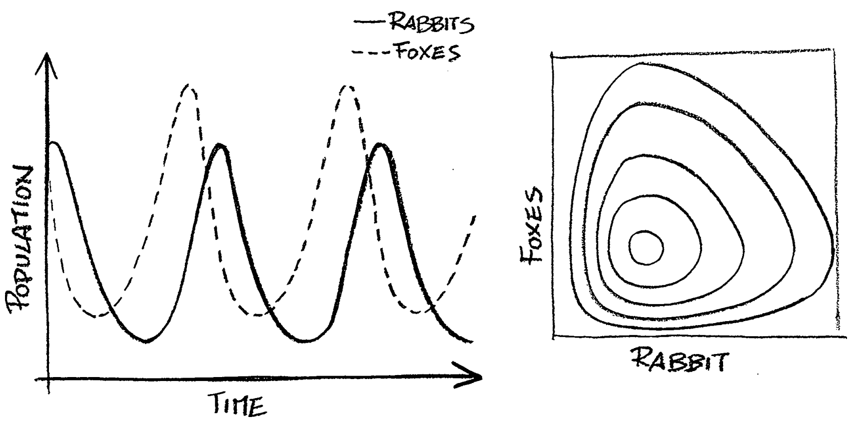
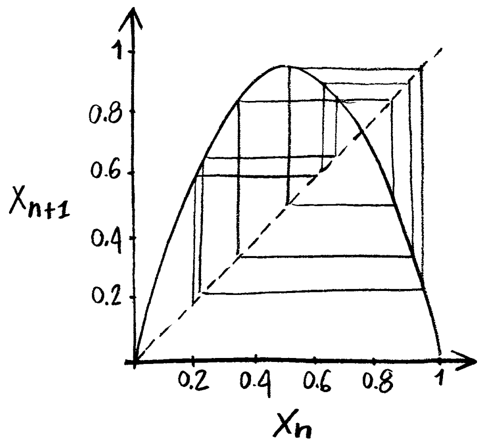


Fig. 4.8 Behavior over time in the Lotka-Volterra predator–prey model

Fig. 4.9 The logistic map



population to the maximum possible population at year n; r is a positive number, which represents a combined rate for reproduction and starvation, and expresses a population's general ability to survive under given physical conditions thereby. The temporal evolution of the discrete variable x_n can be represented through the graphical procedure known as *web diagram*, a procedure that can be executed even with paper and pencil (Fig. 4.9).

The procedure consists in a sort of feedback process, by means of which the function's output at time t_n becomes the same function's input in the following iteration, at time t_{n+1}. Depending on the value of parameter r, this simple map can show complex behaviors such as limit-cycles, bifurcations and strange attractors, similarly to as occurs in continuous systems (Hofstadter 1981).[6] The logistic map application to population biology comes as no surprise, given that the map is the discrete version of an ordinary differential equation—formulated in 1838 by Verhulst:

$$\frac{\mathrm{d}N}{\mathrm{d}t} = \mathrm{aN}(1 - N/K)$$

[6] The best-known fractal—the Mandelbrot set—can be similarly obtained, i.e., by iterating the quadratic polynomial map $z_{n+1} = z_n^2 + c$ in the plane z of complex numbers.

which in turn is a mathematical version of the "population principle", stated in 1798 by Malthus, according to which, when unchecked a population increases by geometrical ratio, while resources increase by arithmetical ratio only. The constant K is the carrying capacity, which corresponds to the maximum sustainable population. The equation is analytically solvable, and its general solution is a "logistic function"—specifically, an S-shaped curve also known as "sigmoid function", the equation of which is:

$$P(t) = \frac{1}{1 + e^{-t}}$$

where e is Euler's number (Fig. 4.10). The curve shows that the initial stage of growth is approximately exponential, then, as saturation begins, the growth slows, and at maturity, growth stops. As we will see further on, the logistic curve has the property of describing a wide range of natural and social phenomena.

It is worth noting that, instead of developing their ecosystem model by extending the logistic model to two species, Lotka and Volterra developed it according to the chemical "Law of mass action", which states that the reaction rate between two chemical species is proportional to the product of their concentrations (Berryman 1992). Based on this law, they assumed that the interaction between two biological species is proportional to the product of their populations, versus to their ratio, as in the logistic equation.

Other features of dynamical systems will be discussed in the next sections, but the important point here is that even a simple system, when considered in a less idealized manner, such as the pendulum, produces unexpected and complex behaviors due only to the nonlinear nature of its equation of motion. Thus, simple systems can produce complex behaviors, and the only way to study them is to simulate them on a computer.

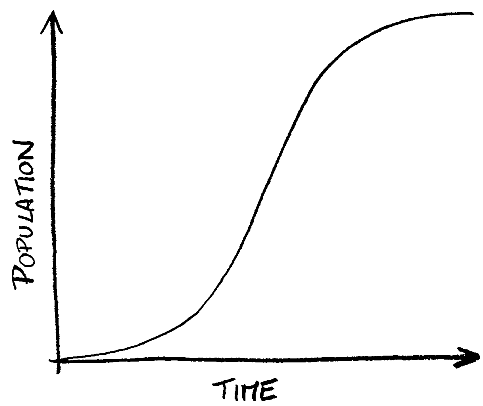


Fig. 4.10 The Logistic curve (sigmoid function)

4.7 Continuum Physics Modeling

In the modeling strategy of classical mechanics, a physical system is considered to be made up of point particles with a fixed mass, and the system's behavior is described by its equations of motion. This is the case of the "point-like masses" described in elementary physics textbooks, such as the oscillating mass of the pendulum and of "rigid bodies"—i.e., ideal solid bodies considered to be a collection of particles maintaining the same distance relative to each other. This modeling strategy has historically shown great efficacy in many theoretical and practical applications, to the extent of being considered the very foundation of scientific thought. The same strategy, however, presents some important limitations when the need is to build less idealized models that more closely represent the phenomena in our empirical world. For example, real solid bodies can be deformed, as in the instance of elasticity and plasticity, not to mention other qualitative states of matter, such as the liquid or gaseous state, and phenomena such as mass or energy transport. A modeling strategy alternative to that of classical mechanics is to consider a body as consisting of a substance continuously filling the space it occupies, which can be deformed. This is the strategy underlying *continuum physics*, a branch of physics originating in the nineteenth century from the studies of Augustin-Louis Chaucy, who studied internal forces acting within a deformable body. He imagined these internal forces as being distributed continuously within the material volume and therefore from an opposite perspective to that of classical mechanics, which considers only the external forces acting on a body. More recently, Clifford Truesdell and Walter Noll used rigorous mathematical methods to contribute to further developments in continuum mechanics (Truesdell 1977; Truesdell and Noll 1965). This field investigates not only the physical properties of solids, but also those of fluids, e.g., liquids and gases. It aims to describe physical processes in terms of spatial variations in macroscopic quantities, such as density, pressure, and temperature and does not consider the atomic and molecular structure of matter. Lautrup (2011) described the premise of this approach as follows: "Whether a given number of molecules is large enough to warrant the use of a smooth continuum description of matter depends on the desired precision. Since matter is never continuous at sufficiently high precision, continuum physics is always an approximation. But as long as the fluctuations in physical quantities caused by the discreteness of matter are smaller than the desired precision, matter may be taken to be continuous" (p. 6).

Nowadays, continuum physics is applied to studies of mechanics, thermodynamics, materials science, fluid dynamics, acoustics, and geodynamics (Hutter and Jöhnk 2004). The most important equations in these studies are *balance equations* and *constitutive equations*. Balance equations express the relations between the macroscopic properties of a system in terms of the flow of a quantity (e.g., mass, energy, momentum, heat, entropy) incoming and outgoing from a given system's volume in a specific time interval. Balance equations are of a general nature and contain no information about a specific material. Constitutive equations, conversely, are specific to an ideal material and approximate the material's response to external forces. The simplest example of a constitutive equation is Hooke's Law of elasticity, which states that the extension of an ideal spring is in direct proportion with the load applied to it.[7]

One of the main application areas of continuum physics is fluid dynamics (Acheson 1990). The description of a fluid as a continuous substance is the conceptual model underlying the Navier–Stokes equations, i.e., a system of partial differential equations describing the behavior of a fluid from a macroscopic perspective. Navier–Stokes equations have a series of interesting practical applications ranging over many fields, from the study of the atmosphere and of ocean currents, to aerospace engineering. Their usefulness is due to the fact that they describe any type of fluid motion, not only the ordered flux of low velocity motion, but also the chaotic flux of turbulent motion, such as that of the air in the vortices flowing around an aircraft wings or that of the gases in an internal combustion engine. A solution for Navier–Stokes equations is not a trajectory, but a "velocity field" or "flow field", and is a description of the velocity of the fluid at a given point in space and time. In most applications, Navier–Stokes equations are nonlinear and therefore their solutions must be obtained through numerical simulation methods. These numerical simulations, however, present a degree of complexity so great as to require a particular branch of fluid mechanics called *computational fluid dynamics*, to be properly investigated. (See Fig. 4.11 for a dynamic simulation based on a computational fluid dynamics engine). The calculation method used is that of *finite volumes*, in which the equations are integrated in a volume, upon which some boundary conditions are imposed, and the inside of which is divided into many elementary volumes of a finite dimension. The shift from the Navier–Stokes equations to the simulation model entails a range of intermediate mathematical and computational models, which are characterized by specific construction assumptions and corrections. These simulations only approximately describe the motion of a fluid, but are precise enough to solve many practical problems in various fields of applied science and engineering.

Fuchs (2010) recently presented a continuum physics-based approach to physical processes in the context of his *dynamic theory of heat*. Specifically, he proposed a unification of the physics of mechanical, hydraulic, electrical, and thermal processes based on *uniform dynamical models* of these processes, i.e., models with properties that vary continuously over time. In Fuchs's approach, rotational, electrical, and hydraulic phenomena are respectively conceived as the results of the storage and flux of angular momentum, electric charge, and liquids. These physical quantities behave equivalently to fluid-like substances flowing from a higher to a lower level of the potential: "In continuum physics an intuitive and unified view of physical processes has evolved: that it is the flow and the balance of certain physical quantities such as mass, momentum, and entropy which

[7] The law sufficiently approximates the behaviour of real materials called linear-elastic materials.

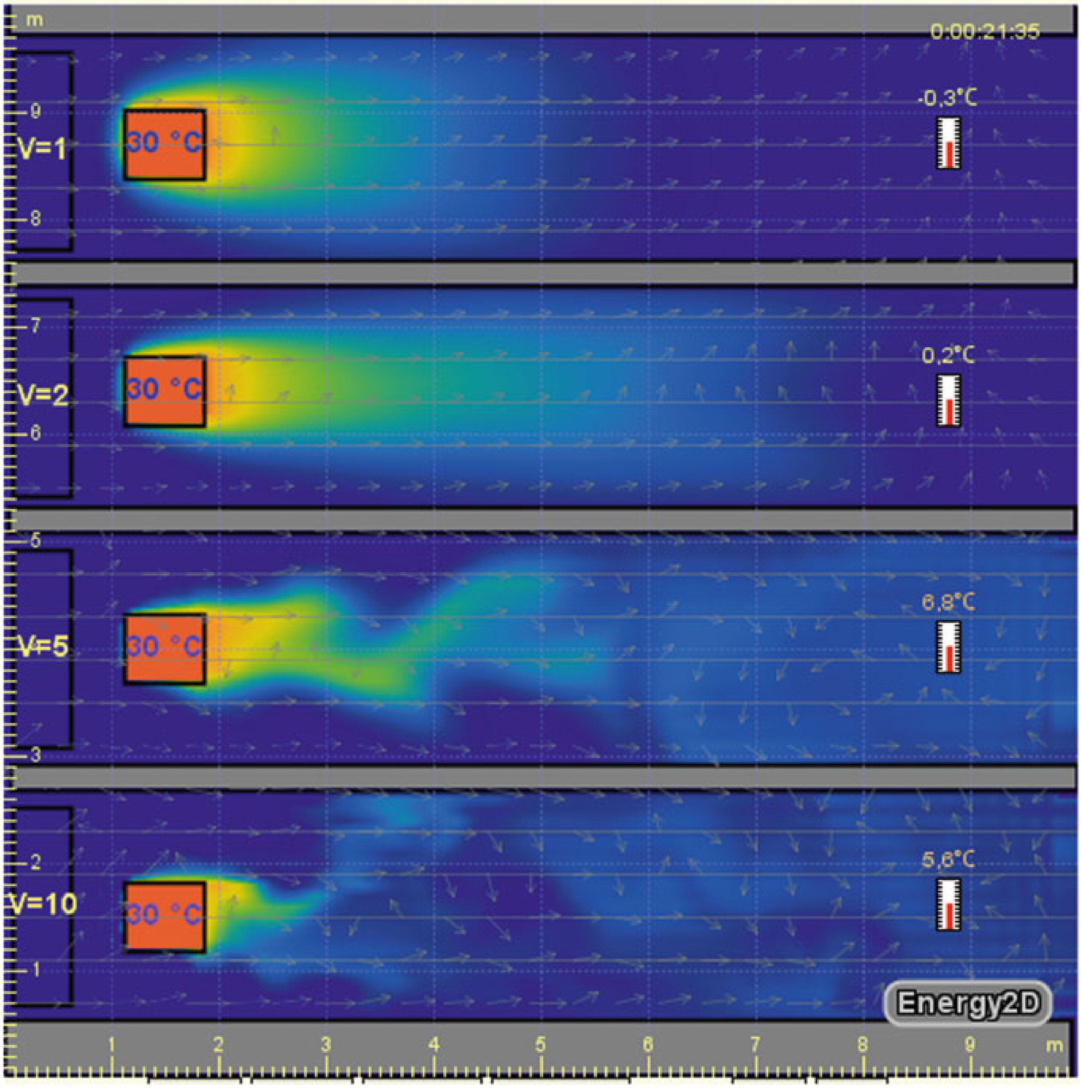


Fig. 4.11 Forced thermal convection at different wind speeds. The fluid motion is laminar under low wind speeds and becomes turbulent under high wind speeds. Image from a simulation conducted with the Energy2D simulation program, courtesy of the Concord Consortium. Web site: http://energy.concord.org/energy2d

govern all interactions. The fundamental laws of balance must be accompanied by proper constitutive relations for the fluxes and other variables. Together, these laws make it possible to describe continuous processes occurring in space and time" (Fuchs 2010, p. 7). By broadening these analogies to thermal phenomena, entropy can be considered as a fluid-like flowing quantity, whose flow depends on the difference of temperature between two systems or between different parts of a system (Table 4.5). Fuchs highlighted how entropy plays a role similar to that of heat in Carnot's "caloric theory" thereby, with the further assumption that entropy can be produced. Thus, the theory views entropy in terms of the everyday intuitive concept of heat.

Table 4.5 Comparison of different physical processes (adapted from Fuchs 2010, p. 59)

Process	Flowing quantity	Current	Potential	Potential difference	Power
Gravity	Gravitational mass (m)	Current of gravitational mass (I_m)	Gravitational potential (G)	$\Delta\varphi_G$	$\Delta\varphi_G I_m$
Hydraulics	Volume of fluid (V)	Current of volume (I_V)	Pressure (P)	ΔP	$-\Delta P I_V$
Electricity	Electric charge (Q)	Current of electric charge (I_Q)	Electric potential (U)	$\Delta\varphi_{el} = -U$	$-\Delta\varphi_{el} I_Q = U I_Q$
Heat	Entropy (S)	Current of entropy (I_S)	Thermal potential (T)	ΔT	$-\Delta T I_S$

4.8 Molecular Dynamics

In the late 1950s Berni Alder and Thomas Wainwright invented the Molecular Dynamics simulation paradigm for studying the physics of liquids and particularly, the transitions of matter among solid, liquid, and vapor states (Frenkel and Smit 2002; Rapaport 2004). Their modeling strategy consisted in considering a liquid as made up of discrete particles corresponding to atoms and molecules. At the time, Alder and Wainwright were using the computers at Lawrence Radiation Laboratory in Livermore to simulate a system made up of a few dozen “hard spheres” in different conditions of density and temperature. Nowadays, however, thanks to advances in numerical algorithms and computing architecture, molecular dynamics allows for the simulation of systems consisting of hundreds to millions of particles interacting in complex ways, for applications that range from materials science to biochemistry and astrophysics. (See Fig. 4.12 for an example of a molecular dynamics simulation).

The idea underlying the method is to solve the equations of motion for each particle at a certain time t_n to determine the velocity and position of each at the subsequent time t_{n+1} and to iterate this computation to follow the particles’ movements until the system reaches an equilibrium state. The following steps can be used to obtain the system’s temporal evolution:

1. define the system’s initial state, which is given by the position and the momentum of each particle, and the boundary conditions;
2. calculate the forces acting on each particle;
3. numerically integrate the equations of motion to determine the new positions and velocities of the particles;
4. repeat steps 2 and 3 until the system state does not change significantly over time;
5. use statistical mechanics methods to measure a macroscopic property of the system (usually temperature, measured as the system’s average kinetic energy).

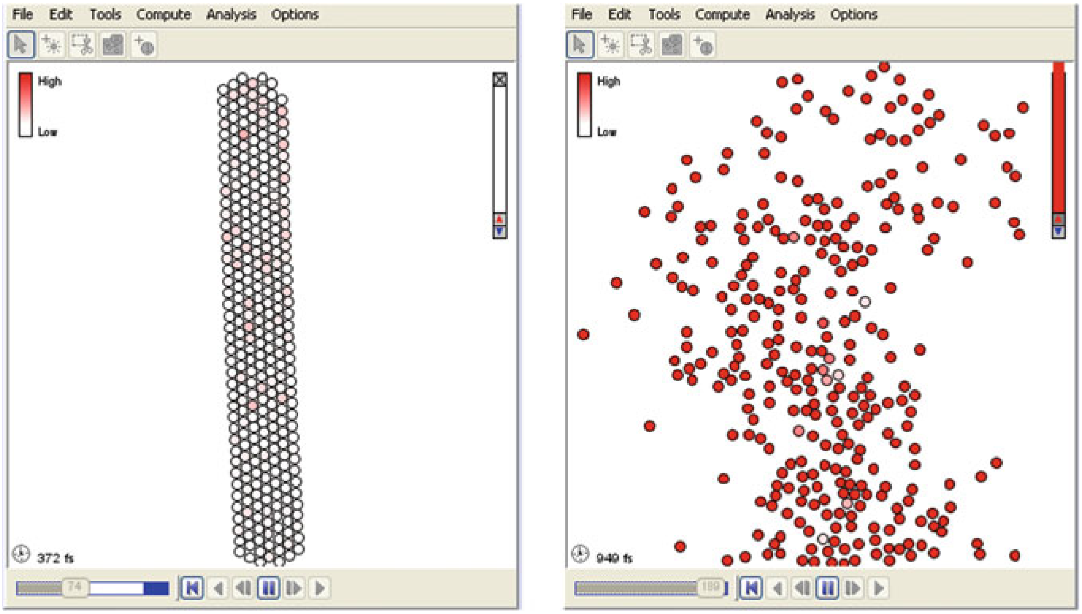


Fig. 4.12 Phase transition between solid and liquid state in a molecular dynamics model of heat propagation. Image from a simulation conducted with the Molecular Workbench software, courtesy of the Concord Consortium. Web site: http://mw2.concord.org

The second step—the computation of the resultant force acting on each particle—is the most laborious part of the computation and requires a model of the interaction between molecules. In the classical hard-sphere model, the particles are considered as impenetrable spheres interacting only by repulsion when at a very close distance. More realistic models express the interaction energy between molecules, called *intermolecular potential*, by using a function that depends on the distance between the molecules' centers of mass. The most used function is the "Lennard-Jones potential", in which attractive interaction prevails for great distances and repulsion predominates for short distances. Molecular dynamics simulations are considered to be a type of "computer experiment". According to Rapaport (2004), "what distinguishes computer simulation in general from other forms of computation, if such a distinction can be made, is the manner in which the computer is used: instead of merely performing a calculation, the computer becomes the virtual laboratory in which the system is studied—a numerical experiment" (p. 3).

The advantage of these numerical experiments over real ones is that they allow for examination of a material's behavior in situations that are difficult or impossible to be reproduced in reality, e.g., under conditions of high density or temperature. As noticed by Fox Keller (2003), the Molecular dynamics simulations of the 1950s constituted an epistemological novelty compared to the numerical simulations initiated in Los Alamos for the purpose of computation only. Whereas the goal of the latter simulations was to solve equations derived from well-known theories, in molecular dynamics, a real physical system was replaced for the first time by a simulated artificial system. The aim, moreover, was to test approximate theories when they existed, and to provide guidelines for constructing them, when they do not.

4.9 Compartmental Models

The *compartmental models* method is an approach to the modeling of "diffusion phenomena" in biological, social, and economic systems. The diffusion can be that of a molecular component in a cell, a pathogen in an epidemic disease, a product in a market, or innovation in a social system. The system to be modeled is conceptually subdivided into "compartments". Data or matter exchanges between compartments are represented by flows, which are modeled by a system of ordinary differential equations, with time as the independent variable. The numerical solution of the equation system yields the behavior of the variables of interest over time. What distinguishes the method from other equation-based approaches is that the modeling process is based on a flow diagram to visually represent the compartments and their mutual relations—a particularly useful tool when the model consists of many compartments.

One field employing compartmental models on a broad scale is that of mathematical epidemiology (Anderson and May 1991). In fact, epidemiological experiments are usually impossible or unethical, and mathematical models are therefore important tools for gaining a better understanding of the transmission of infectious diseases and evaluating various management strategies (Brauer et al. 2008). Compartmental simulations in epidemiology are generally based on mathematical models of increasing complexity, such as the SIR model and its variations. The SIR model considers each individual in a population as being in one of three states: Susceptible, Infectious, and Recovered, represented respectively by the letters S–I–R. These states could be conceived as compartments and the interactions among them as the transition of a person moving from one compartment to the next (Fig. 4.13).

The model's underlying hypotheses are that the people within each compartment are assumed to be homogeneous and "perfectly mixed", i.e., any inter-individual differences and spatial positions are thought to be irrelevant.[8] Moreover, the system is considered to be deterministic, and the transitions among states are modeled as their expected value. A system of three coupled ordinary differential equations is used to model the assumptions about the nature and time rate of transfer from one compartment to another:

$$\frac{\mathrm{d}S}{\mathrm{d}t} = \mu N - \mu S - \beta \frac{1}{N} S$$
$$\frac{\mathrm{d}I}{\mathrm{d}t} = \beta \frac{I}{N} S - (\mu + v) I$$
$$\frac{\mathrm{d}R}{\mathrm{d}t} = vI - \mu R$$

[8] The term "perfect mixing" is used in chemical engineering to indicate the substances that are mixed in a stirred tank reactor.

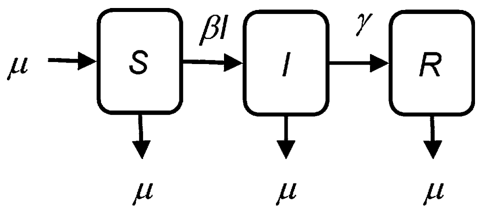


Fig. 4.13 Visual representation of the SIR Model

where N is the population size, β is the contact rate, v is the recovery rate, and μ is the death rate (equal to the birth rate). It can be easily verified that the sum of all these variations is zero, and therefore:

$$S + I + R = N$$

which expresses the constancy of population size, based on the hypothesis that the death rate is the same as the birth rate. One of the most important aspects to consider when using the model is that of optimizing the parameters present in the equations on the basis of experimental data. As shown in Fig. 4.14, the population of infected people very quickly reaches a peak value, after which it slowly decreases, whereas the population of susceptible people soon begins to decrease, asymptotically tending to zero. The population of recovered people gradually increases up to a saturation point, following the typical "S-shape" of a logistic curve.

The model can be rendered more realistic in many ways, for example by considering the possibility that recovery from infection is not definitive and that a person can be susceptible to infection again in the future. One need simply add a feedback loop from the last compartment the first one (Fig. 4.15). In mathematical terms, this corresponds to the introduction in the first equation of a new positive term:

$$\frac{\mathrm{d}S}{\mathrm{d}t} = \mu N - \mu S - \beta \frac{I}{N} S + \alpha R$$

where α is the immunity loss rate.

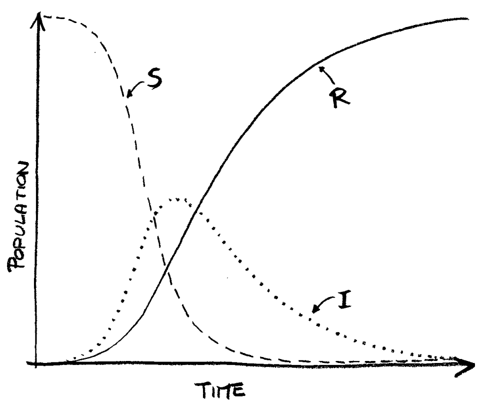


Fig. 4.14 Time-related behavior of the SIR model

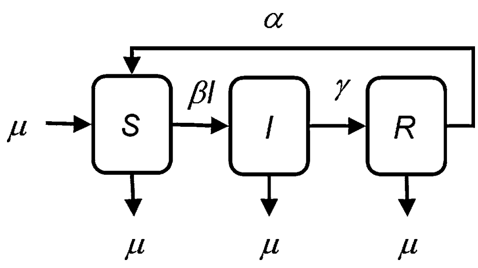


Fig. 4.15 SIR model with the additional hypothesis of people losing their immunity after a certain time

Compartmental models are also used in marketing and the social sciences. The Bass model is a product-forecasting mathematical model that describes a product diffusion process (Bass 1969). In the compartmental models approach to the Bass model, the diffusion of a given product can be modeled as occurring between two compartments respectively corresponding to potential customers and to customers who have already bought the product. Potential customers are influenced to buy the product by advertising and by word of mouth from existing customers, whom are contacted through social interaction. A fraction of these contacts results in the purchase of the new product, similarly to a contagion phenomenon, and the advertising causes a constant fraction of the population of potential customers to buy in each time period. One of the reasons for the success of the Bass model is that it fits the data for nearly all product introductions, notwithstanding a wide range of decision variables, such as product pricing and advertising expenses. The Bass model has been extended to the diffusion of technological innovations (Mahajan et al. 2000), by aggregating the population into the two categories of innovators (the first to adopt a new technology) and adopters. Both the number of customers of a new product and the number of adopters of a new technology follow a logistic curve, as in the infection diffusion model.

4.10 Agent-Based Modeling

Agent-based modeling is a simulation paradigm allowing for the study of the behavior of physical, biological, computational, and social systems. These systems are conceived as if formed by a large number of elements, called “agents”, which interact with each other and with their environment. The nature of these elements and of their interactions depends on the type of model; this can range from highly idealized models for systems of theoretical interest to models that aim to represent a real system for supporting policies and decision-making in detail. Agent-based modeling is the result of studies conducted during the 1980s and 1990s on *cellular automata* (Wolfram 1984), *adaptive complex systems* (Epstein and Axtell 1996; Holland 1995; Kauffman 1995) and *artificial life* (Langton 1989). In turn, these made up part of a research strand that had begun as far back as the 1940s with John von Neumann’s studies on the construction of self-replicating machines. Von Neumann, the inventor of computer logical architecture, began to investigate the

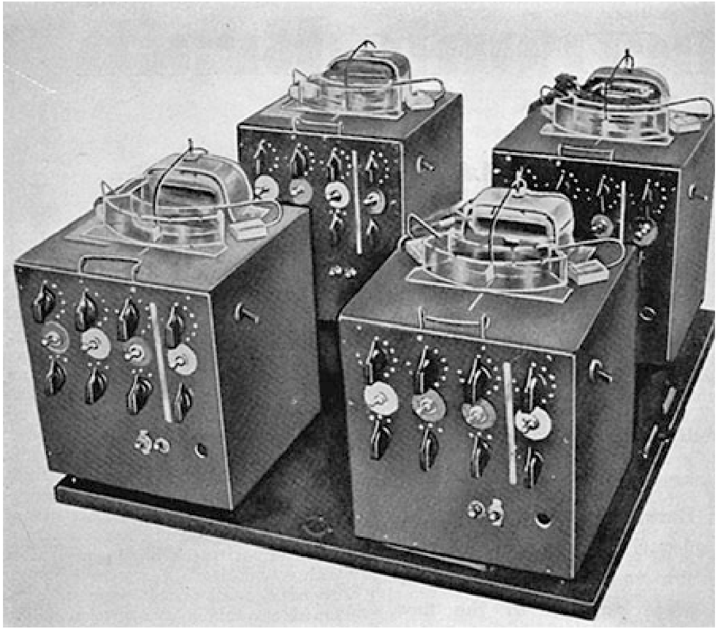
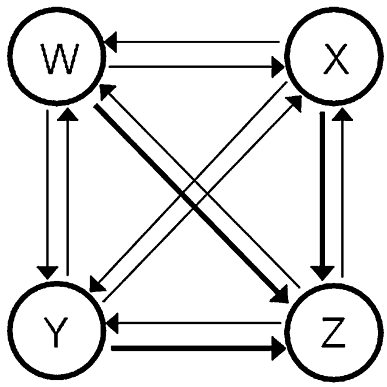


Fig. 4.16 The Homeostat (Ashby 1949, p. 78)

possibility of building a machine that would be able to self-replicate, i.e., a computer containing instructions both for its operations and for creating a copy of itself. The goal was to imitate the mechanisms of biological reproduction in a machine. Thus, following a suggestion by Stanislaw Ulam, von Neumann employed the mathematical construct of *cellular automata*—a computational architecture consisting in a grid of cells, each containing its own data and instructions for changing its state based on input received from neighboring cells. Over the following years, the construction of artificial self-organizing systems was also a goal of Cybernetics. In particular, Ashby's Homeostat (1949, 1952) was a device made up of four units, each able to exchange information with the other three about its condition (Fig. 4.16). The variables examined were the units' deviations from their equilibrium state represented by the position of a needle in a dial.

If deviation from stability exceeded a certain threshold, a system component able to randomly modify the matrix went into action, and the system sought equilibrium in this new condition. Ashby considered the Homeostat to be a biological systems model: "It's process is clearly similar to that occurring in evolution. There the rules are: test the organism against the environment; if the organism is unfit, remove it; replace it by a new organism that differs from it in some random way. In the homeostat the rules are: test the matrix for stability in the imposed conditions; if it is unstable remove it; replace it by a new matrix with random elements". (1952b, p. 292). Pickering (2010) noted that Stuart Kauffman's studies on random Boolean networks (Kauffman 1969) represented the ideal intermediary between cybernetics' analog simulations and the agent-based simulations of the 1980s. Kauffman introduced these networks as a model of genetic regulatory



t			t+1
W	X	Y	Z
0	0	0	0
0	0	1	0
0	1	0	0
0	1	1	1
1	0	0	1
1	0	1	0
1	1	0	1
1	1	1	1

Fig. 4.17 A random Boolean network. The larger arrows show the connections from genes W, X, Y to gene Z. A possible Boolean function of three variables is represented on the right; this defines the state of Z as a function of the states of the other genes

networks, i.e., of the interactions between DNA segments in a cell.[9] In the model, a gene is represented by a binary device, with *on* and *off* states respectively symbolizing the *de-repression* and *repression* of a gene, i.e., the transcription of its DNA in mRNA and in proteins. The functional links between these "genes" are represented by a network, in which the state of each gene at a certain discrete time $t + 1$ depends on the states of the other genes at the previous time t, and the relations of any gene with the others is given by a Boolean function. Figure 4.17 shows a simple network made up of 4 elements, the state of gene Z at a certain discrete time depends on the states of the other three genes. (The reader might also note the structural similarity between this network, and Ashby's Homeostat!).

It is, of course, impossible to study the evolution of these networks without a computer, and that is why Kauffman's research was based on simulation, which actually yielded unexpected results. Networks in which every gene was randomly connected to two or three other genes behaved in an ordered and stable manner. As stated by Kauffman, "the genome is a complex net of interacting components commonly thought to control homeostasis and differentiation through precisely constructed control circuits among the genes. But I have found what seems to be a new class of dynamically stable systems, which suggests that even haphazardly constructed control nets of high molecular specificity undergo homeostasis and differentiation" (1969, p. 177).

Research on random Boolean networks would have remained confined to theoretical biology, had not another, more complex, self-organizing artificial system appeared on the pages of the mathematical games section in the journal Scientific American (Gardner 1970). The system examined was a solitaire game conceived by the mathematician John Horton Conway and named "Life". As described by Gardner: "because of its analogies with the rise, fall, and alternations of a society

[9] These interactions occur indirectly through protein synthesis, the transcription factors in turn determining the synthesis, or the synthesis inhibition, of other proteins and therefore, of genetic expression.

of living organisms, it belongs to a growing class of what are called ‘simulation games’—games that resemble real-life processes” (ibid., p. 120). The game develops in an infinite two-dimensional grid of square cells, each existing in only one of two possible states: alive or dead. Every cell interacts with its adjacent cells diagonally, horizontally, or vertically, for a total of 8 cells, and all cells change their state simultaneously, according to the following rules:

1. Every cell alive with less than two neighboring cells alive dies (under-population).
2. Every cell alive with more than three neighboring cells alive dies (over-population).
3. Every cell alive with two or three neighboring cells alive stays alive (survival).
4. Every dead cell with exactly three neighboring living cells becomes alive (birth).

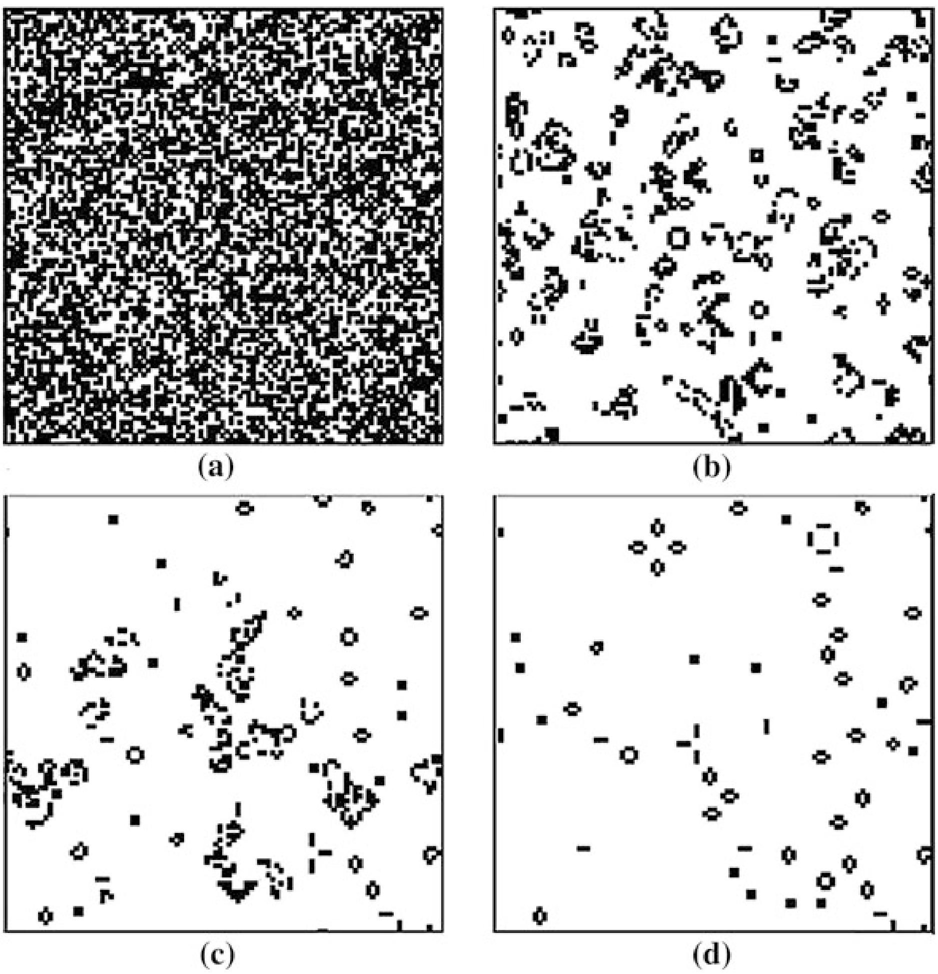


Fig. 4.18 Conways’ Game of Life, starting from an initial random condition. **a** $t = 0$. **b** $t = 50$. **c** $t = 900$. **d** $t = 1350$ (Hanson 2009, p. 775)

The game consists in choosing an initial configuration ("seed") and in letting the system evolve through a series of "generations", corresponding to discrete time-steps (Fig. 4.18). The only way to foresee what will happen to a certain seed is to observe what happens in the simulation. The name "Life" is somewhat justified, due to the range of cell patterns that can emerge:

- Static patterns.
- Oscillating patterns.
- Patterns moving through the cells.

Some initial configurations may grow indefinitely, and others may create copies of themselves, such as in von Neumann's self-replicating machines. The Life game is one of the most convincing demonstrations of "emergent phenomena" in systems ruled by simple evolution rules.

In the early 1980s, these self-organization- and emergent phenomena concepts were not yet based on a theoretical framework and had not found their place in academia. These ideas transmuted into an accepted field of scientific research only after Stephen Wolfram published his studies on cellular automata (Wolfram 1984). Wolfram realized that models such as von Neumann's or Conway's were too complex to be analyzed in detail and that universal rules were unlikely to be derived from them. Wolfram therefore focused on one-dimensional cellular automata. The term refers to automata formed by a single row of cells, each with two only two possible states and characterized by the elementary rules whereby each cell changes state in function of the states of its two neighboring cells. It is possible to code all the possible rules and to use computer simulations to explore the consequences of each one. On the computer screen, the evolution of a cellular automaton is represented by a sequence of horizontal lines, each corresponding to

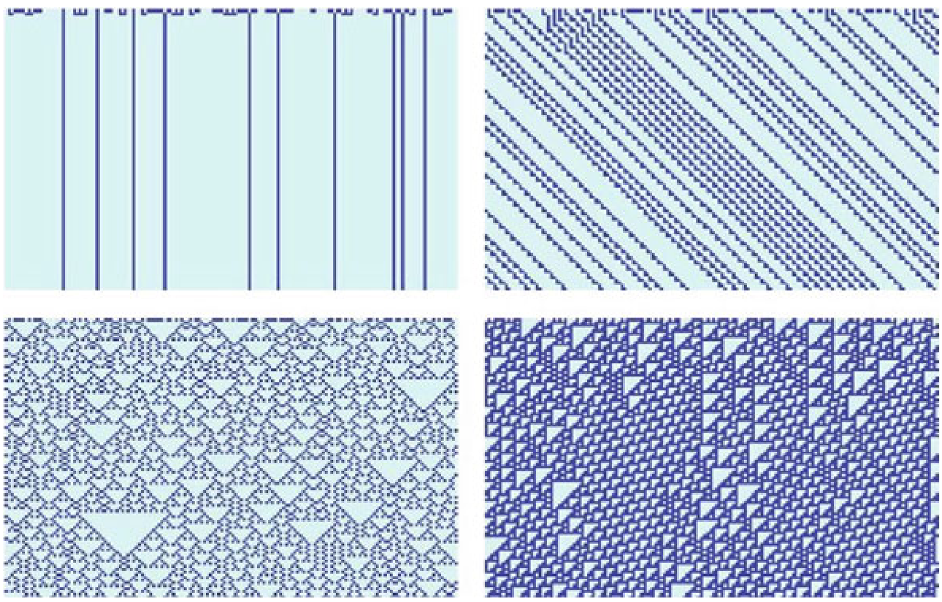


Fig. 4.19 Wolfram classes of cellular automata (Sutner 2009, p. 757)

a generation. A moving image is formed thereby, which reveals many types of patterns, from the simplest to the most complex, which evoke the geometrical design in an oriental carpet (Fig. 4.19). In his landmark paper "Universality and complexity in cellular automata", Wolfram (1984) categorized the patterns produced by one-dimensional cellular automata into four distinct classes:

- Class I: homogeneous state;
- Class II: simple stable or periodic structure;
- Class III: chaotic (non-repeating) pattern;
- Class IV: complex patterns of localized structures.

In terms of dynamical systems, the first three of Wolfram's classes respectively correspond to fixed-point attractors, periodic attractors, and strange attractors These correspondences are not casual, as a cellular automaton can be considered a particular type of discrete dynamical system, i.e., "a spatially-extended dynamical system in which spatially-discrete cells take on discrete values, and evolve according to a spatially-localized discrete-time update rule" (Hanson 2008, p. 768). In two-dimensional cellular automata, each element in a cell can interact only with the cells of its "neighborhood", which can have either five cells (a von Neumann neighborhood) or nine (a Moore neighborhood), as shown in Fig. 4.20.

Some evolution rules are computationally irreducible, which means that any attempt to predict the system's future states will involve *more* computational effort than simply having the system generating its own behavior. In Wolfram's words: "whenever computational irreducibility exists in a system it means that in effect there can be no way to predict how the system will behave except by going through almost as many steps of computation as the evolution of the system itself." (Wolfram 2005, p. 739). In particular, this means that no mathematical formula exists for describing the overall system's behavior. Computational irreducibility is one reason why Wolfram (ibid.) calls the study of cellular automata a "new kind of science". This new kind of science has its fullest expression in

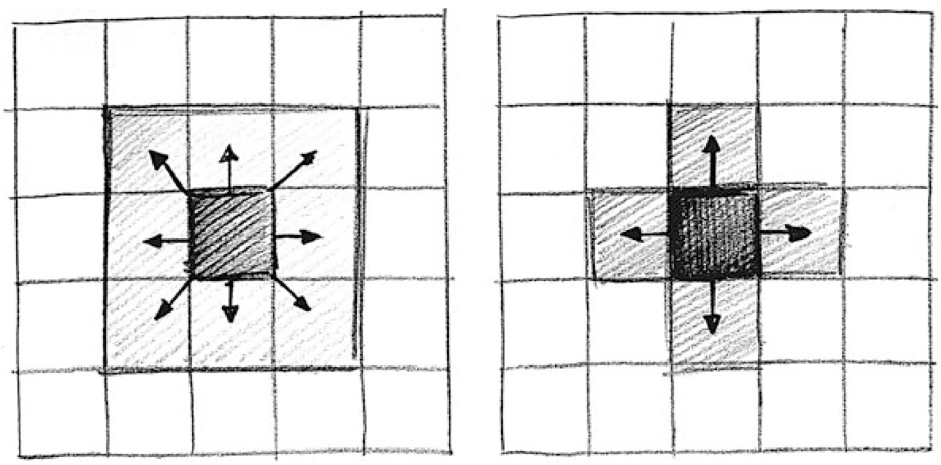


Fig. 4.20 Two types of cellular automata neighborhood: Moore neighborhood (*left*) and von Neumann neighborhood (*right*)

digital physics, a research program derived from cellular automata research, in which the universe itself is considered to be a giant computer, which continuously calculates its future state (Fredkin 1990).

As models of physical systems, cellular automata are an alternative to both classical mathematical models, which are idealized and can be solved analytically, and to numerical models, which are more realistic, but can only approximately solved. Their originality of this new approach is that it is a sort of non-numerical digital simulation: "To appreciate the originality of this type of modeling, one should keep in mind that there is no attempt here to solve any given equation, in fact cellular automata do not engage in any numerical processing, they merely perform simple space-dependent logical decisions" (Vichniac 1984, p. 97).

Wolfram cellular automata are the deterministic limit case of a more general class of *stochastic* cellular automata, which conversely employ a probabilistic evolution rule. Stochastic cellular automata are equivalent to the *Ising model*, a statistical physics model of ferromagnetic materials. Under the action of an external magnetic field, these materials become spontaneously magnetized and retain their magnetization for a long time after the magnetic field has been removed. This magnetization is maintained, however, only below a certain critical temperature called Curie Temperature. If heated above this temperature, the material becomes paramagnetic. The phenomenon is caused by the alignment of

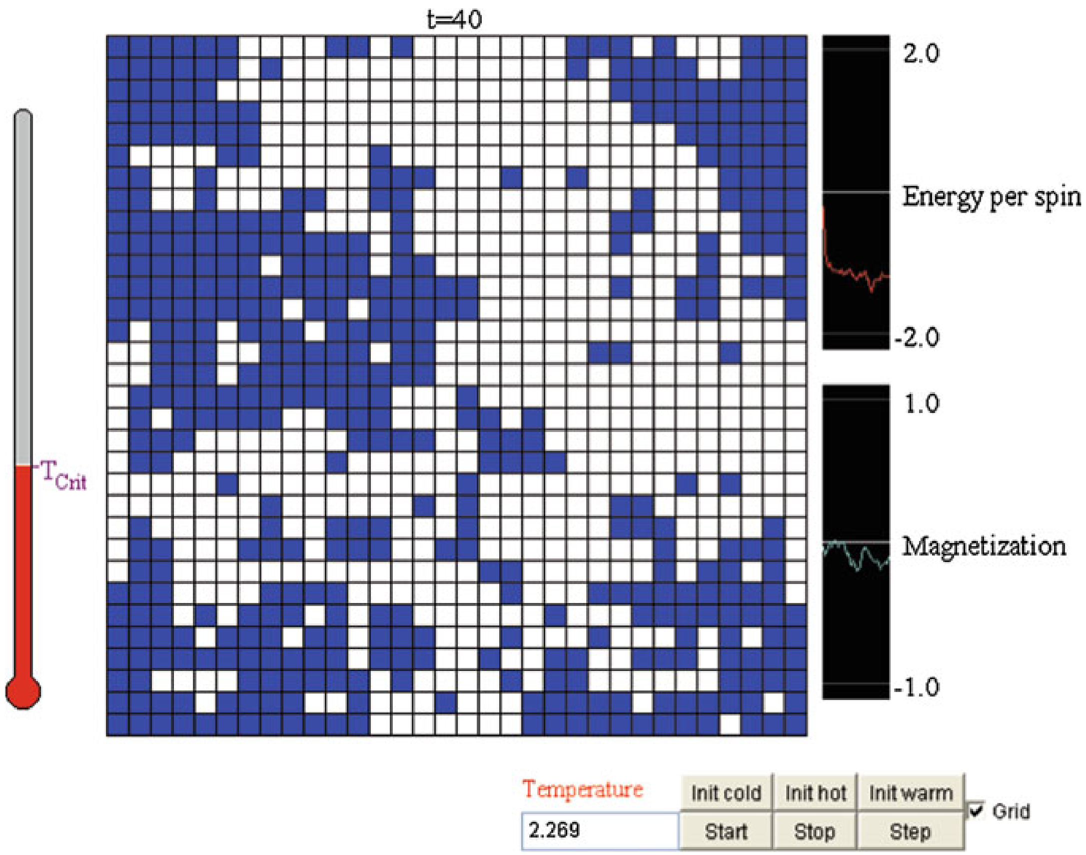


Fig. 4.21 Cellular automata simulation of the Ising model. Image courtesy of Peter Young and Bernd Nottelmann. Web site: http://physics.ucsc.edu/~peter/ising/ising.html

electron spins in the material magnetic domains. In the Ising model, spins may be oriented in only two ways, respectively represented by a binary variable with the values of 1 and −1, usually denoted by the ideograms ↑ (spin-up) and ↓ (spin-down). A spin "flip" (change in orientation) is a random event, the probability of which depends on interaction with neighboring spins; thus the system's behavior depends on simple local rules of a probabilistic nature. As the temperature increases, the Ising model simulation reproduces the phase transition between the material's two different macroscopic states (from ferromagnetic to paramagnetic) (Fig. 4.21).

Another class of models that are equivalent to cellular automata with probabilistic rules pertains to *percolation theory*, a branch of physics examining the properties of disordered media, such as porous rocks, gels, polymers, ionic conductors, and proteins (Stauffer and Aharony 1992). These media are modeled as sites lattices, which can represent properties of the material or connections among molecules (Fig. 4.22). Each site is empty with probability *p* and occupied with probability 1-*p*. The process typically observed is that for a certain critical value of *p*, a phase transition occurs between two macroscopic states of matter, such as isolating or conductor, magnetic or paramagnetic, viscous or gel. An example from everyday life is that of a boiled egg in which heat activates many connections among the egg's protein molecules, leading to a sol–gel transition phase.

Due to their capacity to create order from disorder and to originate self-replicating structures, cellular automata were soon considered a potential

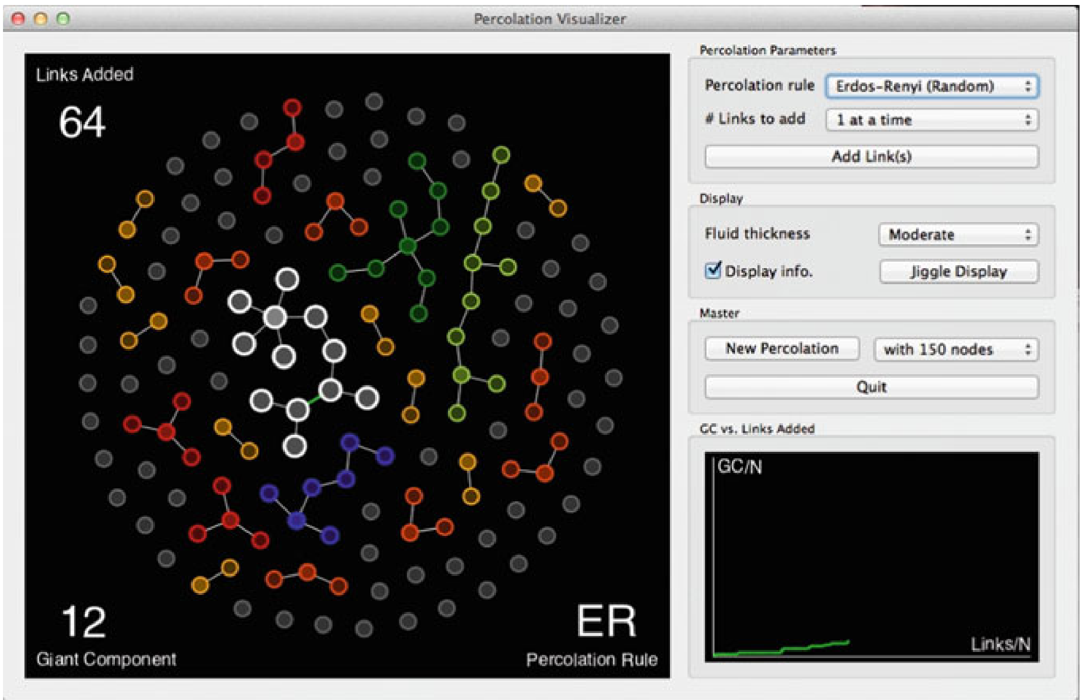


Fig. 4.22 Simulation of a model of percolation on a network. Image made with the PercoVIS software, courtesy of Daniel Larremore. Web site: http://amath.colorado.edu/student/larremore/PercoVIS.html

conceptual model for life evolution. During a workshop held in Los Alamos in 1987, a new research field using cellular automa was created to investigate the emergence of order in nature—i.e., Artificial Life (Langton 1989). The Artificial Life method is that of creating virtual worlds where digital creatures evolve. The first examples of these worlds were Tierra (Ray 1991) and Avida (Adami and Brown 1994). Artificial Life simulated worlds are more complex than cellular automata and their elements must be more autonomous, to interact with a greater variety of behaviors, and to adapt to environmental changes.

These simulation needs led to the development of the agent-based modeling paradigm during the 1990s (Macal 2009). According to Macal and North (2010), a typical agent-based model's elements are:

1. A set of *agents*, their attributes and behaviors.
2. A set of agent *relationships* and methods of interaction: An underlying topology of connectedness defines how and with whom the agents interact.
3. The agents' *environment*: Agents interact with their environment in addition to other agents.

An agent-based model allows for the simulation of any kind of system, the overall behavior of which emerges from the behavior of its individual elements. Due to this feature, agent-based simulation is used to model many kinds of natural or artificial systems, including:

- *ecosystems*, the agents are animals and plants;
- *societies*, the agents are families, citizens, or voters;
- *markets*, the agents are customers;
- *competition and supply chains*, the agents are companies;
- *epidemics*, the agents are people;
- *urban traffic*, the agents are vehicles;
- *transportation systems*, the agents are passengers.

The common feature of these systems is that they cannot be easily described globally via equations. Simulation is the only alternative to observation of the real system. Agent-based simulations are sometimes visually similar to those of cellular automata. Agents are represented with small colored squares that change color or move on the screen creating stable or continuously changing patterns throughout the simulation. An example frequently cited as forerunner of agent-based simulation is the "Segregation model", invented by the economist Thomas Schelling (1971) to describe the behavior of two social groups differing by race, language, or socio-economic class and living in the same urban area. In the model, the agents are the members of both groups and the environment is represented by a rectangular lattice of cells corresponding to houses. A cell can be occupied by an agent of any of two groups or it can be empty. Each agent's state is characterized by a certain "level of happiness", which depends on its preference for having neighbors of its own social group. Each agent interacts with the agents occupying the 8 cells around its own, and at every discrete time-step, it must decide whether to move to another area or not. The rule is that if the number of neighbors of the

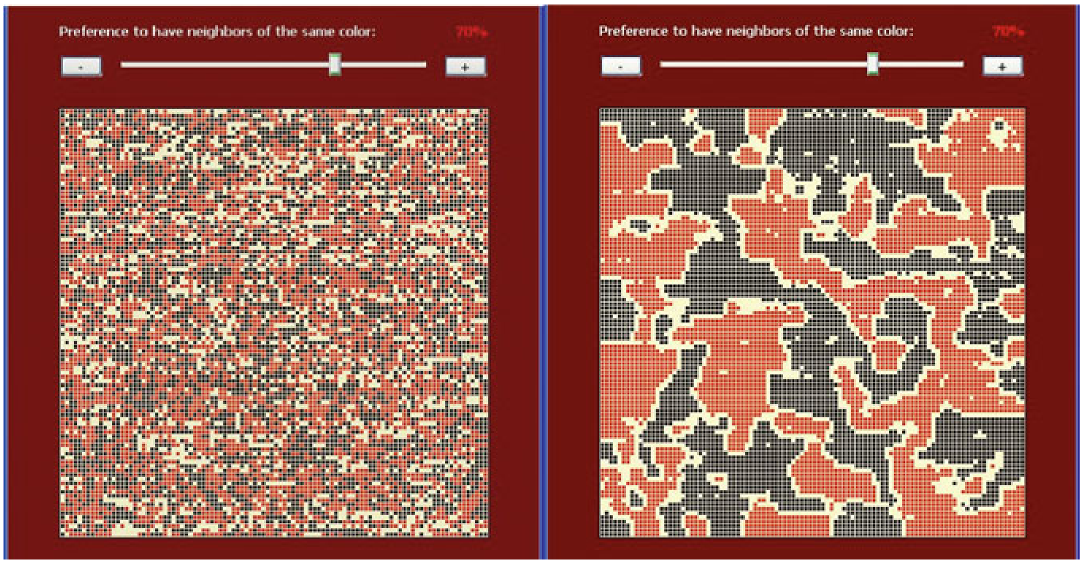


Fig. 4.23 Simulation of the Schelling segregation model. Image courtesy of XJ Technologies. Web site: http://www.xjtek.com

other group exceeds a certain level, the agent moves to a free cell chosen randomly in a nearby area, where it can be "happy"; it otherwise remains in its cell.

A typical simulation begins with a random initial distribution of agents, and each time-step corresponds to a decision and the consequent parallel update of all cells (Fig. 4.23). The threshold by which an agent decides to move to another area is expressed by a parameter p. An analysis of the model's behavior for many different p values throughout the simulation shows that even a small preference for having neighbors of the same social group can lead to a high level of segregation (shown by the formation of same-colored cell clusters). Schelling's model was the first example of an agent-based approach to social phenomena simulation. In the 1990s, this approach was the main research approach used to study complex adaptive systems conducted at the Santa Fe Institute (Axelrod 1997; Epstein 1999, 2006; Epstein and Axtell 1996). The application of agent-based simulation to the study of social phenomena constitutes what Epstein (1999) defined "generative social science" and therefore a science that aims to answer "The Generativist's Question":

- How could the decentralized local interactions of heterogeneous autonomous agents generate the given regularity? (ibid., p. 41).

Epstein holds that agent-based modeling is a new scientific instrument that makes it possible to conduct the "The Generativist's Experiment":

- Situate an initial population of autonomous heterogeneous agents in a relevant spatial environment; allow them to interact according to simple local rules, and thereby generate—or "grow"—the macroscopic regularity from the bottom up (ibid., p. 42).

One of the early agent-based models of human society was *Sugarscape* (Epstein and Axtell 1996). The model's structure is similar to Schelling's segregation model, but in this instance, each cell holds different quantities of "sugar"—the metaphor for the resources available to the inhabitants of an artificial world. The model allows for the analysis of social phenomena, such as seasonal migrations, pollution, sexual reproduction, combat, and the transmission of disease. Another example is Jager et al's (2001) riot behavior model, in which agents, imagined as the fans of two opposing football clubs, move in a two-dimensional space and decide to fight or retreat based on their perceived neighborhood agents' behavior.

A highly researched topic in this field is the relation between individualism and cooperation (Axelrod 1984, 1997). The reference theory for these studies is Game Theory, which was introduced in the 1940s by John von Neumann and Oskar Morgenstern. The situation typically described in this theory is that of two players who interact, each having to select a strategy that could potentially maximize gain. The players are presumed to be rational, i.e., they know the gains or losses associated with every possible move, and they base their decisions on a rational analysis of consequences. One of the most studied games is the "prisoner's dilemma", a simple two-player game with only two strategies: *collaboration* and *defection*. In the simplest case, the players meet only once and the game analysis game reveals defection to be the best strategy. Player strategies, however, become more complex in the iterative version of the game. Axelrod (1997) examined series of simulations in which the two players can meet unlimited times and can even take their adversary's past actions into account. In this instance, however, it turns out that defection is not necessarily the most effective strategy.

Spatial variants of the prisoner's dilemma are cellular automata in which agents are at the vertices of a network, generally a two-dimensional square lattice, and in which every agent chooses the next move in function of the neighboring agents' strategies (Nowak and May 1992). Simulations show that patterns form spontaneously with collaborator areas alternating with defector areas and that these patterns can be stable, periodic, or chaotic. Evolutionary games based on spatial variants of the prisoner's dilemma are used in biology to understand the ways in which altruistic behaviors typical of cooperation can emerge from adaptive mechanisms based on natural selection (Nowak 2006).

Many continuous or discrete-time dynamical systems have a correspondent agent-based representation, which is not however based on equations but on the direct simulation of the system's individual elements' attributes and behaviors, and on their interactions with each other and with the environment. For example, Castiglione (2010) compared the behavior of the Lotka-Volterra equations with an agent-based version of the same predator–prey model, in which prey (e.g. rabbits) and predators (e.g. foxes) occupy the points of a square lattice, and the system's evolution is given by the following probabilistic rules:

1. if a rabbit is close to a fox, then with a certain probability p_b the rabbit disappears and a new fox occupies the point previously occupied by the rabbit;

2. if a lattice point is empty, then with a certain probability p_a, a rabbit is born at this point;
3. if a lattice point is occupied by a fox then with a rate d the fox dies and the lattice point becomes empty.

The conclusion was that the agent-based rules reproduce the same oscillatory behavior as the ordinary differential equations system, the only difference being the presence of spikes in the curves, which are due to the model's stochastic nature (see Fig. 4.24). The agent-based model works more accurately, however, when representing situations in which small fluctuations can drive the system to a completely different state. For example, in the equation-based Lotka-Volterra model, the predator population may diminish to extremely low numbers but then grow again, whereas with chance fluctuations the population may actually become extinct.

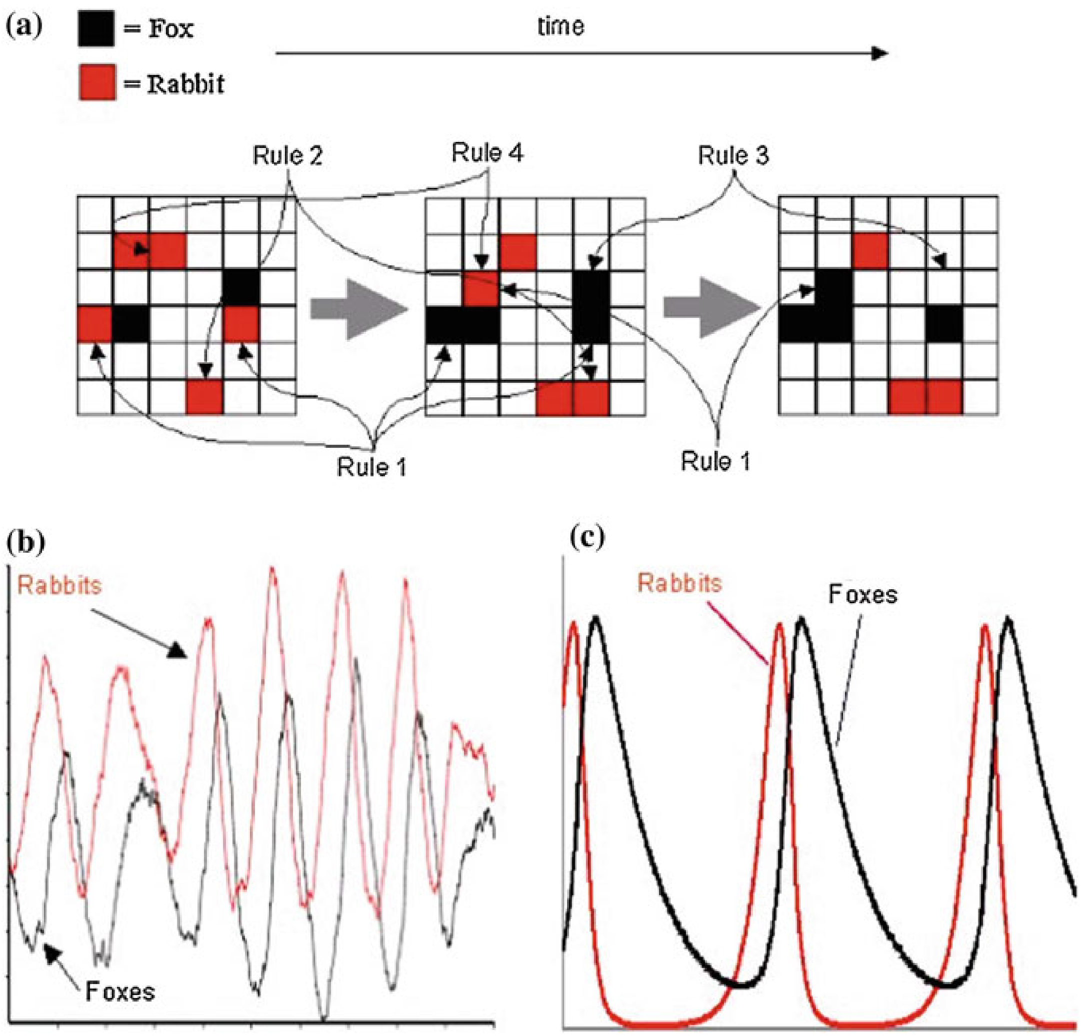


Fig. 4.24 Comparison between an agent-based predator–prey model (**b**) and the numerical solutions of the Lotka-Volterra Equations (**c**). Image courtesy of Filippo Castiglione (2010) and Scholarpedia. Web site: http://www.scholarpedia.org

Agent-based models are therefore able to represent systems in which the random behavior of even a single element can have macroscopic consequences, as occurs in biological evolution, in which even the random mutation of a gene can cause overall organism changes. Barnes and Chu (2010) called this property *irreducible stochasticity*, and distinguished it from *reducible stochasticity*. They specified that the latter allows for the use of statistical methods to extract deterministic features from random events, as in the kinetic theory of gases, or in the study of the Brownian motion of particles suspended in a liquid. A consequence of irreducible stochasticity is that random events cannot be represented by their average values.

An important feature of agent-based models, and one that distinguishes them from equation-based models, is their capacity for reproducing effects that depend on the spatial positions of the system's element or on the topology of their connections. For instance, as shown by de Roos et al. (1991), an agent-based version of the Lotka-Volterra model also allows for the simulation of the effects of individual prey and predators' positions and mobility. Phenomena such as the formation of continuously changing patterns in the spatial distribution of the two populations and regions oscillating differently at different spatial scales are highlighted thereby.

Rahmandad and Sterman (2010) used a compartmental model to compare the results of the SIR model epidemic diffusion simulation with those of an agent-based model presenting the same parameters. In the agent-based model, they

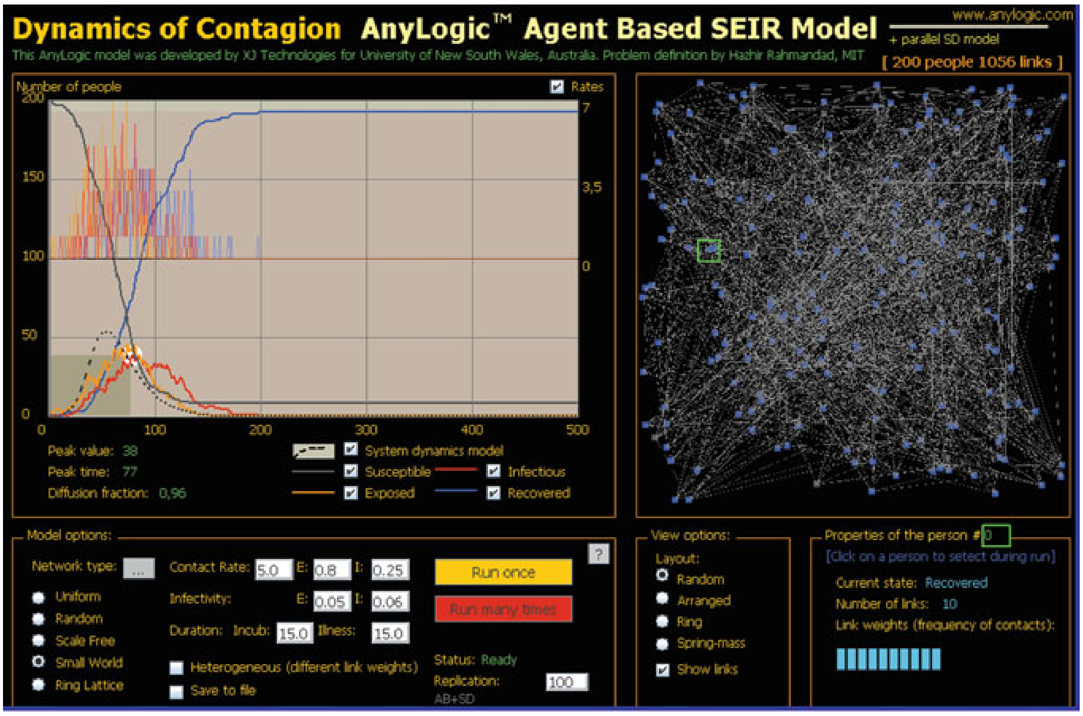


Fig. 4.25 Agent-based simulation model of the SIR dynamics of contagion model. On the *left* are the options which allow for selection of different network structures. Image courtesy of XJ Technologies. Web site: http://www.xjtek.com

explored five different network topologies: fully connected, random, small world, scale-free, and lattice (Fig. 4.25). They concluded that network topologies and individual heterogeneity affect the contagion dynamics, and that the agent-based model allows analysts to examine questions that are not easily modeled in the differential equations approach.

In general, due to their capacity to directly represent the individual elements in a system, agent-based models can describe situations such as the movement of animals in a geographic area, the urban development of a city, the visitor stream in a museum or passenger flow in a subway with a very high degree of spatial realism. In brief, agent-based models gradually freed themselves from some of constraints of cellular automata, and particularly improved the following features:

- *Time*; the agents' interactions with each other and the environment can be asynchronous, i.e., they do not necessarily need to occur all at once or in constant time-steps, but can even depend on events.
- *Rules*; the rules determining the agents' behaviors range from simple local rules to complex decisional algorithms, which can require the use of equations.
- *Autonomy*; agents can have more autonomy, for example they can act proactively or based on the memory of what happened previously.
- *Space*; agent interaction topologies may include networks, continuous space, and geographical maps.

In concluding this section, we shall examine the significant difference between *first-* and *second-order emergent properties*, which originated in the field of Agent-Based Computational Sociology (Squazzoni 2012). A first-order emergent property is generated by localized interaction among agents: it does not pertain to some agent, but only to the system as a whole. It therefore only refers to concepts that were not previously introduced into the model. A second-order emergent property, conversely, is recognized by the agents involved and is consequently supported, modified, or contrasted by them. For this to be possible, the agents must have the cognitive capacity to recognize the characteristics of the system in which they find themselves operating and the consequences of their actions. This second type of property involves direct feedback from the *macro-* to the *micro-level* of system's description.

4.11 System Dynamics

Formulating a mathematical model to represent a part of reality in a non-idealized way is not always an easy or even possible task. This book has already dealt with problems inherent to the modeling of even relatively simple systems when attempting to account for interactions and nonlinearities, which in the real world are the norm rather than the exception. Just imagine then the challenge involved when using equations to represent the management of an organization, the urban planning of a city, the economic policy of a nation, the consequences of energy and environmental decisions on the climate changes, or the motivation level of a company's employees! Which underlying theories should be chosen for the model? How should people's decisions and behaviors be modeled? How should the interactions among the system's different parts be represented?

System dynamics—a modeling and simulation paradigm that originated in the late 1950s—can provide some valid answers to these questions, as it is characterized by a particular conceptual and methodological approach to the study of complex systems (Forrester 1961, 1968; Sterman 2000). According to Richardson's (2009) definition: "System dynamics is a computer-aided approach to theory-building, policy analysis and strategic decision support emerging from an endogenous point of view. It applies to dynamic problems arising in complex social, managerial, economic, or ecological systems—literally any dynamic systems characterized by interdependence, mutual interaction, information feedback, and circular causality" (p. 8967).

In comparison with the approaches described in the preceding sections, system dynamics is a particular and somewhat surprising case. Although it has been applied for many decades to problems in a wide range of fields, and despite the availability of a worldwide community of experts and practitioners, system dynamics is not actually a well-known and used discipline. (It has even encountered direct hostility in some academic institutions!) A brief chronicle of the history of this discipline and its main concepts can help explain at least some of the reasons for this paradoxical situation: The first distinguishing feature of system dynamics is that it is in large measure the creation of only one man—Jay Wright Forrester. Forrester was an electrical engineer who began his academic researcher career at the Massachusetts Institute of Technology in 1939. During World War II, Forrester worked successfully on applying the theory of feedback control systems to the development of servomechanisms to control radar antennas and other military equipment. The servomechanism theory, with its emphasis on the "closed-loop" concept, was also one of the main influences on the then-budding field of cybernetics, although Forrester's work developed autonomously from cybernetics. During the period ranging from the end of WWII to the mid 1950s, Forrester contributed to the development of the first digital computers for military purposes, which reached its peak with the creation of the SAGE national air defense system. In particular, Forrester invented random-access magnetic memory as a part of these projects, i.e., what eventually became the industrial standard for computer memory. In the mid 50s, however, his interests changed course, and he turned to the application of engineering concepts to organizational policy study. In 1956, Forrester became professor at MIT Sloan School of Management, and he began to formulate models of economic and social systems by using computer simulations to analyze the implications of those models. The first result of these studies was the publication of his 1961 seminal book called "Industrial Dynamics", which employed new models based on the feedback concept to analyze a series of business and industrial problems: "Industrial dynamics is the study of the information-feedback characteristics of industrial activity to show how organizational structure, amplification (in policies), and time delays (in decisions and actions) interact to influence the success of the enterprise" (1961, p. 13). In the following years, Forrester extended his models to other application fields, including the dynamics of urban development (1969) and of world growth (1971). His world growth models achieved international fame, when they were popularized in the book "The Limits to Growth" (Meadows et al. 1972), which enjoyed widespread dissemination and became a reference book for the environmental movement. Yet, the book gave rise to (even quite heated) debate, and its models were harshly criticized by professional economists. Perhaps due to this criticism, developments in the field of system dynamics slowed down and for many years, this line of research lay at the fringes of the academic world. During the 1990s, two scientific and cultural advances kindled new interest in system dynamics: (1) the increasing availability of software environments to create this type of simulation on personal computers, and (2) the publication of Peter Senge's book "The Fifth Discipline" (1990), which placed system dynamics in the wider context of *systems thinking*. Moreover, the many entries dedicated to this discipline, which appear in the Encyclopedia of Complexity and Systems Science (recently edited by Meyers 2009), bear witness to the currently healthy status of the approach. These entries pertain to a broad range of topics, such as public policy applications (Andersen et al. 2009); environment, energy, and climate change models (Ford 2009); organizational learning (Maani 2009); and economics (Radzicki 2009).

The conceptual premise of system dynamics is that the behavior of a system depends on the structure of the cause-and-effects relations among its parts. System dynamics' models are usually created to examine specific social, managerial, economic, or ecological/environmental problems. Thus, the problem guides the modeler in defining which key variables must be included to describe the system. System dynamics takes on an *endogenous* point of view: the system is considered to be *causally closed*, and the modeler must create a structure that should be able to reproduce some aspects of the problem on its own, with no need for external explanations. In other words, external elements are seen as triggers of the system's behavior, but the causes of this behavior are considered to be internal to the system. This point of view stems from the observation that organizational or social improvement initiatives frequently fail, not because of external causes but due to internal tendencies, such as tendency toward equilibrium.

The modeling method consists in (1) building the system's causal structure by using basic building blocks to be visually combined in a map, and (2) using equations and rules to describe the functional relations that exist among these elements. The basic elements of a system dynamics model are as follows:

- *Stocks* (or "levels") are the variables representing the system state at a given time and can be imagined as containers storing data or materials. Stocks are visually represented as rectangles with one or more inflow-outflow components, represented by large arrows;
- *Flows* (or "rates") are the materials or data flows incoming or outgoing from a stock. Flows are visually represented as valves on the arrows regulating the flow of input or output and representing the stocks' rate-of-change factors thereby.

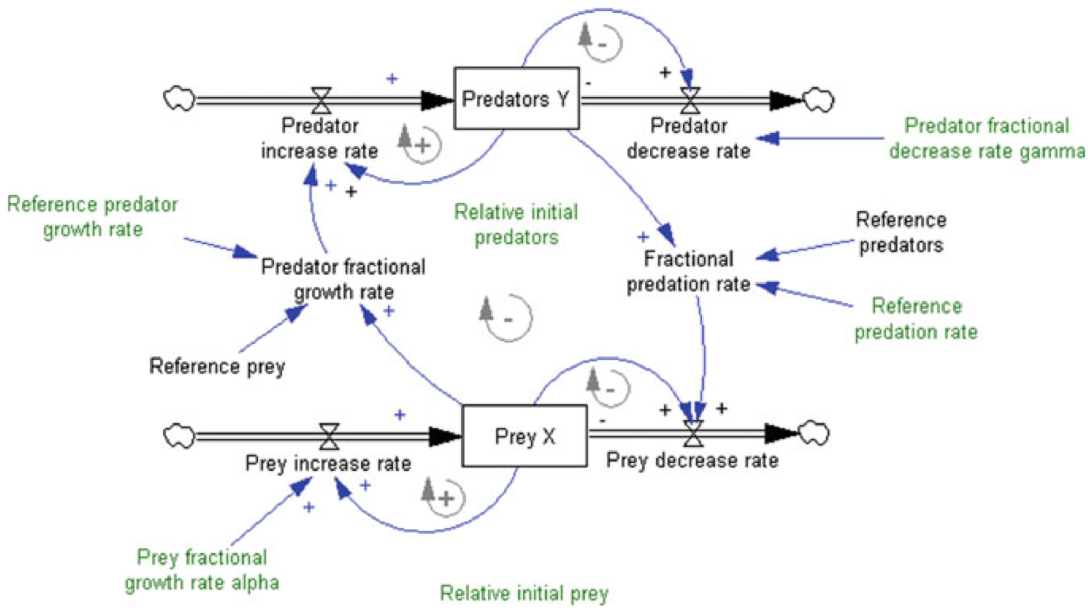


Fig. 4.26 A system dynamics predator–prey model. Image courtesy of Tom Fiddaman. Web site: http://www.metasd.com

Flows can enter a stock either by coming from another stock or from an external source, and the outgoing flows can end up in another stock or in an external "sink" (both sources and sinks are represented by a picture of a cloud);

- *Feedback loops* are closed paths connecting a stock with its flows, i.e., an effect with its causes. The feedback consists in the transmission of information about the state of a stock to other parts of the system, and it can be direct or indirect, through the action of other variables;
- *Limiting factors* are constants that limit the data or material quantity to be stored in the stocks.

Examples of the above elements are illustrated in Fig. 4.26, which is a system dynamics version of the Lotka-Volterra predator–prey model.

From a mathematical perspective, the variation of a stock S can be expressed through the differential equation:

$$\frac{\mathrm{d}S}{\mathrm{d}t} = I(t) - O(t)$$

where $I(t)$ and $O(t)$ are respectively the incoming and the outgoing flows; the level $S(t)$ at any given time can be calculated by integrating the previous equation:

$$S(t) = S(t_o) + \int [I(t) - O(t)]\mathrm{d}t$$

Thus, from a purely mathematical standpoint, a system dynamics model is comparable to a dynamical system the evolution of which is represented by a system of coupled, nonlinear, first-order differential equations, to be solved through numerical methods. It differs, however, from other equation-based

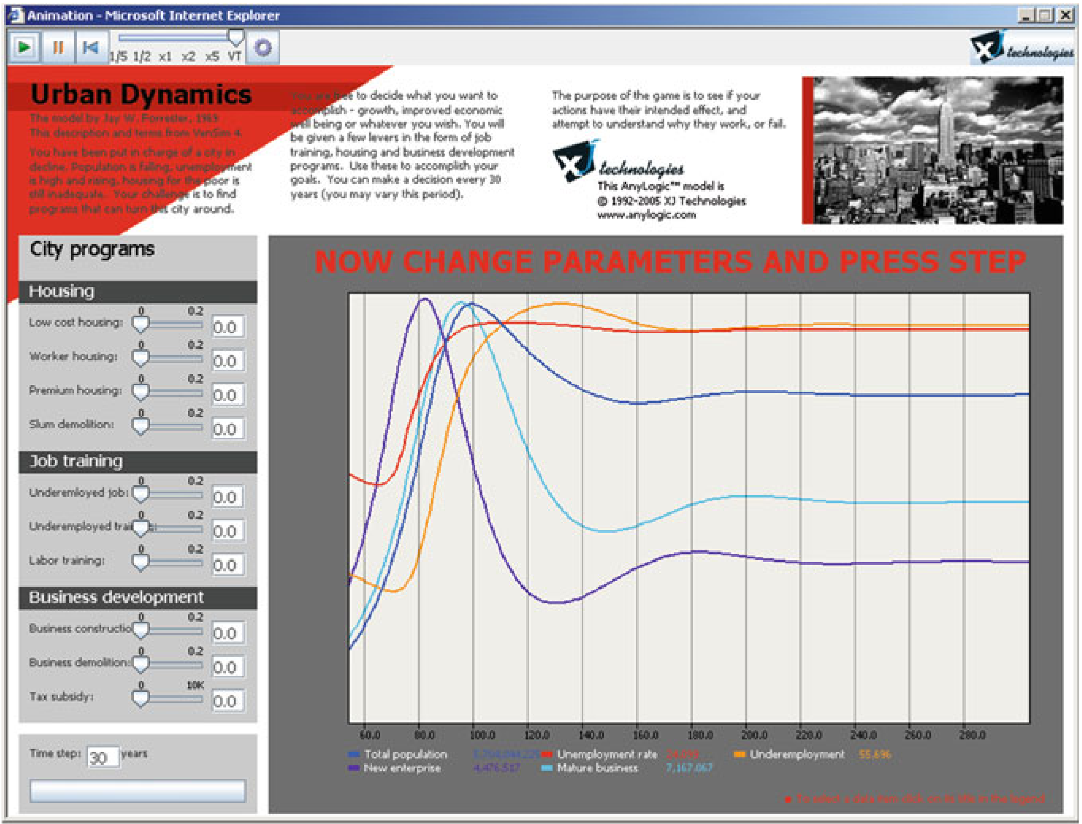


Fig. 4.27 Urban Dynamics model. Image courtesy of XJ Technologies. Web site: http://www.xjtek.com

simulation methods because one does not start modeling the system by writing the equations, but by visually representing the system's causal structure. Once this structure has been created, the relations among variables may be described by way of algebraic equations and logical rules, and the modeling software automatically creates the difference equations to be numerically solved. The modeler must choose a numerical algorithm and an appropriate time-step. The simulation output is usually given by graphs showing the behavior of one or more variables over time. For instance, Fig. 4.27 shows a screenshot of a simulation of Forrester's urban dynamics model. On the left are sliders for modifying input variables related to housing, job training, and business development; the graph shows the behavior over time of the output variables total population, unemployment rate, underemployment, new enterprise, and mature business.

System dynamics modeling environments also allow for the creation of "microworlds" that are simulations of real systems such as a firm, a market, a production system or an ecosystem, endowed with user-friendly interfaces and sometimes, gaming elements. Microworlds provide managers or students with "virtual labs" for testing their strategies and ideas. These are also "microcosms of real business settings where teams of managers together learn by conducting experiments that are difficult or impossible to conduct in real business" (Senge 1990, p. 274).

Another way to represent a system's structure is that of "causal maps", i.e., qualitative representations that are much simpler than a stocks-and-flows diagram representing the inter-variable relations by arrows. Specifically, a causal map describes two kinds of possible relations between two variables A and B:

- *same sign relations*, in which B also increases (or decreases) as A increases (or decreases);
- *opposite sign relations*, in which B respectively decreases (or increases) as A increases (or decreases).

Same sign and opposite sign relations are respectively indicated by the letter *s* (or the *plus* sign) and by the letter *o* (or the *minus* sign). Casual maps are commonly used in the first steps of model creation to elicit experts' knowledge, or later on, to explain the model's structure to users and stakeholders.

To understand the ways in which structure creates behavior in the system dynamics approach to modeling, one can start by analyzing the feedback loop dynamics, which can be of two types:

- reinforcing (or positive) loops;
- balancing (or negative) loops.

Whereas reinforcing loops determine the system's growth or decay, balancing ones lead it to stability. Reinforcing processes are forces that drive the growth (or decline) of a system and respectively correspond to what are commonly called *virtuous circles* or *vicious circles*. Growth of funds deposited in a bank account due to interest payments, or debt accumulated on a credit card are examples of these reinforcing loops. Moreover, in a product diffusion process, an increase in the number of customers leads to further word of mouth communication between current and potential customers (see Fig. 4.28). A positive word of mouth effect results in a sales increase, which, in turn, causes an increase in the number of customers. This feedback circuit determines an exponential growth of the number of customers over time. At the same time, however, empirical reality teaches us that no process can grow indefinitely; thus sooner or later, a reinforcing loop will encounter the limiting effect of a balancing loop.

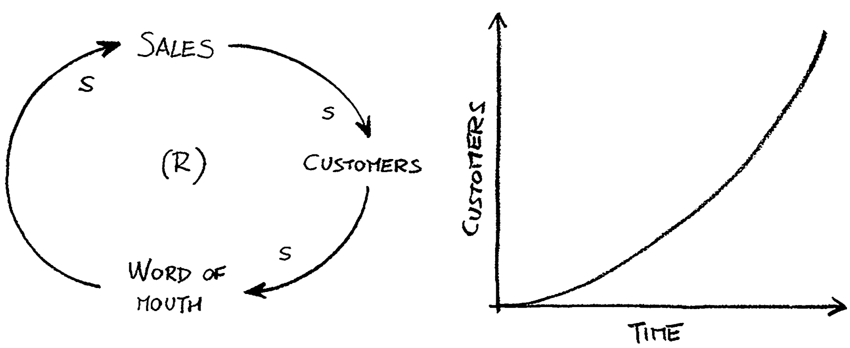


Fig. 4.28 Example of a reinforcing feedback loop

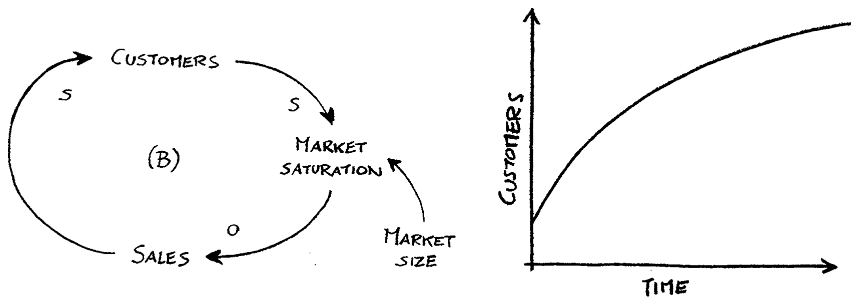


Fig. 4.29 Example of a balancing feedback loop

In a balancing loop, the variables influence each other, such that they stabilize the system. Given that the relation between some variables is of opposite sign, it limits the effect of actions aimed at modifying the system. Examples of these feedback loops are the functioning of a thermostat or a product's potential market saturation. In the example of product diffusion (see Fig. 4.29), an increase in the number of customers causes an increase in market saturation (due to the market size limiting factor); this situation leads to a decrease in sales, which in turn causes the number of customers to decrease. The net effect is that the number of customers starts below a certain equilibrium level and over time moves toward that level. In general, a balancing loop generates goal-seeking behavior by detecting a gap between the current and desired levels in a stock, and initiating corrective action.

In a system, feedback loops do not operate separately, but are interconnected, and it is their interaction that produces the system's global behavior. When a positive and a negative loop interact with each other, as is shown in Fig. 4.30, they produce a dynamic known as *shift of loop dominance*. In the first time interval, the dynamic is dominated by the reinforcing loop (R), and the curve slope therefore increases. In the second time interval, however, it is dominated by the balancing loop (B), which leads to a curve slope decrease. The system eventually reaches stability and thereby yields the same logistic curve appearing in other types of models (see Sects. 4.3 and 4.6). Only nonlinear systems are able to dynamically

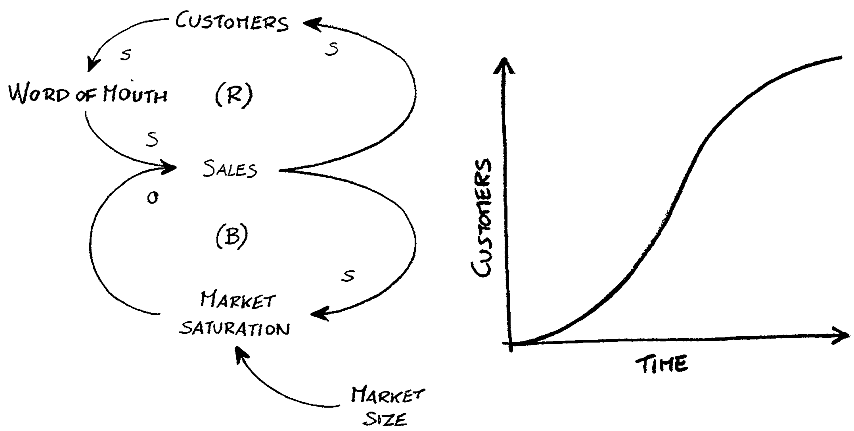


Fig. 4.30 The shift of loop dominance phenomenon

change their behavior due to the effect of an internal mechanism such as the shift of loop dominance.

The concept of *delays* is another important system dynamics model feature; these are represented by a double line interrupting the arrow connecting two variables. Actions do not always result in an immediate consequence. A long period of time may pass before change in a variable affects the other variables linked to it. This delay can explain how problems arising in a system are not necessarily the consequences of recent decisions, but can date from a long time previously, even if the consequences become evident only in the present. A linear view of a problem conversely does not take this aspect into account. The presence of delays, moreover, renders the task of solving the problem more complicated. The solution needs time develop, but the problem can worsen, even significantly, during this period, because another feedback loop remains dominant. Furthermore, the presence of delay in inter-variable relations usually causes some oscillations around the target value, which proportionally increase in amplitude with delay duration.

One of the strengths of the system dynamics approach, as compared to other organizational, economic, and social systems research methods, is its potential for including both "hard" and "soft" variables in the model. The former are quantitative and the latter more qualitative (or only semi-quantitative) and are linked to human factors such as motivation, satisfaction, or stress. In many application contexts, the knowledge in the models is provided by experts and therefore, by *people* having gained some knowledge of the system through study or experience, which is useful to describing the model's boundaries, structure, and expected behaviors. Hence, the field of system dynamics provides a series of methods for eliciting, articulating, and describing the knowledge contained in these experts' mental models as well as for constructing simulations on the basis of these models (Ford and Sterman 1998).

4.12 Cellular Modeling and Simulation

Progress in the fields of biochemistry, molecular biology, and cell physiology, coupled with emerging laboratory techniques, have led to an unprecedented amount of data and information on biological processes, resulting in the creation of bioinformatics databases. Some important examples are the *Reactome*[10] database of biological pathways, and the *Human Connectome Project,*[11] the goal of which is to map anatomical and functional networks within the human brain. In fact, the next step on the scientific frontier is to understand the mechanisms that regulate the functioning of biological systems. In the endeavor to achieve this goal, scientists are now focusing on simulation as an instrument to be used alongside

[10] Web site: http://www.reactome.org.

[11] Web site: http://www.humanconnectomeproject.org.

laboratory research. Thus, in addition to in vivo and in vitro testing, biologists today have at their disposal *in silico* testing, i.e., a new type of testing performed via computer simulation.

One constantly growing field that shows great synergy among theory, experimentation, and simulation is that of *cellular modeling and simulation* (Bolouri 2008; Palsson 2011; Szallasi et al. 2010)—a new paradigm examining the functioning of living cells. A cell is a complex system, but unlike the other complex systems examined herein, one cannot account for its functioning by using equations derived from a few general laws, e.g., as occurs in physics or chemistry, nor by referring to the interaction of many individual elements, as in the instance of emergent phenomena, which characterize agent-based models. Indeed, a cell is a structure made up of functionally specialized components, which are organized in a hierarchy of molecular components, modules, and systems. Thus, a cell is similar to a surprisingly complex machine, and it is no surprise that scientists have compared the reconstruction of cellular pathways to a task of "reverse engineering" (i.e., discovering a cell's biological mechanisms by analyzing its structure and function). Moreover, the feedback mechanisms in cellular simulation models are thought to be similar to those of control theory (Rice and Stolovitzky 2004). In this engineering-based approach, a *theoretical reconstruction* of the functioning of biological systems is currently underway. The aim of this endeavour is to pave the way for *synthetic biology* (Fu and Panke 2009; Schmidt et al. 2009), which will lead to the *actual construction* of biological systems not found in nature.

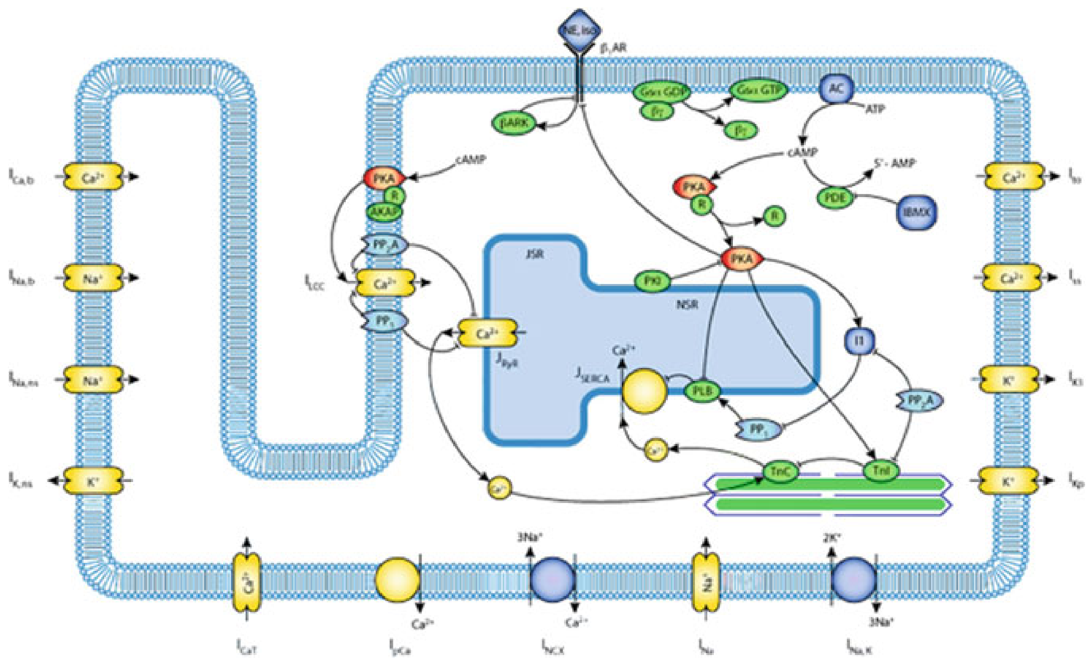


Fig. 4.31 Schematic diagram for the Saucerman-McCulloch (2004) cardiac myocyte model. Image courtesy of The CellML Project. Web site: http://www.cellml.org

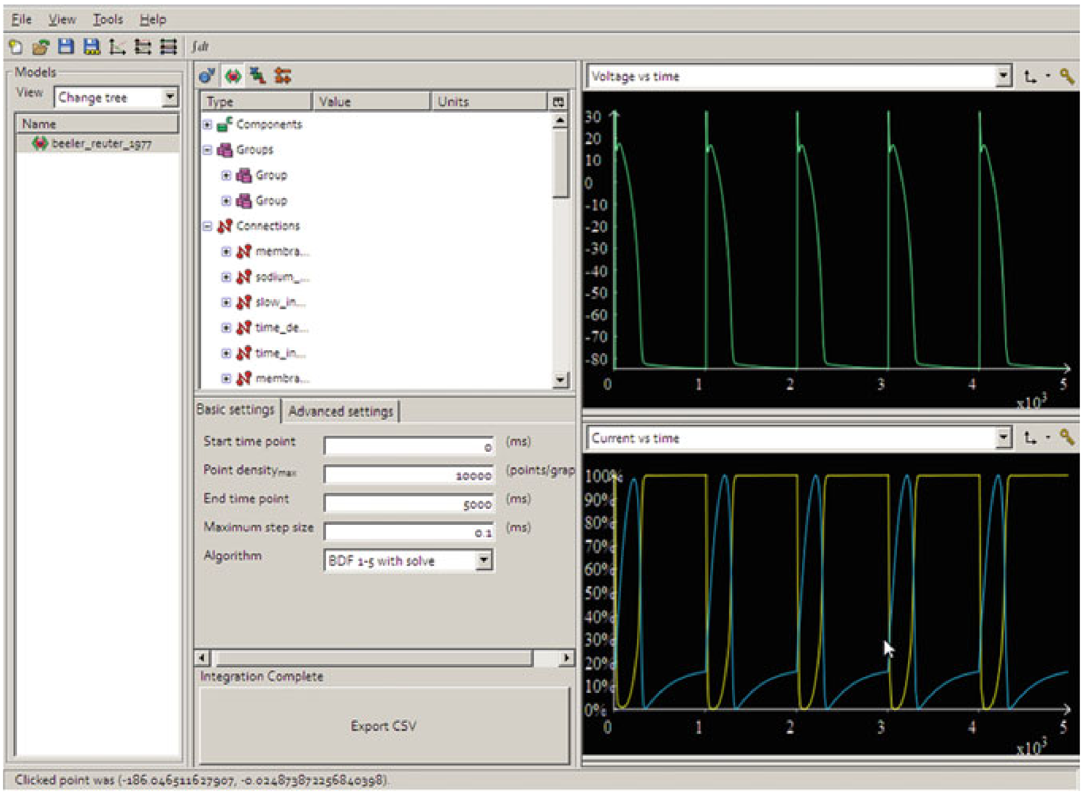


Fig. 4.32 Comparison of two plots representing the simulation of cellular oscillations in the OpenCell modeling environment. Image courtesy of The CellML Project. Web site: http://www.cellml.org

Simulating cellular pathways (e.g., signaling, metabolic, or gene regulatory pathways) can be done in many ways. In general, two stages in the modeling and simulation process can be identified:

1. the creation of a map that visually represents the entities constituting the system (e.g. proteins, metabolites, or genes) and their functional connections;
2. the description of these connections through a system of nonlinear ordinary differential equations.

In most of these applications, the map can include tens of elements and may resemble a technical diagram or an electronic circuit (Fig. 4.31). Cellular simulation modeling environments include tools to allow scientists to visually create this type of map by using pre-existing graphical objects to represent functional elements. Similarly to as occurs in the analysis and design of control and electronic circuits, biologists seek basic functional modules that can be conserved and reused as building blocks, or even as "standard biological parts" (Cooling et al. 2010). One of the most frequently used techniques to translate the map into a system of equations is *mass-action kinetics*, a model of enzyme kinetics used in biochemistry to describe the behavior of reactants and products in a chemical reaction. The initial conditions are the concentrations, diffusion coefficients, and locations of the molecular species that made up the model. The simulation software then executes the calculations required for the numerical resolution of the equations and visualizes the results as graphs, expressing the time-related changes in molecular component concentrations (Fig. 4.32).

As a modeling method, ordinary differential equations may be accompanied by other methods such as partial differential equations and stochastic methods, respectively, to model spatial diffusion processes, and to account for the noise present in biological systems. Simulation results are compared with real bioinformatic database data or with those of new experiments. For example, the simulation model predictions for metabolic and cardiac cell models were later experimentally validated. Thus, in a virtuous circle, simulation results may be used to redefine experimental protocols, which in turn can generate new data to improve simulation results.

4.13 Comparing Paradigms

In many situations, the nature of a studied system may naturally lead to the selection of a specific modeling strategy. The choice may be based on an existing theory of reference or on some specific feature of the system. For instance, whereas the study of the motion of a body is commonly described by using Newton's mechanics methods, studying the turbulent motion of a fluid calls for Navier–Stokes equations. The question of simulation paradigm selection can become more complex, however, in situations allowing for a system to be modeled in different ways. For example, as described in the present chapter, matter can be modeled as if made up of atoms and molecules or as a continuous substance. Furthermore, some biological and social systems can be modeled via compartment, agent-based, or system dynamics models, and the relative effectiveness of these different approaches is not easily comparable, as it depends on the purpose of the model (Rahmandad and Sterman 2008; Schieritz and Milling 2003). In educational contexts, the instructional and epistemological implications of different options must also be considered.

Thus, the use of a paradigm should start from comprehension of its conceptual foundations, limitations, and relations with other paradigms. In spite of their differences in perspective, simulation paradigms are best considered as being complementary, because they are different ways of representing a given facet of reality—whether one is examining a liquid, an ecosystem, the spreading of a disease among a population, or a genetic regulatory network. Indeed, only by comparing and integrating different simulation paradigms can we achieve a better understanding of reality and our relation with it.

A taxonomy of potential *modeling strategies* for representing a system is proposed here below, as a framework for understanding the conceptual differences among the various modeling and simulation paradigms. From a general standpoint, the aim of these strategies is to help the modeler answer two key questions:

1. What is the system made of?
2. How does the system work?

The answers respectively consist in the description of (a) the system's composition and structure and (b) the way it changes. The most recurring strategies can be classified into only a few categories. In terms of its composition and structure, a system can be represented by:

1. a collection of homogeneous elements;
2. a continuous substance (i.e., a substance that completely fills the space it occupies and that is deformable);
3. a collection of heterogeneous elements; or
4. an entity made up of components that perform different functions.

These descriptions do not necessarily represent properties of the "real" system, but are merely ways in which the system is conceived for modeling purposes. They correspond to conceptual models, but more generally to models of a more fundamental type than those involved in the modeling of a specific system, as they are ontological in nature. These descriptions are actually cognitive schemas, which are similar to the conceptual metaphors and image-schemas studied in cognitive linguistics.

Once we have decided "what" the system consists of, we should find a way to represent and explain how it changes over time. As shown by some of the examples reported in this chapter, most of the equation-based modeling approaches are based on the assumption that studying the behavior of a limited number of global variables is equivalent to studying the behavior of each element. This assumption is called the *aggregation hypothesis* (or *aggregation principle*). This view is in turn justified by the hypothesis of system homogeneity and by the *Law of large numbers*, which states that for a sufficiently large system, the mean value of a random variable is stable over long periods of time or large number of samples, and that stochastic variables can therefore be represented with average values. An additional hypothesis underlying the use of aggregated variables is that of perfect mixing, i.e., that the effects due to the elements' positions are negligible. For instance, the Lotka-Volterra model is based on the assumptions that, to predict the time-related behavior of the prey and predators' populations, one need not know the individual features of each animal, such as age, gender, state of health (aggregation hypothesis), or their position in the environment (perfect mixing hypothesis). These assumptions make it possible to aggregate all information about the prey into the single variable of number and to do likewise with the predators. It is therefore possible to represent the state of the system with two variables only and to use the previously described differential equations (see Sect. 4.3) to model the interactions between them. In cases not allowing for application of the aggregation and perfect mixing hypotheses, the strategies of *direct representation*, i.e., modeling the behavior of each element of the system, or *mechanistic explanations*, i.e., modeling the behavior of the system in terms of the functions performed by its components, can be employed.

Table 4.6 Strategies to model the evolution of a system

Modeling strategies	
What	A collection of homogeneous elements
	A continuous substance
	A collection of heterogeneous elements
	An entity made up of components, which performs different functions
How	Aggregation, i.e., incorporating different elements of the system in one or more global variables
	Direct representation, i.e., modeling the behavior of each element of the system
	Mechanistic explanation, i.e., modeling the behavior of the system in terms of the functions performed by its components

Table 4.7 The *what* and *how* of simulation paradigms

Simulation paradigms	What	How
Equation-based modeling	A collection of homogeneous elements A continuous substance	Aggregation
Molecular dynamics	A collection of homogeneous elements	Direct representation
Agent-based modeling	A collection of heterogeneous elements	
System dynamics	An entity made up by components which perform different functions	Aggregation
Cell modeling and simulation		Mechanistic explanation

In brief, the main modeling strategies for answering the second of the above-mentioned questions, i.e., how does a system work, are:

1. aggregation;
2. direct representation; and
3. mechanistic explanation.

Table 4.6 summarizes the strategies to model the evolution of a system described in this section.

The ways in which this schema can be applied to the heretofore described simulation paradigms are listed here below.

- *Dynamical Systems Modeling*. In this modeling method, the system is represented as a collection of homogeneous elements—e.g., in classical mechanics a body is represented by a point mass or a set of point masses. In the study of dynamical systems, the approach of classical mechanics has been extended to any time-related variable on the basis of the aggregation principle. This approach makes it possible to represent a system by a point in phase space and its evolution, by an orbit in the same space;
- *Continuum Physics Modeling*. The system is represented as a continuous substance. System change is studied from an aggregated perspective, with macroscopic variables conceptually deriving from the effects of microscopic elements and equations connecting these variables;

- *Compartmental Models.* The elements (e.g., molecular species, people) in a given compartment are represented as being homogeneous (e.g., in the same state) and perfectly mixed; their collective behavior can therefore be represented by aggregated variables. The system's evolution is described by a system of ordinary differential equations, with time as the independent variable. Stochastic effects are modeled as average values;
- *Molecular Dynamics.* The system is represented as a collection of a great number of homogeneous elements (e.g., particles), which all follow the same rules. The system's evolution is represented by directly simulating each element's movement and by measuring the values of macroscopic variables through statistical mechanics techniques;
- *Agent-Based Modeling.* The distinctive feature of the agent-based modeling paradigm is its capacity to directly represent a system as being made up of many heterogeneous individual elements, i.e., elements that do not necessarily obey the same rules or laws; these are therefore systems to which the hypotheses of homogeneity and perfect mixing do not apply;
- *System Dynamics.* The system is represented as an entity made up of components, i.e., stocks and flows organized in a causal structure. These components represent aggregate variables with relations represented by feedback loops. Stochastic effects are represented by average values, and spatial effects generally are not modeled. This approach presents some interesting analogies with continuum physics, as the value of a stock is based on the metaphor of the level of a liquid in a container, and the incoming and outgoing flows are modeled by equations similar to those used in the study of transport phenomena;
- *Cell Modeling and Simulation*. The system is represented as an entity made up of functionally specialized and hierarchically organized components (e.g., molecular components, modules, and systems). Representing the system's complexity requires diagrams that are similar to those of electronic or control circuits. The structure/behavior relation is described by ordinary differential equations or other mathematical methods Table 4.7.

Chapter 5
Simulation-Based Learning

Time is the father of truth, its mother is our mind.
Giordano Bruno, The Ash Wednesday Supper (1584)

5.1 Simulation-Building Versus Simulation-Using

Learning is intrinsic to simulation, as it allows, e.g., scientists to learn new aspects of natural and artificial systems, engineers to design new products and processes, and organizations to learn how to adapt to a changing environment. It is indeed this link with learning that differentiates simulation from other information- and knowledge technologies. Applications such as wikis, blogs, or social networks let users find information, create content, and share ideas and experiences. They can also foster learning in various ways and have therefore become taken center stage with teachers and students. Compared to these highly popular tools, however, simulation is more intimately linked to the human capacity to reason, make predictions, imagine alternative actions, and solve problems. Thus, only computer simulations and dynamics modeling software have been characterized as *tools for thinking* (Papert 1980), *learning laboratories* (Senge 1991), and *mindtools* (Jonassen 2000b).

To understand the ways in which simulation can foster learning in so many different contexts, one must understand that simulation-based learning occurs in two main ways:

1. by building a simulation; or
2. by using an existing one.

In the first case, students must use either a programming language or the features of a given modeling and simulation software environment to build a simulation model on their own. To achieve this aim, they must (a) analyze a specific system, (b) develop a conceptual model of it, (c) create a computational model, (d) implement the computational model as a simulation program, (e) conduct numerical experiments on it to validate the computation model. Lastly, (f) they can use the simulation program to solve a problem or understand the causes of the phenomenon under study. Each of these activities requires understanding, reasoning, and prediction abilities and the construction of mental models thereby. The latter moreover, undergo modification as a consequence of these

F. Landriscina, *Simulation and Learning*, DOI: 10.1007/978-1-4614-1954-9_5,

activities, such that the entire process can be viewed as a progression of internal and external models (Fig. 5.1).

Instructional scientists have emphasized the highly instructional value of having students build, evaluate, revise, and elaborate their own visual or material models (Gobert and Buckley 2000). Notably, David Jonassen recurrently stated in his characterization of system dynamics modeling software as "mindtools" (Jonassen 2000b, 2004) that students can learn more by building their own models rather than using expert-provided ones. Yet, we also know that simulation model building is not always feasible in instructional contexts: Some students lack sufficient knowledge of the system to be modeled; do not have the necessary modeling skills; or there simply may not be enough time available to carry out all steps required. Thus, the need frequently arises to use an already existing simulation, which might be an instructional resource available on the Web or software purchasable in educational simulation and games market.

In this context, it is important to distinguish between simple simulation programs allowing students to change only a few variable values and view the consequences of their decisions in a graph, and more structured simulation-based learning environments. The latter also feature instructional supports and resources aimed at facilitating and enriching the students' learning experience (Fig. 5.2), for example:

- background information;
- questions;
- hints;
- explanations;
- exploration guides;
- exercises;
- graphing tools;
- planning tools.

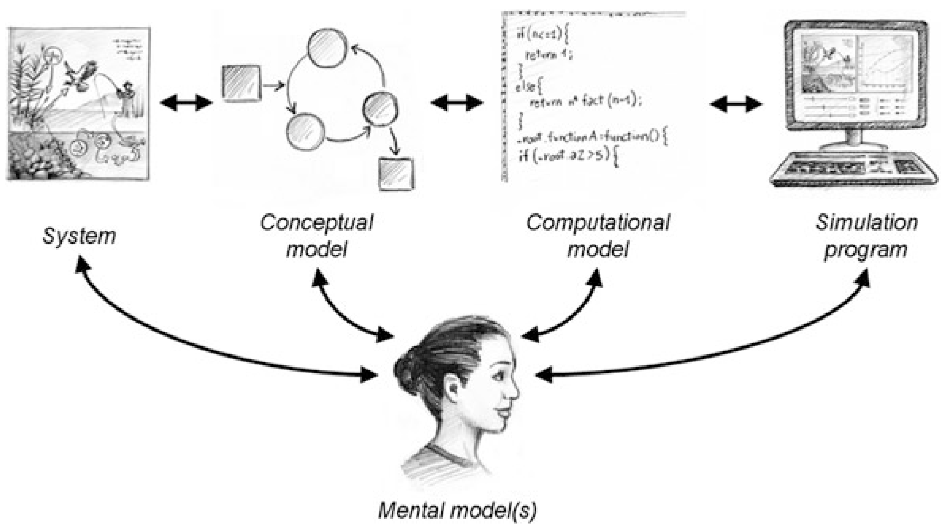
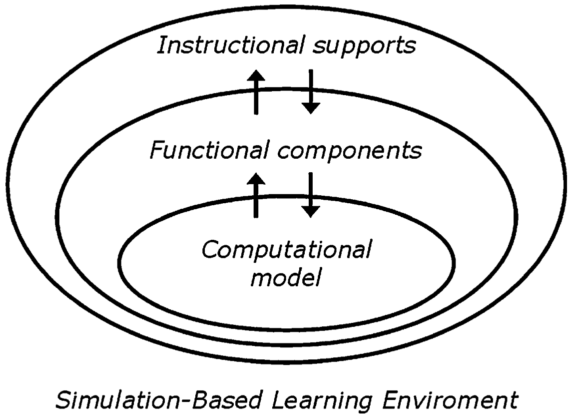


Fig. 5.1 Learning by simulation-building

Fig. 5.2 The components of a simulation-based learning environment



The design of these instructional supports is usually guided by an *instructional model*, i.e., a set of explicit and/or implicit assumptions about the simulation's learning goals and the instructional strategies considered most likely to positively impact the students' learning process.

Other terms which are to be encountered on this context are *microworlds* and *synthetic learning environments*. The term "microworld" comes from Seymour Papert's researches on children's learning, which gave birth to the LOGO programming language (Papert 1982), and it is used by educational researchers to indicate an exploratory learning environment aimed at children and centered around problem solving and experimentation, not necessarily with the use of a simulation, or, in the context of system dynamics, to indicate a learning environment in which a system is simulated with many details to support systems thinking (Senge 1990). The notion of a simulation-based learning environment is also similar to that of a "synthetic learning environment", which has been defined by Cannon-Bowers and Bowers (2008) as "a learning environment characterized in terms of a particular technology, subject matter, learner characteristics, and pedagogical principles; a synthetic experience, as opposed to a real-world interaction with an actual device or process, is created for the learner through a simulation, game, or other technology" (p. 317).

The epistemic activities of students involved in simulation-using are: (a) using the simulation program as requested by the learning task at hand, (b) constructing their own mental models of the system or problem at hand, (c) comparing their own mental models with the target conceptual model and, (d) using the knowledge they acquire about the conceptual model to gain a better understanding of the system represented by the model (Fig. 5.3).

It is important to note that simulation-using activities do not require students to interact directly with the conceptual model (the most important aspect of the simulation), nor with the computational model. Interaction occurs exclusively through the mediation of the simulation program's user interface, and through the learning activities the instructional model affords. Simulation-based learning research refers to this phenomenon as the "opacity" issue, represented in Fig. 5.3

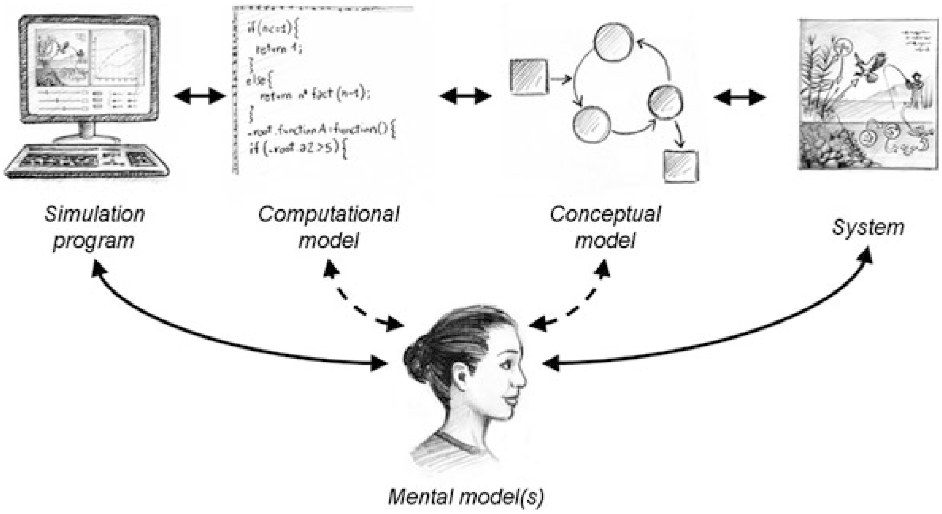


Fig. 5.3 Learning by using simulation

by the dashed versus solid lines connecting the student with the different conceptual entities lying "behind" the visible part of the simulation.

Simulations can therefore be differentiated in terms of the commonly made distinction between "black-box model" simulations and "glass-box model" (or "transparent") simulations. In black-box model simulations, students can explore a system's behavior, but the underlying conceptual and/or computational models remain hidden and can only be inferred by what appears on the screen. For example, many simulation games present thousands of scenarios, but do not show the rules constraining these scenarios as established by the game's creator(s). This type of "black-box" situation could lead students to believe that their partial conclusions are undisputable assumptions, as suggestively reported by Turkle (1997) in her analysis of the ways in which simulation can affect education:

> I ask Marcia, a student in her second year of secondary school, some questions about SimCity®; she, who thinks to be very good at the game, lists what in her opinion are "the ten most useful rules of the simulation". My attention was captured by the rule number six: «Tax rises always cause uprisings». It seems that Marcia does not possess a language to distinguish between this rule of the game and the rules in force in a "real" city. She has never programmed a computer. She has never designed a simulation. She does not possess a language to ask how you can rewrite the game so that you can obtain that a tax rise may determine an increase of productivity and a harmonic society (p. 82).

The opacity issue is not limited to simulation games or complex simulations. Students facing any type of simulation tend to automatically attribute rules to the system, based on their own mental models formed in that moment. These rules may match those actually present, but they can also be wrong or incomplete inferences, and in this latter instance, they can actually interfere with proper learning. For example, imagine a student watching a computer animation showing the chaotic motion of a damped driven pendulum (see Sect. 4.5). Observing that the pendulum oscillates unpredictably and erratically, she might infer that some form of random force is acting on it, whereas the only factors involved in the phenomenon are the force of gravity, friction, and the applied periodic force.[1] Similarly, the emergent phenomena characterizing agent-based simulations can give the appearance of behavior regulated by complex laws, when only simple local rules are conversely at work.

"Glass-box model" or "transparent" simulations have alternatively been proposed to obviate the above-described problems, as they overtly show relations among variables, i.e., the structure of the computational model underlying the simulation. This approach has frequently been used in system dynamics' learning environments, which show their stocks-and-flows diagram, and in some instances, the relative equations to students using the simulation. Yet, Groesser (2012) pointed out that the extra information provided by the high visibility of system dynamics models can benefit only learners who are familiar with system dynamics methodology, and who are thus able to read and interpret a stocks-and-flows diagram. In general, it is reasonable to assume that the main effectiveness criterion for glass-box model simulations is that the model's structure be reasonably understandable to students. A potentially effective way to render the model's structure more understandable is to present it to the student step-by-step, in the form of a narration or guided tour. For example, Fig. 5.4 shows an intermediate presentation step for the structure of the model underlying a virtual laboratory designed to explore literature's plot and character development.

Another risk involved with glass-box models, which show students the equations underlying the model is of a more epistemic nature—i.e., that students may mistake these equations for the conceptual model, although the same conceptual model can actually be implemented by using different equations or algorithms.

In any event, despite the practical utility of highlighting differences among simulation-based learning environments, the black-/glass-box model distinction tends to overlook a more fundamental aspect of the opacity issue—i.e., that:

- Every simulation model is cognitively opaque.

Cognitive opacity derives from the fact that it is difficult or impossible to predict the behavior of a computational model based on knowledge of its structure or equations only. Thus, to study the model, one must resort to simulation, as described in the all of the examples reported in Chap. 4.

One way of rendering the model more "transparent" is to have students (to the extent that this is possible) retrace the modeling processes used by the simulation's creator(s). This can be achieved by using multiple representations of the conceptual model (e.g., images, animations, maps, graphs, explanations) and discussing its nature with students. They should also be asked to render the hypotheses underlying the simulation explicit. Moreover, even when a simulation is based on a simple equation, such as that of the simple pendulum, a more detailed analysis can help students become more aware of the equation's underlying

[1] Indeed, many phenomena currently studied in chaos theory were long considered to be purely random ones.

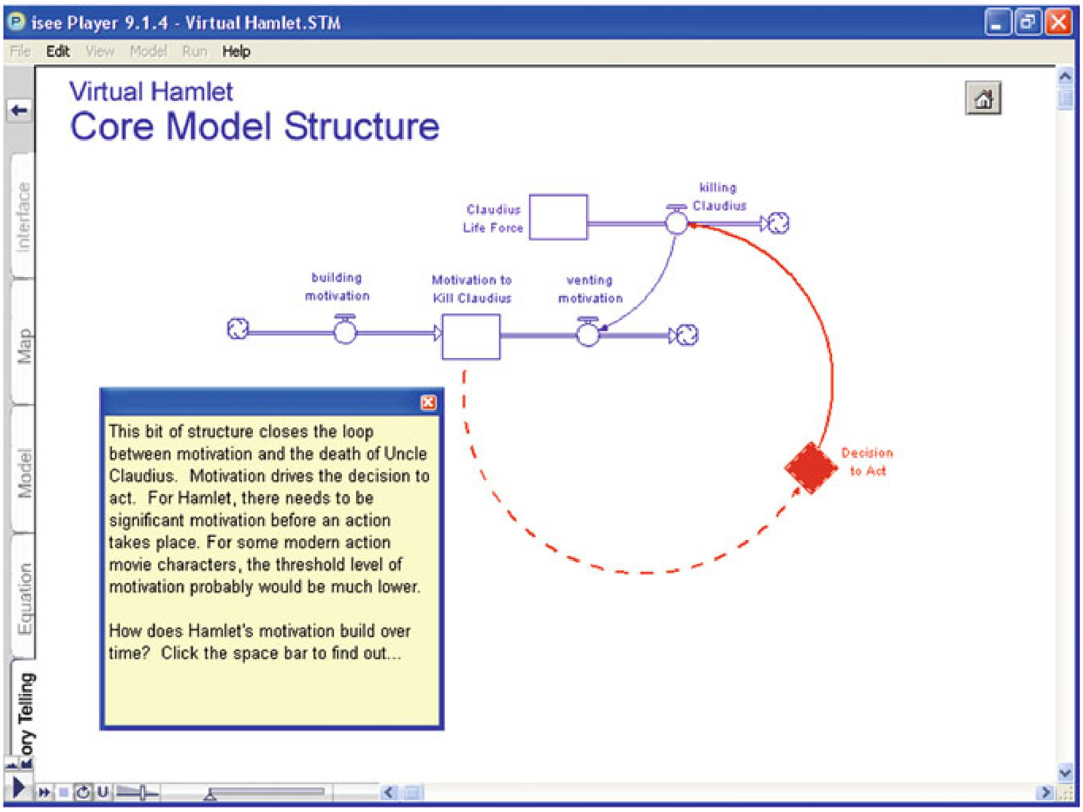


Fig. 5.4 A screenshot of the Virtual Hamlet, a learning laboratory created with the STELLA® modeling software. Image courtesy of isee systems. Web site: http://www.iseesystems.com

abstractions and idealizations—awareness that does not develop when students are asked to simply “put the numbers into the formula”.

Delving into the merit of a given simulation’s conceptual aspects requires that teachers also survey the students’ mental models and the ways in which these models change during the learning process.

The next section will present an example illustrating some of the cognitive processes that accompany students’ learning activities and changes in their mental models.

5.2 The Cognitive Processes Involved in Simulation-Based Learning

When studying simulation as an educational method, a simulation program’s features (e.g., technology, visualization methods, level of interactivity) might more easily capture our attention, but the mental processes involved in student’s *interaction* with them must also be considered. These processes depend on many factors related to the learning context, e.g., learning task, prior knowledge, interest, instructional method, degree of instructional support, type of assessment. The role of some these factors in simulation-based instruction will be examined in Sects. 5.6 and 5.7. The present Section focuses on the more general issue of the ways in which simulation- and cognitive processes are related.

Consider the case of a middle school student, Mary, who is using a simulation to study the relation between temperature and particle motion in a gas. Let us assume that: Mary can change the gas temperature by moving a slider on the screen; the gas molecule motion is visualized via animation; and that a graph represents the statistical distribution of molecular velocities (Fig. 5.5).

The conceptual model underlying the simulation is the kinetic theory of gases, which is based on the following hypotheses:

1. The gas consists of molecules that have the same mass and are in a constant and random motion. The molecules collide with each other and with the walls of the container.
2. The number of molecules is so large that statistical methods can be applied.
3. The total volume of the gas molecules is negligible compared to the container volume.
4. All the collisions are perfectly elastic, and the interactions between molecules are negligible, except during collisions.
5. The molecules are considered to be perfectly spherical in shape.
6. Relativistic and quantum-mechanics effects are negligible.

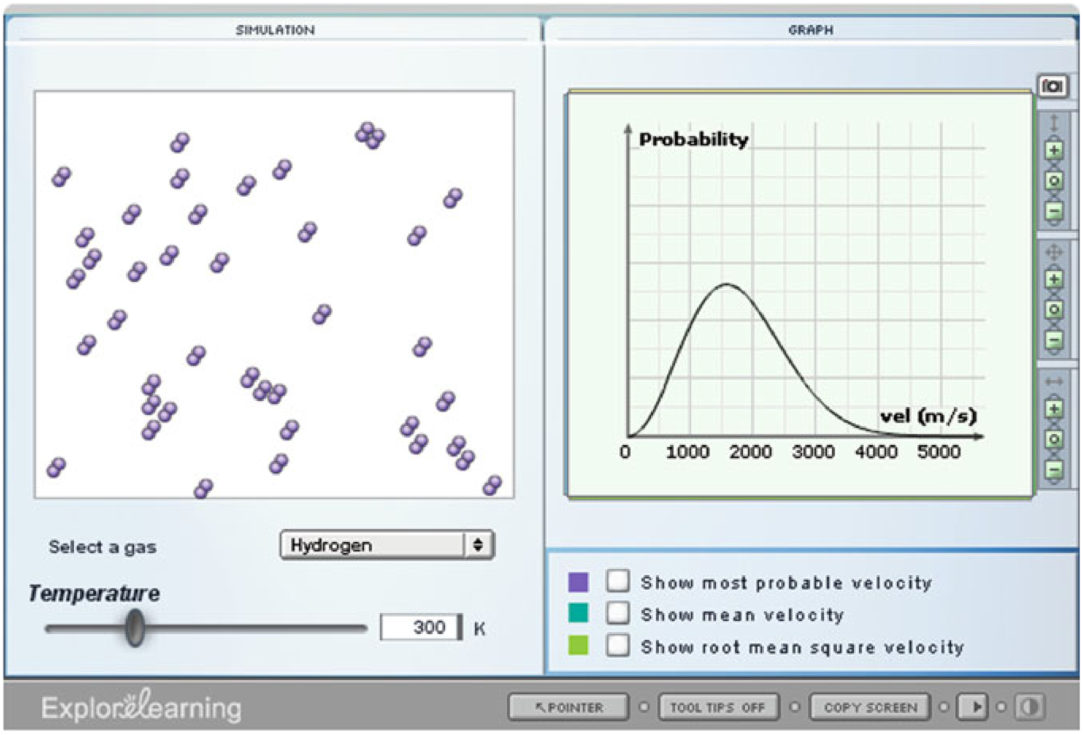


Fig. 5.5 A simulation-based learning environment about temperature and particle motion in gases. Image courtesy of ExploreLearning Gizmos™. Web site: http://www.ExploreLearning.com

Kinetic gas theory was first established in 1738 by the mathematician Daniel Bernoulli, who assumed a gas to consist of “very minute corpuscles, which are driven hither and thither with a very rapid motion” (in Newman 1956, p. 774). Bernoulli was also the first to recognize that pressure is caused by particle collisions with a container’s walls, and that particle speed increases with increasing temperature. This model is also called the “Billiard ball model” of a gas, because the molecules in it are considered to be rigid spheres, such as the balls used in billiard games. A possible learning goal for this type of simulation is to understand the statistical mechanics’ explanation of temperature, and in particular, the Maxwell–Boltzmann distribution of molecular velocities, which express the percentages of molecules with velocities differing from the average velocity. How might Mary achieve this goal? By moving the temperature slider back and forth, she observes the corresponding changes in the motion of the molecules. A hypothetical dialogue between Mary and her teacher follows here below:

TEACHER What did you notice in this activity?

MARY Oh, that’s very simple; the molecules move faster as the temperature increases and slower when the temperature decreases.

TEACHER Great! At the highest temperatures, are there still a few slow particles?

MARY Obviously not, by increasing the temperature, all the molecules are moving faster—that is what temperature is all about.

Previously, when introducing simulation use, the teacher had explained the meaning of the graph on the right side of the simulation panel, by clarifying that the curve represents the probability of a particle moving at the velocity shown on the x-axis of the graph. The higher the curve, the greater the probability of finding a particle moving at that velocity. She then asks Mary the following question:

TEACHER And what kind of changes did you notice in the graph?

MARY If I increase the temperature, the peak of the curve moves to the right, and this confirms the fact that molecular speed increases with temperature.

TEACHER What about the shape of the curve?

MARY (thinking) If I increase the temperature, it becomes flatter… but to be honest I don’t know why this happens, I suppose it has something to do with the movement of the molecules.

Shortly afterwards, the teacher assigns another activity, telling the students to focus on the motion of individual particles as shown in the animation. The students’ task is to verify whether all the molecules move faster (or slower), by increasing (or decreasing) the temperature, and imagining how this may be related to the changes observed in the shape of the curve. While carrying out the task, Mary notices, to her great surprise, that some molecules move more slowly than the others, even at the highest temperatures:

MARY I can't believe I'd never noticed this before! The speed may actually vary a lot from one molecule to the other, and the widest variety of particle speeds occurs at the highest temperature, although the speeds are more similar to each other at a lower temperature.

TEACHER Great Mary! And you've probably also noticed how this correlates with the shape of the curve…

MARY (moving her hands to show the changes in the curve) Of course! The pointier the curve becomes, the more the speeds concentrate around their mean value; and the flatter the curve, the more dispersed they are.

TEACHER That's right! And you'd be surprised to discover how many other things you can learn about the gases just from studying this curve.

We shall now analyse what presumably occurred in this fictionalized account of simulation-based learning. Although our reconstruction is hypothetical, it may help us gain a better understanding of the ways in which simulation can support learning: While using the simulator, Mary constructed her own internal representation of the system. This internal representation is constructed ad hoc to make inferences on the causal relation between the change in temperature and the observed phenomena. It may therefore be interpreted as a mental model, in the sense of it being a temporary structure in working memory (WM). From the perspective of embodied cognition theories, this initial mental model is presumably grounded in the sensorimotor experience of setting the temperature value by moving the slider indicator while watching the animation, and in the correlated introspective state. At the same time, Mary is probably retrieving prior knowledge about temperature and gases from long-term memory. She already knows that gases can vary in temperature, as with hot or cold air. She also remembers an educational cartoon she saw in elementary school, which represented molecules as tiny coloured balls moving in all directions. Later, Mary expresses her mental model to her classmates in the form of a verbal rule:

MARY The molecules move faster as temperature increases, and slower as temperature decreases.

This rule is easy to remember and communicate, but fails to captures a basic feature of the statistical account temperature, and namely, that the molecules of any gas will move at a variety of velocities. In statistical mechanics, the temperature of a gas is a measure of the average kinetic energy of its particles. Moreover, the relative proportions of molecules moving at different velocities is yielded by the Maxwell–Boltzmann distribution, which is the equation underlying the curves shown in the graph of molecular velocities. By focusing on the motion of individual particles, Mary realizes that the molecules move more quickly with a temperature increase, but that even at extremely high temperatures, a few molecules still move slowly; this insight changes her mental model of the phenomenon thereby. The new mental model also allows her to better understand the concept underlying the Maxwell–Boltzmann distribution. Interestingly, Mary's own initial mental model is not unknown in the history of science; even Rudolf Clausius, who made a great contribution to the kinetic theory of gases, assumed that all molecules move with the same speed. It was only with Maxwell that the notion of a statistical distribution of velocities was introduced into the physics of gases.

As an additional activity, the teacher asked Mary if she can express her mental model visually, so as to communicate her idea to the other students. After several attempts, she proudly showed the class her picture (Fig. 5.6), explaining that the arrows represent molecular velocities. In brief, Mary did not use her mental models to draw logical inferences only, but actually ran a mental simulation of these models. She then expressed the results of her mental simulations as external models (e.g., verbal explanations for both the teacher and the class, gestures accompanying these explanations, and a picture drawn at the teacher's request), so as to share her ideas with others.

We conclude this section by assuming that simulation-based learning can involve an epistemically rich interplay among different kinds of models even when students do not build simulation themselves, but use existing ones—as long as the learning activities involved thereby are sufficiently structured. This type of interplay is not exclusive to simulation-based learning in educational contexts, but may also occur in other contexts.

5.3 Simulative Reasoning in Science

Mental simulation is a cognitive strategy available to humans, essentially to reason and solve problems (see Chap. 2). People prefer to use this strategy in situations requiring them to understand how a given system functions, so they can predict the potential consequences of several alternative courses of action. Understanding and

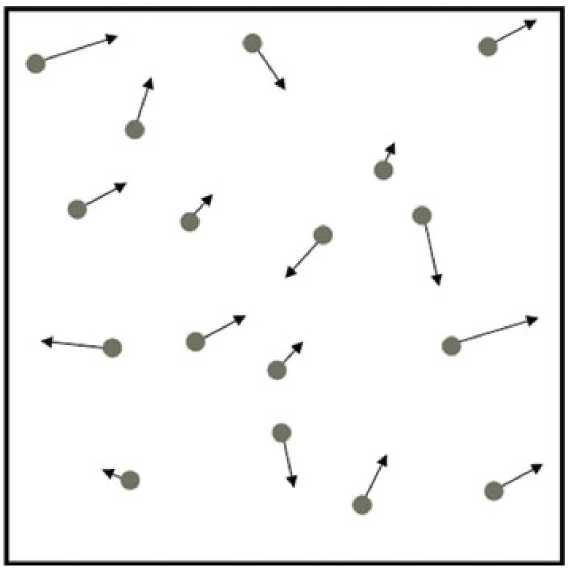


Fig. 5.6 A graphical model of molecular velocities

prediction are also psychological processes that are typical of scientific thinking. For example, molecular biologists attempt to understand the way proteins fold to predict their functions, and metereologists try to understand ocean–atmosphere heat exchange mechanisms to predict climatic events in different areas of the globe. It is therefore reasonable to wonder whether scientists also rely on mental simulation. The answer is… of course they do! Recent studies on the ways in which scientific inquiry is carried out in practice have yielded evidence that scientists use mental simulation to generate hypotheses (Clement 2008), create novel concepts (Nersessian 2002, 2008), and to interpret data in complex knowledge domains (Trickett and Trafton 2002, 2007).

Philosophers of science have traditionally placed more focus on the ways in which hypotheses are tested, than on the ways in which they are generated. The origins of this preference are to be sought firstly in the separation introduced by logical empiricists between the "context of justification" and the "context of discovery" of scientific theories. The former refers to objective relations among premises and conclusions, or theory and facts, whereas the latter concerns subjective ways to find those relations (Reichenbach 1938). As a consequence, philosophers of science have shown greater interest in the topic of empirical verification (or falsification) of theories, than in the origin of scientific ideas, considering the latter to be of an exclusively psychological nature.

The first philosopher to reject the distinction between the context of justification and the context of discovery was Thomas Khun, in his seminal book, *The Structure of Scientific Revolutions* (1962). With the exception of this effort and a few others (Gruber 1974; Holton 1978), however, the source of scientific creativity has remained relatively unexplored territory to date.

According to Clement (1989, p. 345), the question of how scientific hypotheses are formed has traditionally presented three answers:

1. *The Hypothetic-Deductive Method plus Induction*. Hypotheses originate by means of inductions made from a series of specific observations; once a hypothesis is generated, it can be corroborated or falsified by a test on observable data.
2. *Creative Intuition*. Hypotheses originate from extraordinary and mostly unconscious thinking processes.
3. *Analogies and Successive Refinement Cycles*. Hypotheses originate from analogies and models. In particular, empirical laws, which merely summarize observed regularities, can be distinguished from explanatory models, which provide descriptions of hidden processes and explanations in the form of causal relationships.

Clement followed this latter view by proposing a model-based account of the scientific process of hypothesis formation, based on a cyclical process of hypothesis generation, evaluation, and modification (or rejection). The model, called the generate-evaluate-modify (GEM) cycle, is shown as a diagram in Fig. 5.7. Clement then extended the model to the process of explanatory model construction by experienced problem solvers in technical fields. According to the

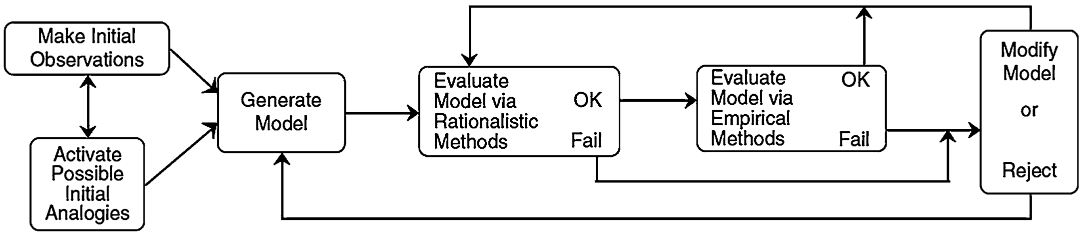


Fig. 5.7 The GEM cycle of model construction (Clement 2008, p. 86)

GEM cycle, scientists and experts alike generate a model not only by making initial observations, but also by activating various possible initial analogies. Once generated, a model is evaluated by testing its consistency both with established theories and the empirical data at hand. The model may be modified or rejected in function of the results of these evaluations.

Clement investigated the activation of these initial analogies, by examining the mental processes of individuals involved in creative problem-solving tasks. Specifically, he conducted a series of experiments based on the protocol analysis method—i.e., by eliciting verbal reports from the participants. The subsequent analysis of the thinking-aloud protocols of these participants allowed him to develop the idea that the mental processes involved in the construction of a model are examples of *nonformal reasoning*, i.e., a type of reasoning that includes:

1. analogical reasoning;
2. mental model construction;
3. imagistic simulation;
4. physical intuition; and
5. thought experiments.

Clement maintained that scientists' nonformal reasoning processes are not actually extraordinary and that they conversely "appear to be describable as natural extensions of everyday reasoning and intuition" (2008, p. 444). To provide an explanation of the cognitive mechanisms underlying these processes, Clement closely examined the role of *imagery*, which he defined as "a mental process that involves part of the perceptual/motor systems and produces an experience that resembles the experience of actually perceiving or acting on an object or an event" (2008, p. 205). Two related concepts are those of:

1. *Dynamic imagery*, i.e., processes that involve imagining a situation that changes with time; and
2. *Imagistic simulations*, i.e., processes involving dynamic imagery to generate predictions of changes or movements.

Clement considered the sources of imagistic simulations to be *perceptual motor schemas*, i.e., permanent cognitive structures residing in long-term memory. These can be activated during the various phases of model construction to interpret or explain the system under study. The premise that even the cognitive processes students activate to achieve a deep understanding of novel scientific concepts are similar or equivalent to those involved in the construction of a model by scientists and experts, led to a series of studies conducted by Stephens and Clement (2006, 2009, 2012), on the role of nonformal reasoning and in particular, imagery and mental experiments, in science instruction.

The role of nonformal reasoning in scientific practice also has a key role in Nancy Nersessian's "cognitive-historical" approach to conceptual change in science. Nersessian (1999, 2008) maintains that the hypothetic-deductive account of theory formation does not adequately describe the way in which scientists construct their theories, because it excludes scientific creativity from the investigation, and therefore, the ways in which scientists create novel concepts. In fact, findings derived from the analysis of historical sources, such as scientists' notebooks, publications, and instruments, have revealed that scientific reasoning does not consist in deriving deductive or inductive logical inferences from observable facts, but is based on the use of analogies, imagery and thought experiments. Nersessian underscored (Nersessian 2008) that "model-based reasoning"—i.e., a kind of reasoning in which inferences are made by means of creating models and manipulating, adapting, and evaluating them—could serve as a valid alternative to the logic-based account of scientific reasoning. Model-based reasoning is not exclusive to scientists, because "the cognitive practices of scientists are extensions of the kind of practices humans employ in coping with their physical and social environments and in problem-solving of a more ordinary kind" (2002, p. 135). Model-based reasoning can occur in three forms:

1. analogical modeling;
2. visual modeling;
3. simulative modeling.

In particular, "simulative modeling" is a form of reasoning in which "inferences are drawn by employing knowledge embedded in the constraints of a mental model to produce new states" (Nersessian 2002, p. 149). It should be noted that these modeling processes frequently occur together in scientific reasoning, for example when a scientist or an engineer:

(a) constructs a mental model of a system to be studied (e.g., an electrical circuit) using an analogy with a more familiar system (e.g., a mechanical system);
(b) visually imagines the model; and
(c) predicts the model's behavior on the basis of mental simulation.

From an historical perspective, Nersessian assumes that model-based reasoning is prevalent in periods of radical conceptual change, during which scientists cannot rely on time-consolidated theories. This is the process, for example, that James Clerk Maxwell used to derive his field equations for electromagnetic phenomena. In any event, due to space reasons, it is not possible to retrace the historical-cognitive reconstruction that Nersessian dedicated to this scientific conquest in detail herein (see Nersessian 2008, Chap. 2), but several aspects are worthy of note, as they shed light on model-based reasoning.

Maxwell's initial hypothesis was an analogy between the target domain of electrical and magnetic phenomena and the source domain of continuum mechanics (see Sect. 4.7). In particular, he considered ether to be an elastic material entity, capable of sustaining stresses in response to electromagnetic forces. Yet, the domain of continuum mechanics had no mathematical solution available to be mapped directly onto the electromagnetic domain, whose phenomena (e.g., the lines of force around a magnet) differ from those in any known mechanical system. Maxwell therefore developed a series of what Nersessian calls "hybrid models", i.e., models that stand in between the target and source domain and provide contexts in which to reason and draw inferences. These hybrid models, expressed in the form of written descriptions, images, and equations, eventually allowed Maxwell to derive his equations of electromagnetic phenomena. In fact, Maxwell referred many times in his writings to his reasoning processes, and in many instances, these corresponded to mental operations that can be considered as simulative modeling occurrences.

Another similar line of research is that of Trickett and Trafton (2002, 2007), who examined the topic of scientific reasoning in the context of scientific visualization research: a branch of computer science concerning the graphical representation of data as a means to gain understanding and insight into natural systems. They adopted the in vivo methodology advocated by Dunbar (1995) for studying the "on-line" reasoning of expert scientists occurring in naturalistic situations. They therefore focused on the mental operations scientists perform while examining external scientific visualizations, e.g., weather forecasters examining visualizations of atmospheric data, astronomers analyzing the optical and radio data of a galaxy, physicists evaluating the match between a computational model and empirical data. The two authors then described these mental operations in terms of *conceptual simulation*, which they characterized as sequences of dynamic mental images, similar to a "movie in the mind". They also compared conceptual simulations to scientists' "thought experiments", i.e., mental processes that consist in (1) visualizing some situation, (2) carrying out one or more mental operations on it, (3) seeing what happens, and (4) drawing a conclusion (Brown and Fehige 2011). They found that experts most frequently use conceptual simulation when evaluating hypotheses. To do so, they mentally "overlay" the end product of the conceptual simulation on the actual data represented in the image displayed on the computer screen. The degree of alignment between the two representations is then evaluated, to support or oppose the hypothesis. The authors also stated that:

1. scientists are more likely to use conceptual simulation under situations of informational uncertainty, i.e., when the available data are unclear or anomalous;
2. conceptual simulations are of a strictly qualitative nature, rather than precise numerical representation.

In line with the hypothesis that scientists' cognitive practices do not differ substantially from those that humans use in everyday reasoning, but are extensions of the same type of practices, Trickett and Trafton (2007) emphasized that conceptual simulation is also used in a type of everyday reasoning called "what if" reasoning. We use this type of reasoning, for example, to figure out the steps required to assemble a piece of furniture in the absence of written instructions (Lozano and Tversky 2006).

Lastly, it can be noted that the cognitive processes described in this section—i.e., imagistic simulation, simulative modeling, conceptual simulation—are in many ways analogous to the mental simulation described in theories of embodied cognition (see Sects. 2.4 and 2.5). In particular, due to its emphasis on the role of perceptual and motor systems, Clement's notion of imagery very closely overlaps with that of "modal simulation" in Barsalou's grounded cognition approach, and perceptual motor schemas have an analogous role to that of Barsalou's simulators and the image-schemas of Cognitive Linguistics.

These analogies bring us back to the topic of mental models, whose role in learning will be the subject of the next section.

5.4 Model-Based Learning and Teaching

Considering the interrelations among simulation, models, and learning described in the previous sections, the present one will be dedicated to examining the relation that exists between models and learning, also from the perspective of the sciences of learning. The discussion will therefore help us pinpoint simulation-based learning aspects that are in common with learning based on other types of models (see Table 3.1) and those that are conversely unique to it.

Based on Norman's (1983) perspective, mental models are naturally evolving and unstable; this leads to the assumption that, as students learn, they continue to modify their own mental models until achieving a result they consider satisfactory. As early as the 1980s, various research areas in Cognitive Science produced several explanations of learning based on changes in mental models. For example, Johnson-Laird (1989) stated that an important mental model issue is that of "how such models develop as an individual progresses from novice to expert" (p. 485). This topic, however, was not his main focus of research, which mostly examined mental model use in speech comprehension and logical reasoning.

Learning did play a key role in the development of the knowledge-based approach to mental models. Many of the contributions in the 1983 book "Mental Models", edited by Gentner and Stevens, dealt with the learning of scientific concepts and related instructional aspects—see, e.g., Gentner and Gentner's chapter on analogical thinking, which investigated the role of mental models in the comprehension of electricity concepts. In the same knowledge-based approach, White and Fredricksen (1990) presented a theory of expertise and its evolution, which viewed learning in the domain of electrical circuits as a process of acquiring a set of coordinated mental models having a causal nature and evolving through stages of increasing complexity.

The role of mental models in science education has also been examined from the perspective of conceptual development and conceptual change. Vosniadou and Brewer (1992, 1994) represented students' knowledge in terms of mental models, in their studies of children's concepts of the shape of the earth and of the day/night cycle. Chi (2000) also represented students' knowledge in these terms, in her research on middle school students' conceptions of the human circulatory system. The latter studies, however, also revealed that mental models do not always facilitate learning, but can also impede it, as with the occasionally flawed mental models students use to study scientific concepts—e.g., a model of falling bodies in which heavy objects fall at a greater speed than light objects do, or a model of the moon's orbit around the earth in which earth's shadow causes the different phases of the moon. Furthermore, mental model modification is not a process students easily undertake on their own, even when faced with objectively cogent empirical evidence, but it requires a series of teacher intervention steps aimed at overcoming the barriers to conceptual change.

The relation among models, learning, and instruction is the specific topic of investigation in a new approach in the sciences of learning, called "Model-Based Learning and Teaching" (Gobert and Buckley 2000), which highlights the role of students' mental models, their externalization into external models, and the changes that occur in them as students learn new concepts. Buckley specifically defined *model-based learning* as the formation and subsequent development of mental models by a learner, and *model-based teaching* as instruction designed to support the development and evolution of learners' mental models (2012a, b). Other denominations used in this approach are "Model-Centered Learning and Instruction" (Seel 2003) and "Model Based Learning and Instruction" (Clement and Rea-Ramirez 2008).

One of the most significant influences in the development of Model-Based Learning and Teaching has been science educators' growing recognition of the role of models in the formation of scientific theories and in scientific practice (Gilbert 1991; Ingham and Gilbert 1991).[2] This approach has focused on investigating the various types of models available, the function of models in teaching and in learning, and on the process with which students and teachers create their models. Gilbert and Boulter (1998) proposed a taxonomy of models based on their different roles as teaching tools, distinguishing among:

- *Mental model*—a personal and private internal representation of a target system formed by an individual either alone or in a group.
- *Expressed model*—a mental model, which have been expressed by an individual through action, speech, written description, and other material depictions.
- *Consensus model*—an expressed model that has been agreed upon by any social group, for example, a school class or a group of scientists.

[2] Recognition occurring also following as a consequence of the new concepts of the scientific method emerging in the history and philosophy of science (see Sects. 3.4 and 3.5).

Gilbert, Boulter, and Elmer (2000) further classified consensus models into four subtypes:

- *Teaching model*—specially-constructed to aid the understanding of a consensus model.
- *Scientific model*—a consensus model that has gained acceptance by a community of scientists, following formal experimental testing, as manifested by its publication in a refereed journal.
- *Historical model*—a consensus model produced in a specific historical context and later superseded for research purposes by new models.
- *Curricular model*—a version of an historical or scientific model that is included in a formal curriculum.

Furthermore, these models may be expressed in different *modes of representation* (i.e., *concrete*, *verbal*, *mathematical*, *visual*, *symbolic*, and *gestural*) (see Sect. 3.4). Gilbert (2004) identified the main functions for models as being:

(a) simplification of complex phenomena;
(b) visualization of abstract entities;
(c) interpretation of experimental results;
(d) explanation of and prediction about phenomena.

To describe the process students use to construct their models (both mental and expressed ones), Justi and Gilbert (2002) developed a "model of modeling" framework, which is essentially based on Clement's (1989) account of scientists' and students' model construction processes (see Fig. 5.7). The framework is represented in the form of a diagram (see Fig. 5.8), which depicts "a non-linear creative process comprised of multiple and complex stages mainly concern[ed] with: acquiring information about the entity that is being modeled (from empirical observations and/or from previous knowledge), producing a mental model of it, expressing that model in an adequate mode of representation, testing it (through mental and empirical experimentation) and evaluating its scope and limitations" (Justi 2009, p. 32).

Yet, the mechanisms by which mental models undergo these changes during learning-linked processes remain unclear. Norman Seel investigated the issue from the perspective of instructional psychology, instructional design, and multimedia-based instruction.[3] Seel et al.'s research examined the ways in which instruction can facilitate the construction of students' mental models (Seel 1995, 2003; Seel et al. 2000; Seel and Dinter 1995) and the methods instructional psychologists or teachers can use to assess the change in these models (Seel 1999; Seel et al. 2009).

The central concept in Seel's instructional paradigm is that of a *learning-dependent progression of mental models*. He introduced this concept in the context

[3] Seel's earlier studies on the relation between knowledge mental models were published as early as the 1980s, but remained relatively unknown on the international scale, as they'd been published in German (Seel 1986, 1991). Seel's concept of models and of their functions was also influenced by Herbert Stachowiak's neopragmatic epistemology (see Sect. 3.7).

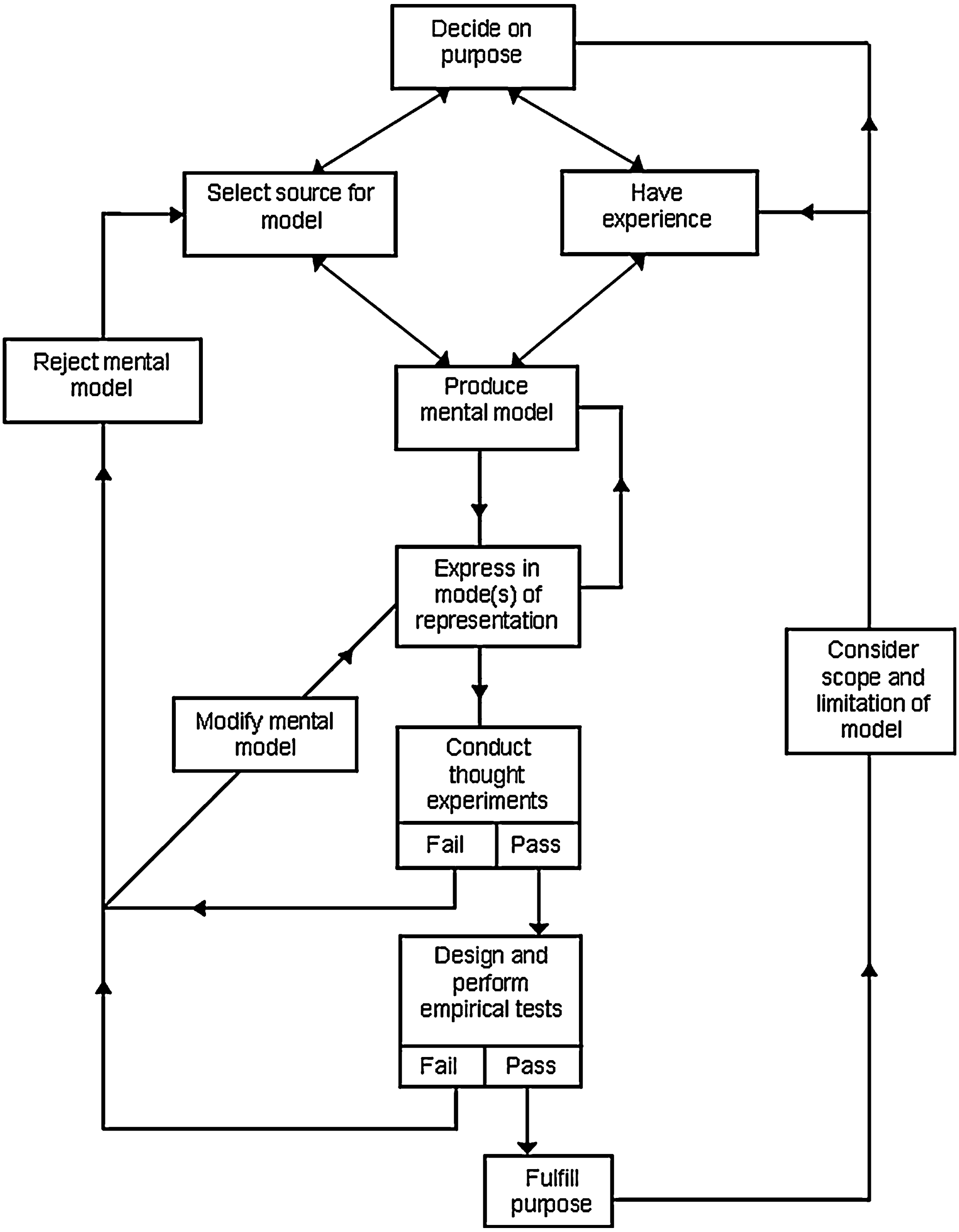


Fig. 5.8 The "model of modeling" diagram (Justi and Gilbert 2002, p. 371)

of experimental studies examining the effects of different instructional methods (i.e., expository teaching versus discovery learning) on students' learning of physics concepts. Seel (2003) defined the learning-dependent progression of mental models as a specific kind of transition between *preconceptions* (i.e., the initial states of the learning process) and *causal explanations* (i.e., the desired end states of learning). He maintained that if the learning process is to be effective, it should start by presenting a conceptual model (e.g., a concept map), the aim of which is to help students create an initial mental model as the foundation for constructing subsequent models. The student's initial mental model then undergoes a series of transformations that Seel described as follows: "When the model is used successfully, it is reinforced and may eventually become a precompiled, stable model. If it turns out that the model is unsatisfactory, it may be revised or rejected in a progression of mental models" (ibid., p. 72).

Clement (2000) proposed a theoretical framework for model-based learning, from the perspective of his research on model-based reasoning (see Sect. 5.3). The framework includes: (a) the goal of a *target model* that one wishes students to possess after instruction, (b) a map of the student's *preconceptions* and *natural reasoning skills* present before instruction, and (c) the *learning processes* that can take the student from preconceptions to the target model. Clement emphasized that preconceptions do not necessarily include only alternative conceptions in conflict with the target model—i.e., the "misconceptions" studied so extensively in the field of science education. He stated that they can also include useful conceptions that are compatible with scientific models and can be used as building blocks to develop the target model. A useful conception example is that of the "anchoring intuitions" Clement (1993) described in his research on the role of analogies in lessons designed to deal with students' preconceptions in physics. These anchoring intuitions are characterized as knowledge structures of a concrete rather than abstract nature, which students self-evaluate and are of the same nature of the "physical intuitions" he characterized as an example of nonformal reasoning (Clement 1994).

In summary, all of the heretofore described model-based learning explanations share the idea that the learning process can be viewed as a pathway, which leads from an initial model to a target model, through a succession of intermediate models (see Fig. 5.9).

As a consequence, the main model-based teaching issue has now become that of how to facilitate this learning pathway, both in individuals and in groups of learners. Clement and Rea-Ramirez (2008) extensively researched this topic in a

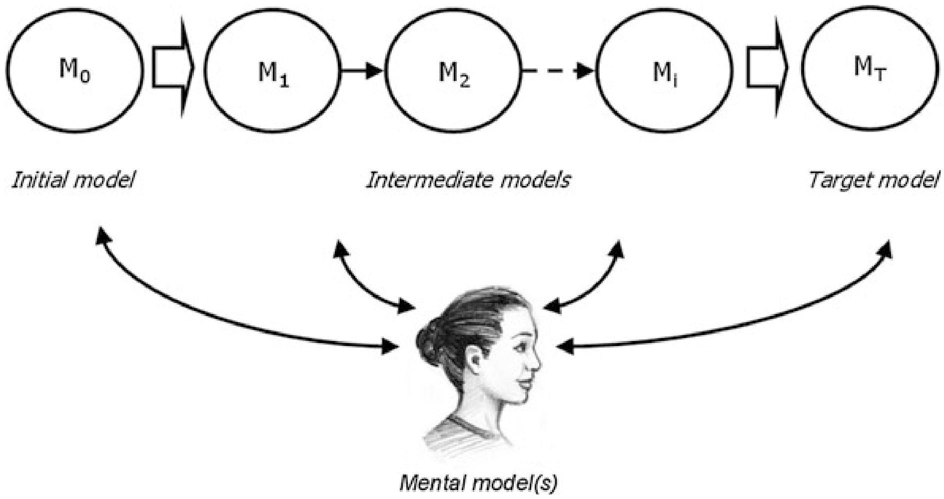


Fig. 5.9 The model-based learning pathway

series of studies examining model construction in the classroom. They described new and innovative model-based teaching methods in science instruction, and proposed an organizing framework that can help teachers design and conduct activities developed to create “flexible” mental models in students’ and to prompt their need to progress from one mental model to another.

An important area of research is that of the assessment of changes in the mental models of students during the learning process. The measurement and comparison of students’ mental models in successive moments (e.g., before and after studying a specific topic) in the learning pathway are of fundamental importance for the planning and facilitation of that pathway’s various steps. It is equally important to compare the mental models of novices with those of experts. It must be noted, however, that the concept of mental model is a theoretical construct introduced in psychology to account for a wide range of phenomena—e.g., in perception, memory and reasoning—and is not directly observable as such. Thus, the methods of the researchers in this field are necessarily indirect ones, which can be divided into two categories:

1. the observation and analysis of any behaviors produced as a consequence of mental model construction and use (e.g., verbal descriptions, hand motions, student-generated drawings);
2. the use of computer-based diagnostic tools for the automatic or semi-automatic analysis of verbal or graphical representations of knowledge.

Nunez-Oviedo and Clement’s (2009) study of a model-based teaching strategy presented an approach of the the first category type shown above, based on what they called “co-construction modes”, i.e., model construction modes that build on both student- and teacher-generated model elements. Teachers used questions, discussions, drawings, and diagrams representing teacher-student interactions along the various learning pathway steps to assess student’s mental models and their progression.

The use of computer-based diagnostic tools for assessing change in cognitive structures has been undergoing rapid development, due to advances in knowledge modeling methods and computer technology (for an introduction, see the essays collected in Ifenthaler et al. 2010). The main idea underlying the use of these tools is that external representations, such as *concept maps*, *causal models*, and *belief networks*, can yield insight into internal constructs such as mental models and thinking processes (Shute et al. 2009). This comparison is usually conducted via algorithms, which calculate the degree of structural similarity between pairs of representations and provide the output of both numerical indices and visual representations. In particular, new software tools are being developed to use natural language expressions, such as texts written by students or experts, as input for the analysis, representation, and comparison of mental models (Pirnay-Dummer and Ifenthaler 2010). This type of software automatically uses a sufficiently long text to generate an associative network, which is visually represented as a graph and also calculates structural and semantic measures for the analysis and comparison of mental models.

A remaining, open question in the sciences of learning and cognition is that of the relation between mental models and other types of more stable and permanent cognitive structures, such as schemas (see Sect. 2.1) and beliefs. This issue is particularly evident in the study of conceptual change, which requires researchers to account for the role of students' prior knowledge when learning new concepts. For example, Vosniadou (2002) considered mental models to be mental representations constructed by students to deal with the demands of specific situations, but also allowed for the possibility that these models might be stored in long-term memory. Chi (2008) defined mental model as "an organized collection of individual beliefs" (p. 67) and equiparated science misconceptions with mental models that students retrieve to answer questions and make predictions, but which must eventually be repaired or removed (i.e., mental representations highly resistant to change). She also proposed the two learning processes of "assimilation" and "revision" as mechanisms that can enrich a mental model or repair an incorrect one. In fact, these are very similar to the processes of schema assimilation and accommodation described by Piaget.

Seel (2003, 2012b) examined the issue of the relation between mental models and schemas by integrating Rumelhart and Norman's (1978) three modes of learning—i.e., accretion, tuning, and restructuring—into a cognitive architecture grounded on Piaget's epistemology. In this architecture, mental models play a key role in the accommodation process. When people cannot assimilate an experience to an existing schema, they construct a mental model of the situation based on their world knowledge. If the model is evaluated as being unsatisfactory for the task at hand, it may be revised or rejected, but if it is deemed adequate, it is reinforced and may eventually become "a precompiled, stable model" (Seel 2003, p. 72). (For a detailed comparison of Johnson-Laird's and Seel's approaches to mental models, see Al-Diban 2012, p. 2202.)

The possibile relations between schemas and mental models can also be analysed from the perspective of naturalistic decision making (NDM), a research approach which investigates how people make decisions in real-world settings (Klein 1998). In particular, Klein et al. (1986) formulated a recognition-primed decision (RPD) model of how experienced people can make rapid decisions in situations characterized by time pressure, ambiguous information, ill-defined goals, and continually changing conditions.[4] According to the RPD model, in these situations individuals don't base their decisions on analytical strategies to compare options, but they use experience to rapidly generate a plausible course of action. In the case of *Simple Match*, the decision maker recognize a familiar situation—i.e., it identifies *plausible goals*, *relevant cues*, *expectancies*, and a *typical action*—and reacts accordingly. A more complex case is that of *Evaluate a Course of Action*, in which the course of action is deliberately assessed by conducting a mental simulation to see if the option will work as it has been envisioned or it requires to be

[4] As in the case of fireground commanders, army officers, naval commanders and emergency room doctors.

modified or rejected. According to Lipshitz and Shaul (1996), the RPD model is compatible with the constructs of schemas and mental models, as when a situation is recognized as familiar, the generation of an option corresponds to the activation of a schema, and the possibile evaluation of a course of action to the construction of a mental model, which is driven by the schema. However, in an unexpected situation, or in case that a course of action fails in a mental simulation, the available schemas may be inappropriate and the decision maker may collect additional information prior to taking action, resulting in the construction of a novel mental model (see also Marshall and Seel 2012). An additional component has been added to the RPD model (Klein 1997), the *Diagnosis of a Situation*, in which, in response to an anomalous situation the decision maker attempts to link the observed events to causal factors, thus trying to obtain an explanation for the events. Interestingly, from our perspective, a common diagnostic strategy is *story building*, which often involves a type of mental simulation (Klein and Crandall 1995).

In conclusion, if mental models are to serve an integrative function between new and existing knowledge, they must combine both kinds of knowledge. Thus, their creation or modification most probably requires a process of intense interplay between information processed in WM and that stored in long-term memory—a process, in fact, about which relatively little is known.

5.5 Learning by System Modeling

This section examines the similarities and differences between model-based learning in general and simulation-based learning. Some of the features of model-based learning—i.e., model taxonomy, epistemic functions, modeling processes, learning pathways—can be directly mapped onto simulation-based learning. Analogies between these two ways of learning can be established thereby and are listed here below.

- *Model type*. An instructional simulation is a particular type of teaching model, designed to facilitate understanding of a consensual model (which is generally a scientific or historical model).
- *Epistemic functions*. The epistemic functions usually assigned to models (i.e., simplification, visualization, interpretation, explanation, prediction) are also typical of simulations.
- *Modeling process*. The activities that characterize the process of model construction and revision are by and large the same as those of simulation model construction and revision. For example, Clement's and Justi and Gilbert's model construction diagrams (Figs. 5.7, 5.8, respectively) can be easily compared with Birta and Arbez's diagram depicting the activities of a typical modeling and simulation study in the field of systems engineering (Fig. 4.1).

- *Learning pathway*. Similarly to as described in the previous section, simulation-based learning is also characterized by a progression of mental models, which go from a student's initial model of the system under study to a more precise and scientifically correct conceptual model, passing through a series of intermediate models (see Fig. 5.10).

Can simulation-based learning be considered a particular instance of model-based learning? The answer is yes… but only in part! A closer examination reveals that, in addition to their common features, they also present significant differences. To highlight these differences, simulation-based learning environments can be imagined as made up of four layers corresponding to (1) the computational model, (2) the user interface, (3) the instructional support, and (4) the complementary activities—each of which leads to specific actions and has implications for learning.

5.5.1 Computational Model Layer

The most-studied models in model-based teaching are static models, such as small scale models, pictures, computer graphics images, diagrams and formulas. Conversely, computational models are *dynamic models* and therefore able to autonomously reproduce some aspects of a system's time evolution. The most typical feature of a dynamic model is that a succession of system states are mapped onto a succession of model states (as described by Ashby—see Fig. 3.6 and relative description). Most likely, the dynamic aspect of computational models influences students' cognitive processes and, in particular, changes in their mental models.

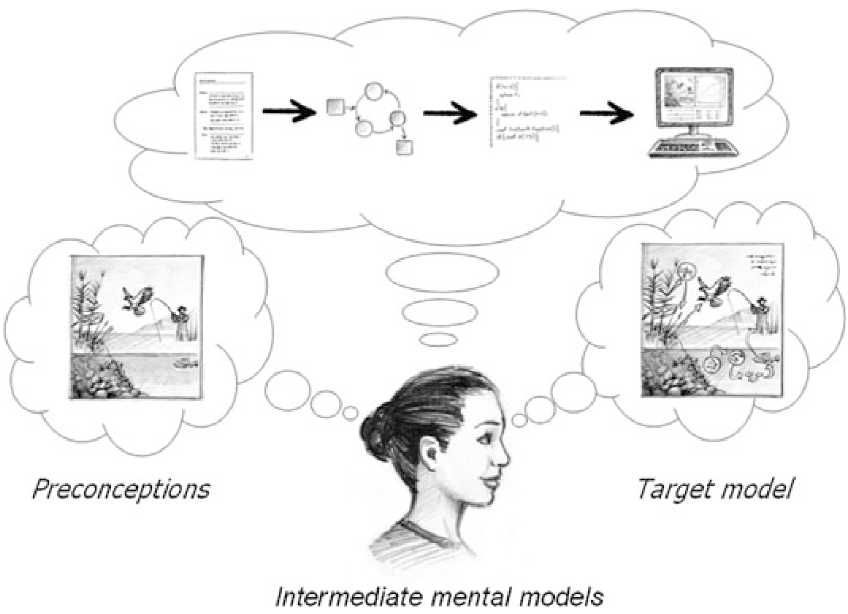


Fig. 5.10 Simulation-based learning as progression of mental models

As stated by Seel (2012a), dynamic modeling provides a new perspective, called "learning by system modeling". In this perspective, "Learning occurs by comparing the expected results of operations on a system with the observed consequences of transformations. In the case of gaps between expectations and observations, the outcomes are used to update or revise the mental model" (ibid., p. 1053).

Moreover, when using simulation modeling software, students do not merely create the model of a given system, but can create models of any type of system and phenomenon. From this perspective, computational models are not models like any others, but can be considered to be general-purpose templates, which can simulate many other types of models. In fact, computational models are frequently based on analogies with other models, e.g., system dynamics models, which are based on an analogy with hydraulic models and are therefore ideal tools for facilitating analogical reasoning.

5.5.2 User Interface Layer

The simulation program's user interface allows students to visualize the simulated phenomena which would otherwise remain inert, and to interact with the computational model, which becomes not only dynamic, but *interactive* thereby. Thus, a range of behavior can be created in function of students' decisions. In suitable conditions, a student-program "epistemic loop" can be activated, in which:

1. the student performs an action to explore the model's behavior or to verify a hypothesis;
2. the action prompts a change in the information shown on the screen; and
3. the student then decides to perform a new action, starting a new cycle thereby.

Moreover, simulation-based learning environments are very frequently "multimodal", because they integrate knowledge about a system's structure and behavior expressed through different representation modes (e.g., verbal, visual, mathematical, symbolic). Coordinated multiple representation use can help students construct and revise their own mental models. For example, the interactive animation of molecules in a gas heating simulation is a visual model of the hypothesis that a gas consists of molecules in constant and random motion, which elastically collide with each other and with the walls of the container.[5] From a more abstract perspective, the causal maps rendered visible in system dynamics learning environments are symbolic representations of the cause and effect relations existing among the system's variables.

[5] Massironi (2002) defined the images that are visualizations of scientific hypotheses on parts of the natural world, which cannot be directly observed, as "hypothetigraphs".

5.5.3 Instructional Support

In many instances of model-based teaching, the instructional support of the students' activity is external to the model, i.e., teacher-provided. In simulation-based learning environments, instructional supports of various nature—ranging from simple questions and hints to detailed exploration guides and exercises—are conversely typically software-integrated. This type of support can provide students with opportunities for reflective thinking and metacognitive awareness tailored to their individual needs. It can also be compared to what occurs in other interactive multimodal learning environments that also feature similar levels of student guidance and support (Moreno and Mayer 2007).

5.5.4 Complementary Activities

The term "complementary activities", as used herein, refers to individual and group learning activities conducted by students as an adjunct to simulation program use and which do not necessarily require the use of a computer. Examples of these activities are:

- observation of a real system;
- conduction of laboratory experiments;
- formulation of hypotheses;
- presentation and analysis of results;
- explanation of observed phenomena;
- discussion of different ideas.

These activities, which are typically prompted and guided by teachers, are important because they allow students to externalize their own mental models in various ways and therefore, to communicate them and share them with others. The teacher can use these activities both to diagnose the level of students' understanding and facilitate progression from one mental model to another.

In brief, simulation-based learning is characterized by several distinctive aspects—i.e., dynamic modeling, epistemic loop, coordinated integrated instructional support, links to extra-technological activities—based on both the construction and revision of new knowledge and critical reflection. Moreover, simulation-based learning environments are communication- and problem-solving environments, which give students many opportunities to reflect on content and on the learning process itself. Thus, simulation can be used as a cognitive tool to extend other learning- and teaching approaches and may be particularly effective when learning objectives require the restructuring of students' knowledge, as in the instance of conceptual change.

Any powerful instrument, however, presents its own risks, if not used appropriately. In simulation, the risk is that students are unable to effectively carry out the tasks requested. The next section will be dedicated to examining some of the causes of these potential problems and the strategies that can conversely maximize the instructional potential of simulation.

5.6 A Cognitive Load Perspective

Until recently, research on the instructional use of computer simulation was characterized by an attitude of generalized optimism: Simulation was described as an inherently valid teaching method, and its instructional effectiveness was rarely questioned. In addition to its widely acknowledged safety- and economic advantages, simulation was viewed as a technology that allows students to "learn by doing" through multimedia-rich, interactive, and authentic learning opportunities. It was therefore frequently considered to share many aspects with games and virtual worlds. Moreover, most researchers presented simulation-based learning as an example of *active learning* and *discovery learning*, and thus in line with instructional methods strongly promoted by constructivistic pedagogy. In particular, with its emphasis on positing hypotheses, conducting experiments, recording data, and drawing conclusions, simulation was considered one of the most suitable technologies for facilitating *inquiry-based learning*—i.e., the prevailing science instruction approach over the last few decades.

This optimistic scenario has clashed, however, with empirical observations that do not always coincide with researchers' and educationists' expectations. As mentioned in Sect. 1.1, simulation presents the paradox of an instructional technology that receives lavish praise but actually has a poor extent of application as a teaching tool in school programs. As stated by the National Research Council (2011) report on *Learning Science Through Computer Games and Simulations*, this limited diffusion is paralleled by a lack of in-depth research on the instructional effectiveness of simulation. For example, only a few studies clearly articulate an examined simulation's learning goal and in much of this research, unique simulation effects are confounded with the overall effects of curriculum units integrating simulation with other learning activities. The above-cited report therefore stated that evidence as to whether simulations support the development of science learning goals, other than motivating students' interest in science, are quite scarce.

More importantly, some studies have shown that students encounter difficulty in exactly the types of discovery learning and inquiry-based learning that (according to the most widespread view) represent the theoretical foundation of simulation as an instructional method. In fact, since 2004, many constructivist tenets have been questioned by some researchers upholding the superiority of direct instruction and "explicit learning" over that of discovery learning (Kirschner et al. 2006; Klahr and Nigam 2004; Mayer 2004). A heated debate has arisen thereby, which will not be covered herein, due to space reasons.[6] What is underscored here, however, is that some ideas, with unquestioned validity until only a few years ago, are now undergoing closer examination, to better define their limits and areas of application. For example, recent research has elicited doubts about two aspects in particular: (1) that a direct relation exists between interactivity (the concurrent use of different media) and learning, and (2) that an authentic learning- or inquiry-based environment is always preferable over one presenting knowledge in an explicit and guided way.

Regarding the first aspect, although interactivity and multimedia are concepts that pertain significantly to learning processes, they should be analyzed and evaluated in terms of specific educational needs, especially in light of indications from the cognitive theory of multimedia learning (CTML) (Mayer 2005) and from Cognitive load theory (CLT) (Sweller et al. 2011).

Researchers developing SimQuest[7] (de Jong 2006; de Jong and van Joolingen 1998) investigated the problems students typically encounter in discovery learning with computer simulations (including means for supporting learners in the discovery process). The evidence they reviewed showed that students operating in complex simulation environments generally have considerable difficulty in all phases of the inquiry process (i.e., in hypothesis generation, design of experiments, interpretation of data, and regulation of learning). For example, they "have difficulty choosing the right variables to work with; they find it difficult to state testable hypotheses; and they do not necessarily draw the correct conclusions from experiments" (de Jong 2006, p. 532). To obviate these problems and increase the instructional effectiveness of simulation, the researchers suggested that simulation be integrated with "cognitive tools" aimed at guiding and supporting the students' activities. Examples of these tools, which were integrated into the SimQuest program, are assignments, explanations, background information, monitoring tools, hypothesis scratchpads (software tools to create hypotheses from predefined variables and relations), experimentation hints, process coordinators, and planning tools. Thus, instruments of this type present learning environments that are based less on free exploration and more on guided discovery—an approach also strongly suggested by other researchers (as described in the following section).

Three levels of design can be used to examine the causes of potential problems in a given simulation-based learning environment:

- *Cognitive ergonomics*—problems at this level are generated by a user-interface that is difficult to understand and use, or burdened by unnecessary details, which aim more to capture students' attention than to illustrate important problems.

[6] For a detailed account of different various viewpoints, see the volume edited by Tobias and Duffy (2009), which integrates scientific thought from both sides of the debate by presenting research findings for and against the constructivistic paradigm.

[7] SimQuest is a software developed to create equation-based scientific simulations developed at the University of Twente (http://www.simquest.nl).

Students therefore find it difficult to translate their goals into intentions and action sequences, and to perceive and interpret the system's state.[8]

- *Instructional design*—problems at this level are due to a lack of, or insufficient consideration of important instructional factors, such as the students' background knowledge, learning goals, content sequence, characteristics of the learning task, and/or classroom dynamics.
- *Instructional strategies and methods*—problems at this level originate in the choice of instructional approaches that are not based on the cognitive processes involved in model-based reasoning and learning (see Sects. 5.3 and 5.4).

Thus, how might program designers obviate these problems and maximize simulation's instructional potential? CLT provides some indications for identifying design features that can greatly impact learning (positively or negatively). The remaining part of this section will therefore be dedicated to a brief description of these suggestions.

Cognitive load theory was developed in problem-solving research in the early 1980s by the Australian psychologist John Sweller. It has gained much ground over the last decades, with many research groups producing a large body of published experimental findings, both in Europe and in the United States.[9] The success of CLT is due to the fact that its learning principles are based on empirical evidence; are applicable to any type of content and media; and allow for the creation of efficient learning environments (i.e., in which to learn with better results, less effort, and in less time). Moreover, these principles are founded on the characteristics of human cognitive architecture and, in particular, on consideration of limits in the information processing capacity of WM. The main CLT premise is that learning consists in the construction of mental schemas, and can be optimized if students are enabled to use their WM resources to the greatest extent possible to construct the schemas required by the learning task at hand. Vice versa, learning can blocked or hindered if WM is occupied in processes not pertaining to the construction of these schemas. (The term "mental schema" used in this context is only broadly linked to its meaning in other psychological theories—see Sects. 2.1 and 5.4).

As mentioned in the previous chapters, WM plays a determining role in processes such as attention, the selection and organization of information, and problem solving. It is nevertheless markedly limited in its capacity for storing and processing new information. As first shown by Miller (1956), WM can, at the most, simultaneously contain 7 ± 2 "chunks" of information. In situations requiring not only remembering of information (e.g., a list of words) but also processing (as in the execution of an arithmetical operation) WM capacity is even lower, ranging

[8] Cognitive ergonomics is a field of research and practice concerned with the application of the cognitive sciences to problems of human–machine interaction (Long and Whitefield 1989). A fundamental cognitive ergonomics topic is that of human–computer interaction.

[9] See Plass et al. (2010) and Sweller et al. (2011) for a detailed overview of the theory and its implications.

from 3 to 5 elements (Cowan 2001). Moreover, the information present in WM is subject to rapid decay (remaining present for only approximately 20 s), which can be avoided only by keeping the information active through rehearsal. WM therefore presents the paradox of being essential to learning, but with functional limits that easily render it an information processing bottleneck.

Schemas play a key role in CLT because the approach underscores their nature of organized nowledge structures in long-term memory, which allow for the chunking of many elements of information into a single, higher-level element, reducing information processing demands on WM thereby. According to this interpretation, the concept itself of an information chunk in Miller's studies of short-term memory can be conceived of as a schema. Moreover, multiple schemas can be linked together and organized into hierarchical structures (Kaliuga 2010). In fact, a key criterion that differentiates experts from novices is that the former possess a higher number of complex mental schemas and are able to use them automatically.[10]

"Cognitive Load" is defined as the total quantity of activity imposed on in WM at a given moment. Intuitively, cognitive load corresponds to learner-perceived mental effort and therefore, to the subjective difficulty of a learning task.[11]

It must also be noted that CLT shares several assumptions with the CTML, (largely the creation of Richard Mayer; 2005), such as learning as schema construction in long-term memory, limited WM capacity, separated verbal and visual processing channels. Both theories state similar principles and are at times nearly indistinguishable. Moreover, Wolfgang Schnotz (2005) proposed an integrated model of text and picture comprehension (ITPC) which also assumes a cognitive architecture with multiple memory stores and presents some similarities and differences to Mayer's theory.

The "standard" cognitive load model defines three types of load:

1. *Extraneous cognitive load*—associated with cognitive processes that are not necessary for learning, such as operations that do not pertain to learning, or the processing of redundant information.
2. *Intrinsic cognitive load*—caused by the complexity of the learning materials in and of themselves, which is given by the degree of interconnectedness among essential information elements requiring simultaneous processing in WM.

[10] Students demonstrate expertise when they have familiarized with material and have mastered the knowledge therein, which also means knowing how to apply it in solving specific problems.

[11] Australian and Dutch researchers developed a method to measure mental effort, by using questions that ask students to subjectively evaluate the difficulty they had experienced while studying material and responding to learning assessment tests (Paas et al. 2003). The combined assessment of learning and mental effort led to development of the concept of "learning efficiency", which states that, given equal learning outcomes, the most effective teaching methods are those demanding the least mental effort (Paas and Van Merriënboer 1993).

3. *Germane cognitive load*—associated with cognitive processes that pertain directly to learning, such as schema construction in WM and schema automation.[12]

Sweller (2010b) and Kalyuga (2011) recently modified the above described model (a rather surprising choice, given the model's popularity!) by reducing the types of cognitive load to only two categories—i.e., extraneous and intrinsic—and redefining germane load as the student's actual WM resources for dealing with the intrinsic cognitive load associated with information to be learned.

The total cognitive load in a given learning task depends on the degree and quality of interaction among contents, student, and instructions (Fig. 5.11). Learning is compromised when the sum of extraneous and intrinsic loads exceeds available WM capacity.

Let us now take a more in-depth look at different types of cognitive load—by also considering the triarchic model's recent modification. In particular, their potential role in simulation-based learning will be examined by linking extraneous load to the cognitive ergonomy level of instructional design, and the issue of WM resources intentionally allocated to learning, to the instructional strategy method level.

CLT's main aim in learning environment design is to reduce extraneous cognitive load to a minimum. This type of load essentially depends on the way in which the information is presented to the student, and is typically caused by:

- the presence of irrelevant information, which interferes with learning;
- the need to integrate spatially- or temporally separated information.

The above presentation modes waste students' time and mental effort because they have to elaborate unnecessary information. Simulation contexts frequently present situations with texts, images, and sounds that are not directly linked to the learning task at hand. These "seductive details" therefore negatively impact learning (Harp and Mayer 1998). Another frequently recurring instance is that of sliders or buttons not being presented close to animations or graphs showing the simulation's time course.

Thus, the first aspect to consider in simulation design is that of user interface: One that is overly complex and/or presents the user with too many choices is a source of extraneous cognitive load that can interfere with learning. In particular, factors requiring design-phase evaluation are:

- the type and number of elements—"widgets"—students can use to communicate their decisions to the program (e.g., sliders, buttons, text boxes);
- the relative position of certain interface elements with respect to the others;

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[12] In Mayer's cognitive theory of multimedia learning, the same types of cognitive load are respectively mapped to three types of cognitive processes termed *incidental processing*, *essential processing*, and *generative processing*.

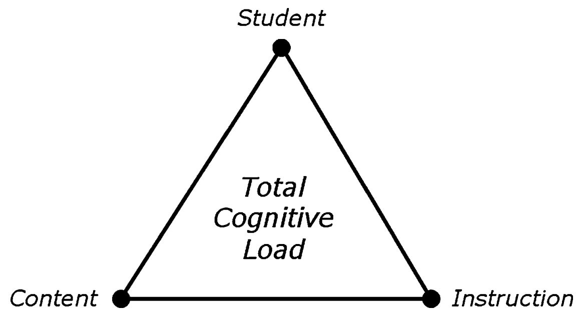

Fig. 5.11 Factors influencing total cognitive load in a learning context

- the type and number of graphs showing students the consequences of their actions;
- the type of images and animations representing the simulated phenomenon—of great relevance in helping students form a correct mental model of the simulated system;
- the navigation among interface items that are not simultaneously visualized (e.g., the possibility of using tabs to visualize additional graphs or to open a separate window with hints and guides);
- the possibility for students to control the simulation's time course.

The other fundamental aspect to consider is that of information representation. The informational elements typically used in simulation-based learning are texts, pictures, and animations, which must be considered both alone and in their possible interrelations. With a written text, for example, one must decide on the representation's format (font, colors, dimension), its function in explanation of the contents, its position with respect to pictures, and its relation to any audio-narrated texts. Based on Schnotz's (ITPC), the same types of elements can be dealt with from a cognitive-semiotic perspective, which distinguishes between symbolic and iconic types of information representation (corresponding, respectively, to text and pictures), and emphasizes the combined processing of verbal and pictorial information in the construction of multiple mental representations.[13]

Experiments comparing the efficiency of alternative instructional formats (Mayer 2005) have shown several effects linked to specific combinations of elements such as images, written text, and spoken text. The effects reported here below are of particular interest for user interface design and for information representation:

- *Split-attention effect*. Multiple sources of information that are unintelligible in isolation result in less learning when presented in a split-attention, versus integrated format (Ayres and Sweller 2005).

[13] The application of this theory to simulation is limited by the fact that, from a semiotics perspective, many of the elements characterizing a simulation program are neither symbols nor icons, but, indexes—e.g., sliders, and bars—in which the indicator's position visually signals the value of a given variable.

- *Modality effect*. Multiple sources of information that are unintelligible in isolation result in less learning when presented in a single- (e.g., visual) versus dual-modality format (e.g., visual and auditory) (Low and Sweller 2005).
- *Redundancy effect*. The presence of information sources that do not contribute to schema acquisition or automation interfere with learning (Sweller 2005).
- *Expertise reversal effect*. With increasing expertise, instructional procedures that are effective with novices can lose their effectiveness, whereas ineffective techniques can become effective (Kalyuga 2005).

These effects take on special relevance in conditions that are defined as "high-load" situations in the cognitive load framework and which are typically characterized by a high number of interacting elements requiring simultaneous processing in WM. Situations of this type are frequently present in simulation-based learning environments, when students must mentally integrate dynamically changing multiple representations of information, while carrying out complex tasks, such as testing hypotheses or exploring alternative courses of action.

It is important to note that the expertise reversal effect shows us that *any* presentation format or teaching method must always be examined in light of the students' expertise. For example, a picture explanation can be particularly effective, when accompanied by audio versus a written text, for students with little knowledge of the subject, whereas the opposite can be true for expert students.

Some design factors for increasing the effectiveness of educational simulations have been examined by experimentally manipulating variables such as the grouping and position of sliders and the use of icons, in addition to text in scientific simulations (Lee et al. 2006; Plass et al. 2009). For example, the effectiveness of ideal gas simulations, which represent temperature in symbolic and iconic form (e.g., by numbers and by flames, respectively, below the container) was compared to that of simulations showing the temperature in symbolic form only. An expertise reversal effect was observed, given that students with lower levels of general scientific knowledge learned better from the first type of simulation than the latter, and the opposite was true for students with higher levels of prior knowledge.

The idea of reducing extraneous cognitive load does not concern only the effects linked to user interface design and to information representation, but also to the method of formulating problems and the use of examples, as described by the following effects:

- *Worked-example effect*. Studying worked examples results in better performance on subsequent problem-solving tests than does solving equivalent problems (Renkl 2005).
- *Completion effect.* Asking learners to complete partially solved problems can be just as effective as presenting worked examples (Paas and van Merriënboer 1994).
- *Guidance fading effect.* As their expertise grows, learners should be presented worked examples, followed by completion problems, and then full problems, rather than worked examples alone (Renkl 2005).

Although it is widely believe that one learns better by solving a problem ("learning by doing") rather than by examining an example of it, the experimental evidence underlying the latter effect reveals otherwise. Students who have not yet mastered a subject can learn better through worked examples—i.e., examples showing the way to solve a certain type of problem step by step—rather than by "tackling" problems head on. This is because conventional problem-solving in the form of means-ends analysis requires a relatively large amount of WM processing capacity. The latter is therefore unavailable for schema construction and automation, and thus, for learning. Later on in the process, guided examples can be substituted with completion problems—i.e., problems presenting a partial solution, which the student must complete. The gradual shift from guided examples to problems by providing fewer completed steps each time is called *backward fading*.[14]

Moreover, consistently with the model-based learning approach (see Sects. 5.4 and 5.5), worked examples have been found to positively impact the progression of mental models during instruction. In particular, Darabi et al. (2010) studied the effect of worked examples and problem solving strategies on chemical engineering students' mental model progression, with the learning goal of diagnosing malfunctions in a computer-simulated chemical plant. They found that the worked example strategy significantly contributed to participants' understanding of causal relations among the system's components.

Thus, in the context of a specific learning goal, one must decide whether the use of simulation is actually justified, or whether other teaching methods should be used, such as the worked examples method—or a combination of methods. Lack of consideration of this aspect can result in simulation misuse, which occurs when the features of interactivity and problem solving that are typical of simulation are not suited to a given student's characteristics and learning context.

Intrinsic cognitive load, however, depends on the students' degree of familiarity with the contents to be learned and on the consequent level of learning task difficulty. A learning task that is more difficult than the student's level of expertise causes a high intrinsic cognitive load and therefore, inefficient learning.

According to CLT, the most important student characteristic is that of prior domain knowledge. This view is in line with Ausubel's "assimilation theory of learning", which holds that "the most important single factor influencing learning is what the learner already knows" (Ausubel 1968, p. vi). Gitomer and Glaser (1987) specifically investigated the role of domain knowledge in the construction of mental models and described it in terms of cognitive structure accretion. According to these authors:

[14] In constructivistic terms, the backward fading method is a type of "scaffolding"—i.e., a situation in which students are a given a support structure, which is gradually removed with improvement in knowledge acquired. It is a recurrent topic in instructional science, as a method with similar aims was known in the 1950s in behavioristic instruction as "shaping behavior".

The more knowledge one has about a certain domain, the more inferences that can be drawn and used to construct models, elaborate new information, enhance retrieval, and foster learning. This is, in part, attributable to more potential links existing between stored knowledge and incoming information, which results in better, more elaborative encoding" (ibid., p. 307).

As opposed to extraneous cognitive load, intrinsic load cannot be generically diminished. It must therefore be optimized, and to do so, the following effects must be given due consideration during the design phase:

- *The element interactivity effect*. Cognitive load effects can be observed only when using material with a high, versus low degree of element interactivity (Sweller 1994).
- *The isolated/interacting elements effect*. Learning is enhanced when very high element interactivity material is first presented as isolated elements, followed by interacting element versions, rather than initially in an interacting element form (Pollock et al. 2002).

These effects suggest several techniques to consider during the instructional design- and technological interface development phases, as described here below.

5.6.1 Pre-Training

It is important to provide students with prior instruction about the names and behavior of a complex system's components before presenting the entire system—e.g., presenting a simulation model's structure, step-by-step, in the form of a narration or guided tour, as with the system dynamics learning laboratory shown in Fig. 5.4.

5.6.2 Segmentation

The original task or content should be subdivided into fragments of information corresponding to manageable chunks—e.g., reducing the complexity of a simulation by separating it from one screen into two screens.

5.6.3 Sequencing

Presenting the information by following a certain order—e.g., by gradually increasing the number of variables the student is able to manage. The image in Fig. 5.12 shows a virtual laboratory on clorophyillian photosynthesis with an interface that allows for this type of sequencing. The initial situation corresponds to the "white light" mode and shows only the following sliders: "Temperature"

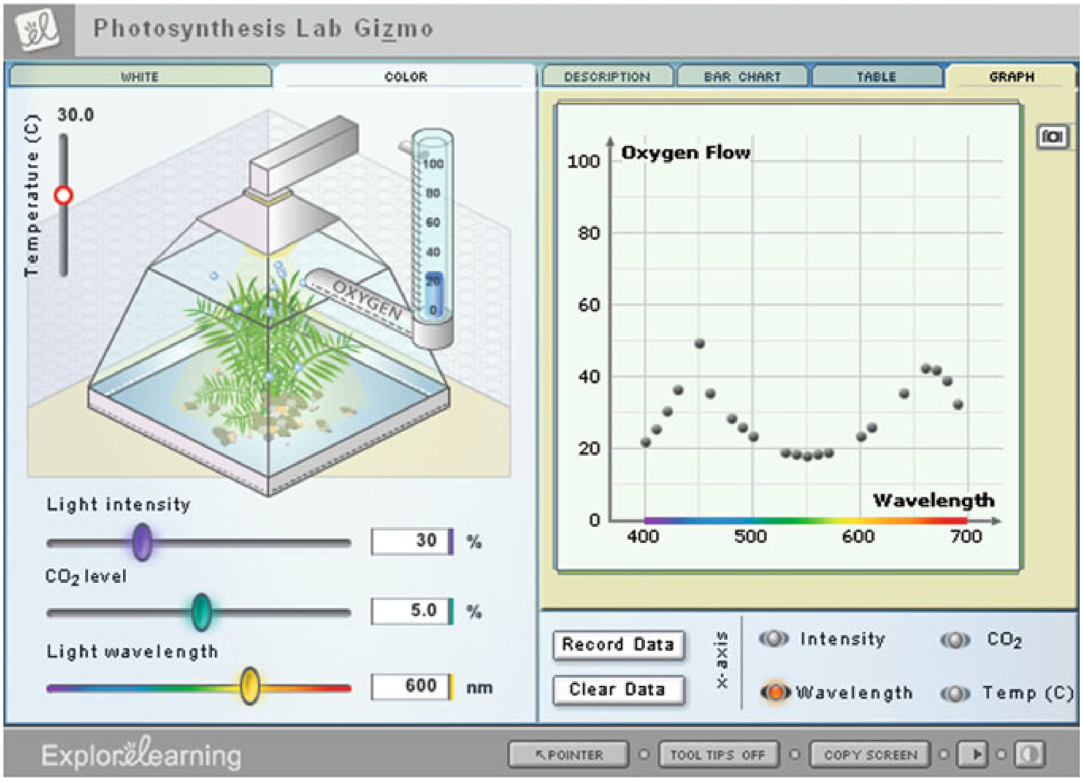

Fig. 5.12 An educational simulation of a photosynthesis lab. Image courtesy of ExploreLearning Gizmos™ (http://www.ExploreLearning.com)

(at the top), "Light intensity" and "Carbon Dioxide Level" (at the bottom of the screen). By switching to the "colored light" mode, the "Light wavelength" tab also appears at the bottom. Students can therefore first carry out the experiments in the most simple situation, and then can pass on to the more complex one to investigate the effect of different colored-light on photosynthesis.

5.6.4 *Pacing*

This criterion allows students to control the rate of information presentation. For example, the molecular dynamics simulation shown in Fig. 4.12 presents a navigation bar that allows students to pause and play the simulation at any time; to move forward and backward between time intervals; to speed it up and to slow it down; and to reverse the direction of time by playing it backward. These actions can correspond to specific cognitive processes, such as directing attention to an important bit of information or linking new information to prior knowledge.

Reducing extraneous and intrinsic cognitive load can create the conditions to free up WM resources, which can be dedicated to the intrinsic cognitive load imposed by the learning task. Some effects that have been ascribed to the use of these germane resources are:

- *The variable examples effect*. Examples with variable surface features enhance learning, as compared with examples presenting similar features (Paas and van Merriënboer 1994).
- *The self-explanation effect*. Asking students to explain their answers to themselves while studying worked examples enhances learning (Atkinson et al. 2003).
- *The imagination effect*. Imagining procedures or concepts enhances learning, as compared to studying materials (Leahy and Sweller 2004).

All of these effects can be tapped in simulation-based learning. For example, a teacher can use simulation to show students a large number of examples with variable features and can help them identify both similar features and differences across many conditions thereby. A commonly used technique is that of a teacher running a computer-projected simulation onto a screen in front of the class. Kalyuga (2009) introduced the notion of "worked-out" simulation, as an instructional format comprising a series of static frames that demonstrate the step-by-step procedures of actual hypothesis testing. The same notion can be extended to the comprehension of procedurally guided numerical experiments. For example, worked-out simulation examples (in the form of mini-projects) were used in the context of an advanced computational physics course to highlight numerical and modeling issues, and to teach numerical-experiment practices (Couairon et al. 2011).

The self-explanation technique can be effectively combined with simulation by asking students to explain their actions or their answers to problems during the simulation. One type of self-explanation well suited to simulation is that of predicting what will happen next as the simulation proceeds. Self-explanations can be prompted by the program or by the teacher; the latter type of prompting can also be used to stimulate group discussion.

Another instructional technique used in designing and structuring simulation-based learning situations is that of *reciprocal learning*, in which students work in pairs: While one student (the "doer") interacts with the program, the other (the "observer") observes and takes notes (see, e.g., Iserbyt's model of reciprocal learning, 2012). Reciprocal learning allows a pair of students to process specific information with an extraneous cognitive load that is lower than what they would have individually experienced by interacting with the simulation exclusively on their own.

Techniques such as varied examples, self-explanation and reciprocal learning can facilitate student reflection and self-regulation of learning, and can make it possible to optimize mental model construction thereby.

Ultimately, however, students must decide whether to consciously apply a learning strategy; whether to re-structure the representation of a problem to solve it more easily; and to meta-cognitively monitor their thinking processes. The germane resources allocated to the learning task (i.e., until recently, "germane load" in the CLT literature) therefore depend on the actual levels of student engagement with the learning environment. Significantly, Kalyuga (2011) stated that "ensuring that sufficient germane resources are actually devoted to learning requires appropriately engaged learners. This is undoubtedly a critical issue in teaching and learning, but it cannot be resolved solely within a CLT framework and requires specific methods and techniques external to CLT" (p. 15).

One effect attracting the attention of cognitive load researchers is that of imagination, which occurs when students imagining a procedure or concept perform better on a subsequent test than learners studying only (Leahy and Sweller 2004). What mechanisms underlie this effect? One hypothesis supported by experimental evidence (Leahy and Sweller 2007) is that imagining conditions more easily allow information to be transferred from long-term memory to WM, and that this process can facilitate learning when students must deal with complex, high intrinsic cognitive load, information. This situation also frequently occurs in simulation-based learning environments.

Yet, what if simulation were inherently more appropriate to facilitating imagination than other, more well-known activities, such as testing hypotheses, designing experiments, and interpreting data? The idea is not surprising, given that cognitive scientists acknowledge imagination to be a key element of the model-based reasoning processes underlying scientific practice (see Sect. 5.3).

Clement (2008) closely examined the link between classroom learning and scientific thinking and found that students achieve deeper understanding of subject matter when using the same nonformal reasoning processes used by scientists and experts in their problem solving activities (e.g., analogical reasoning, mental model construction, imagistic simulation, physical intuition, and thought experiments). As illustrated by Nersessian (2008), constructing a mental model of a system, visually imagining the model, and predicting its behavior on the basis of mental simulation are forms of model-based reasoning that are historically prevalent in periods of radical conceptual change—i.e., in situations that are cognitively analogous to those students face when asked to change or replace their mental models of scientific concepts.

It is therefore proposed herein that:

- If extraneous cognitive load is reduced to a minimum, and intrinsic cognitive load is optimized, then the germane mental resources freed up for learning can be used for mental simulation.

From this perspective, simulation presents great potential as an imagination-supporting tool, by facilitating the comprehension of scientific concepts and stimulating scientific creativity.

For example, Fig. 5.13 shows a screenshot presenting an educational simulation game aimed at creating awareness in children of the ways in which climate change is linked with CO_2 emission levels in the atmosphere.[15] The simulation presents the analogy of CO_2 as water in a bathtub: water (CO_2) enters the bathtub (the

[15] The simulation is based on a system dynamics integrated climate-economy model (Fiddaman 2002).

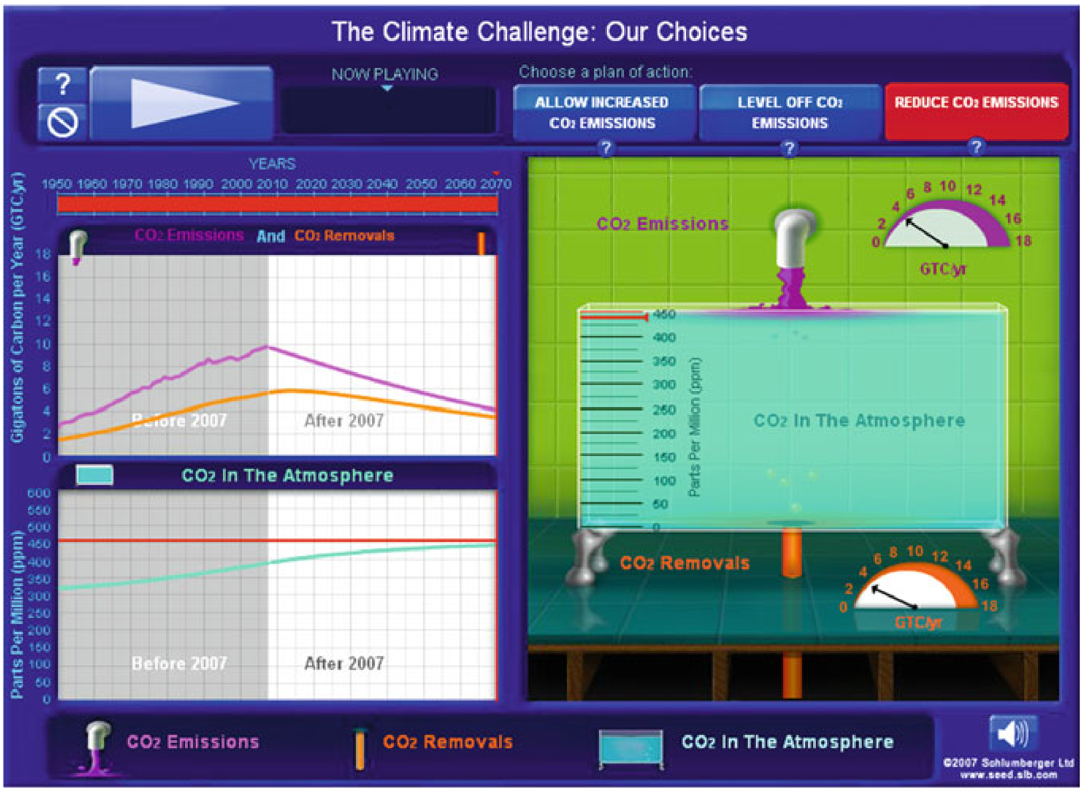

Fig. 5.13 Use of an instructional analogy for linking the concept of climate change with the existing knowledge about the water level in a bathtub. © 2012 Schlumberger Excellence in Educational Development, Inc. All rights reserved. Web site: http://www.planetseed.com

atmosphere) from the spigot above the tub and exits through the drain below, similarly to CO_2 entering and exiting the atmosphere.

The concept underlying the simulation is that of a *dynamic balance* between the inflow of CO_2 in the atmosphere (due to human activities) and the outflow of CO_2 (resulting from photosynthesis and ocean absorption). Without going into the details of the simulation (very interesting in and of themselves) this type or representation can be highly effective in supporting mental simulation of the dynamic balance phenomenon, because students can compare the output of their own mental simulation with that shown on the computer screen.

5.7 Choosing the Right Mix

From the mid 1980s to the end of the 1990s numerous studies were published on the instructional effectiveness of simulation.[16] Various types of computer simulation were compared to other teaching modes, such as lectures, expository texts,

[16] See, e.g., the studies reviewed in Lee (1999), Strangman and Hall (2003), and Sahin (2006), in addition to the previously cited National Research Council report (2011).

laboratory activities, and case studies. The research findings, however, were mixed and at times conflicting, mostly because simulation was considered an *instructional medium* able to foster learning in and of itself. Variables characterizing the learning context in which simulation was examined—especially expected learning outcomes (e.g., conceptual change, skill development, content area knowledge), grade level, student characteristics, instructional methods, teacher training, and teacher support—were nearly always not examined. As revealed by meta-analyses (Bernard et al. 2004; Sitzmann et al. 2006) comparing the effectiveness of other instructional media (e.g., distance learning and classroom-based instruction), all factors being equal, the largest proportion of an observed difference between two types of instructional intervention, is due not to the medium used in either of the two conditions, but the underlying *instructional methods*. The research focus has therefore now shifted to issue of which teaching method is the most suited for optimizing the instructional potential of simulation.

As the constructivist position gained ground over recent decades, simulation was gradually equiparated nearly exclusively with the discovery learning method. This association was facilitated by the similarity between student-conducted activities in a simulation-based learning environments and those characterizing inquiry-based learning, which is a popular discovery learning approach in science education. The National Science Education Standards (1996) defined inquiry-based learning as

> a multifaceted activity that involves making observations; posing questions; examining books and other sources of information to see what is already known; planning investigations; reviewing what is already known in light of experimental evidence; using tools to gather, analyze, and interpret data; proposing answers, explanations, and predictions; and communicating the results (p. 23).

These activities therefore closely correspond to those typically conducted by students in a simulation-based learning environment (see Sect. 5.1). Moreover, the problems one can encounter in these environments (see Sect. 5.6) are similar to those encountered in inquiry-based learning. For example, the instance in which students simultaneously modify too many variables in a simulation is quite similar to the difficulties they experience in designing and conducting scientific investigations (de Jong and van Joolingen 1998).

Simulation is also frequently considered similar to other methods commonly thought to be examples of discovery learning (e.g., problem-based learning, experiential learning, active learning), and it is frequently cited together with these methods in the *Direct instruction versus Discovery learning* debate described in the previous section. (For a recent meta-analysis of discovery based approaches to education, see Alfieri et al. 2011). Yet, is equiparation of simulation with discovery learning justified? A closer look reveals that the methodological options available to teachers and researchers are actually more diverse and stimulating than they might appear at first glance. In fact, direct instruction and discovery learning are frequently viewed dualistically, in opposition to each other, although they can be more usefully considered as the two poles of a continuum ranging from purely receptive learning to purely discovery learning. Romiszowski (1981) proposed the notion of an instructional method continuum based on Biggs' (1972) and Landa's (1976) previous classification of these methods and placed some key teaching methods along the continuum (see Fig. 5.14), specifically:

1. *Impromptu reception learning* (or "accidental reception")—facts and observations are teacher-provided or given by other sources in an unplanned way.
2. *Rote reception learning*—provision of information mostly requiring memorization.
3. *Deductive exposition*—a rule is given, followed by examples thereof.
4. *Inductive exposition*—examples are given, followed by the corresponding rule.
5. *Programmed discovery*—examples are given, and students must discover the underlying rule through a sequence of carefully programmed steps.
6. *Guided discovery*—each learning step's goals are presented, and students are free to explore the learning environment, but are given guidance and help at each stage.
7. *Exploratory learning*—general learning goals are presented, and students may choose sub-goals, methods, and activities.
8. *Impromptu discovery learning* (or "accidental discovery")—facts and observations are discovered by students in an unplanned way.

Expository teaching strategies and discovery teaching strategies correspond, respectively, to the two learning poles of reception and discovery learning. In most practical situations, however, effective instruction requires a mix of strategies and methods, defined in terms of student characteristics and learning goals, modulated over time in function of the student's progress.

It is important to note that both reception learning and discovery learning can be two different types of *meaningful learning*, i.e., learning in which individuals acquire new knowledge by integrating it into their prior cognitive structures (Ausubel 1968). In other words, discovery learning is not synonymous with meaningful learning, nor is reception learning with *rote learning* (i.e., by memorizing facts only). For example, a book or television documentary can be as

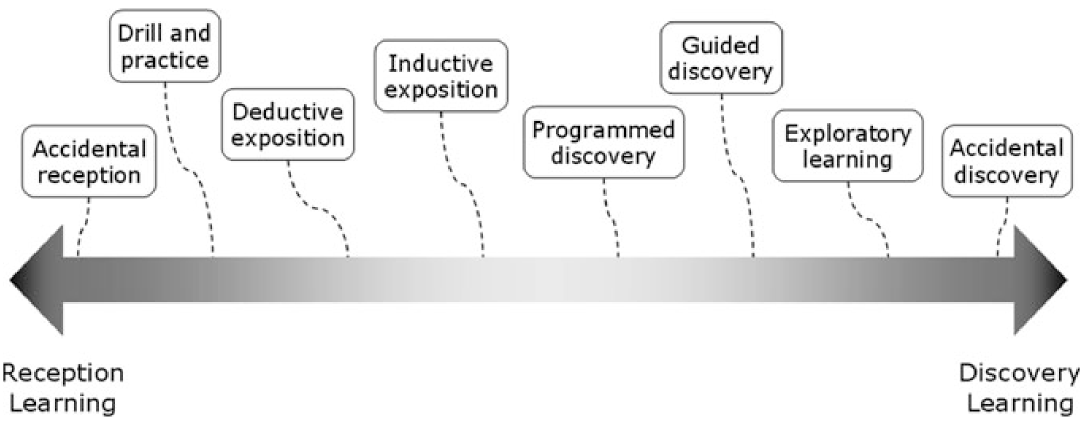

Fig. 5.14 A continuum of instructional methods (based on Romiszowski 1981, p. 179)

engaging, thought-provoking, and relevant to students as can group discussion or a last generation videogame, even when students do not conduct any observable activities (as in the first example). This is because, as Mayer (2004) noted, "activity may help promote meaningful learning, but instead of behavioral activity per se (e.g., hands-on activity, discussion, and free exploration), the kind of activity that really promotes meaningful learning is cognitive activity (e.g., selecting, organizing, and integrating knowledge)" (p. 17).[17] More than generic "activity", we should reason in terms of *active processing*, which can occur even during traditional lessons, as long as teachers are able to stimulate students' attention and interest. It can conversely be absent in simulations that disorient students because they have no clear learning goal or an overly complex technological interface. Moreover, Renkl and Atkinson (2007) maintain that processing should be not only active, but also *focused*, i.e., linked explicitly to the concepts and principles that are crucial to learning a subject.

Findings from a study conducted by Stephens et al. (2010) on the in-class use of simulation suggested that behavioral interactivity can at times be less crucial to learning goals than is cognitive interactivity. The researchers used two conditions to compare the instructional effectiveness of simulation: (a) small groups working hands-on with computers, and (b) whole classes observing a teacher-conducted simulation projected onto a screen before the class. Although students in the small group situation appeared to be more engaged, the whole-class format produced similar or even better learning results. This outcome was due to the fact that when students did not explore the simulation on their own, teachers had more opportunities to ask the class questions and to synthetize, summarize, and restate important aspects of the simulation.

A closer examination of the objections to discovery learning by promoters of direct instruction, however, reveals that they concern instructional situations characterized by "pure discovery" (Mayer 2004), "minimal guidance" (Kirschner et al. 2006), or "unassisted discovery" (Alfieri et al. 2011). In the same vein, Klahr and Nigam (2004) created an experimental condition using a discovery learning exemplar with "no teacher intervention beyond the suggestion of a learning objective; there were no guiding questions and no feedback about the quality of the child's selection of materials, explorations, or self-assessments" (p. 662). These types of minimally guided conditions correspond to the right-most part of the diagram in Fig. 5.14, and specifically, to what is called "exploratory learning". They are also significantly different from guided discovery or programmed discovery methods.

In one study examining the effects of simulation on high school biology students' problem-solving skills, Rivers and Vockell (1987) divided simulations into two categories—guided and unguided. Results showed that students using the

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[17] Similarly, Kennedy (2004) proposed a distinction between *functional interactivity*, which links an instructional event to students' actions, and *cognitive interactivity*, which refers to students' cognitive processes.

guided version of the simulations surpassed the other students on tests of scientific thinking and critical thinking. This finding suggests that students perform better when some form of guidance is provided.

Some types of simulation were initially presented by their proponents as exploratory learning environments, on the foundation of constructivist or inquiry-based premises, but in most instances, these environments gradually developed guiding and support functions for students. They therefore shifted from exploratory learning to varying degrees of guided learning. For example, Van Joolingen and de Jong (1991) offered students a tool to support hypothesis generation while exploring a computer simulation, in the form of "hypothesis scratchpads". These are paper forms containing variables, conditions, and relations aimed at helping them construct hypotheses. As mentioned in Sect. 5.6, the SimQuest software later integrated scratchpads into the program (Fig. 5.15).

Many other studies have shown a similar pattern. For example, Horwitz and Christie (1999) attributed some disappointing learning results observed in the use of the GenScope™ program (a popular exploratory environment designed to help students learn genetics) to a lack of assistance from the software. Instructional activities for guiding students' interactions with the genetics model—in the form of "embedded reflective guidance"—were consequently included in a new version of the program, called BioLogica™.[18]

The shift from exploratory and open-ended learning to a more structured form of instruction is also occurring in the Connected Chemistry™ learning environment.[19] This environment is a set of model-based chemistry instructional units dedicated to students and teachers. The activities making up the units are based on agent-based simulation models (see Sects. 4.10) that allow students to use conceptually interpret macroprocesses, such as the chemical reactions and state changes of matter, in terms of emergent properties that link macroscopic- and molecular-level processes (Stieff and Wilensky 2003; Blikstein and Wilensky 2005).[20] Despite the theoretical references to Bruner and to "constructionism" (i.e., Seymour Papert's theory of science education, which combines Jean Piaget's epistemology with the idea of "learning-by-making"), both the activities making up the instructional units and the simulation environment are organized in several sequential steps of increasing complexity. The steps are described in detail and are carefully programmed, equipped with introductions, stimulus questions, suggestions, thoughts for reflection and final tests. The result is a simulation-based learning environment that is so structured as to be more akin to programmed discovery than to guided discovery or exploratory learning.

[18] Web site: http://biologica.concord.org.

[19] Web site: http://ccl.northwestern.edu/curriculum/ConnectedChemistry.

[20] The Connected Chemistry simulation models are written in the multi-agent modeling language NetLogo (Wilensky 1999b), which has been used in many biology and physics classrooms (e.g., Wilensky and Reisman 1999; Wilensky et al. 1999).

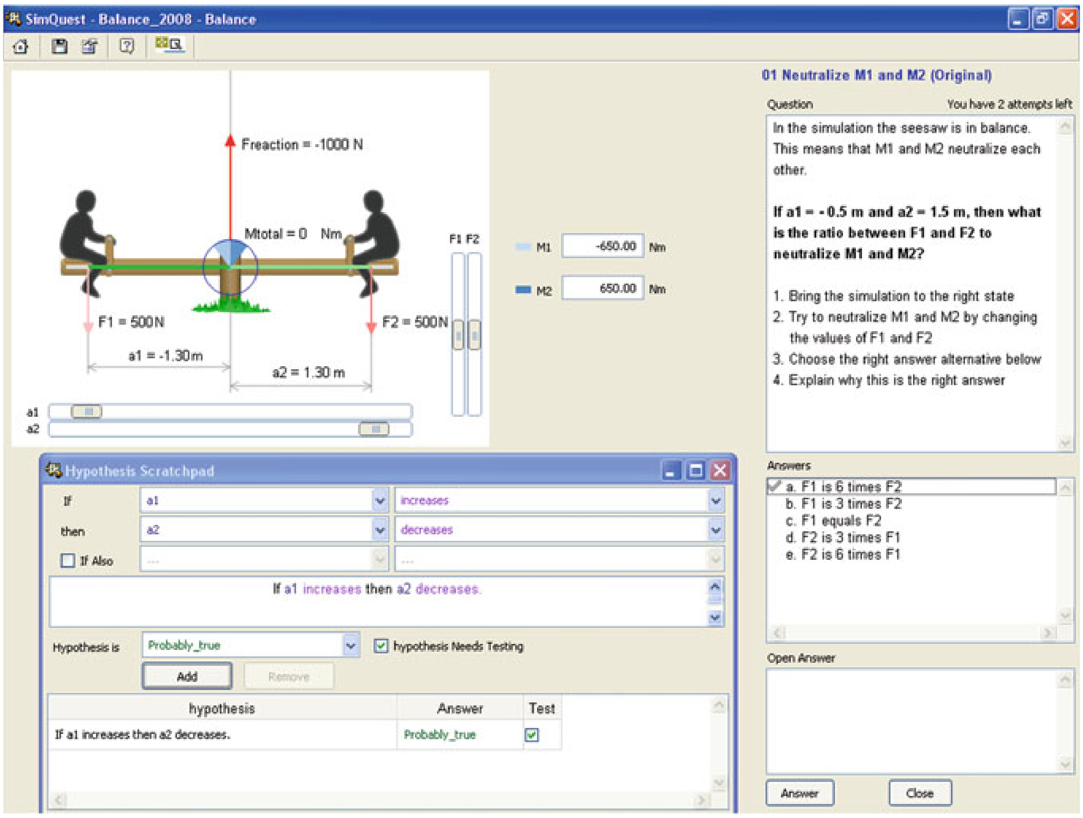

Fig. 5.15 Examples of instructional support provided in a physics simulation. Students can change the two forces acting on the people and the distances to the center of the seesaw and discover the effect on the moment. Image from a simulation conducted with SimQuest software, courtesy of Jan van der Meij. Web site: http://www.simquest.nl

The need to structure and guide students' activities was also acknowledged by the creators of "River City", a multi-user virtual environment (MUVE) for teaching scientific research to U.S. middle schools, which also contains simulation elements (Nelson 2007). The first version of this virtual world contained only tacit and collaborative-type guiding elements, although later versions presented a window with an "individualized guidance system", in addition to the three-dimensional environment window. The guide offers hints designed to help students interpret the data they collect in River City and to facilitate the inquiry process. It contains links to specific pages, an interactive map, a tutorial, and buttons for navigating forward and backward among contents.

All of the above-described guidance modes can be considered to be "cognitive scaffolding", i.e., the support structure provided to students in an initial learning phase. It allows them to carry out a task that would otherwise be too difficult for them to do alone, and is therefore removed as students become capable of doing the task autonomously. According to the hypothesis of an instructional method continuum, provision of this kind of scaffolding can be interpreted as moving from the right to the left extreme of the diagram in Fig. 5.14.

The same type of considerations can be more generally extended to inquiry-based learning. In fact, different levels of inquiry can be defined in terms of the degree of structure and guidance provided to students (Colburn 2000; Bell et al. 2005). A guide published by the National Research Council (2000) presents a classification (p. 29) that lists the essential features of classroom inquiry and their variations in order along two lines: one indicating a varying degree of direction by the teacher or the materials, and the other, degree of student self-direction. This representation is also essentially in agreement with the concept of an instructional method continuum.

The duality between direct instruction and discovery learning is preferably viewed, however, as a *polarity*, which is able to generate "creative tension" ultimately able to generate better ideas or outcomes.[21]

Once one acknowledges the need to integrate activities corresponding to different methods and techniques, the practical issue is that of how to design the sequence for proposing these activities to students. Gagné's "Nine events of instruction" can be a helpful tool here, as it is an instructional design model broadly used by teachers and curriculum designers (Gagné et al. 1988), and the events it lists represent the necessary conditions for learning, and specifically:

1. Gain attention
2. Inform learner of objectives
3. Stimulate recall of prior learning
4. Present the stimulus information
5. Provide learner guidance
6. Elicit performance
7. Provide feedback
8. Assess performance
9. Enhance retention and transfer.

The exact format of any of these events cannot be generally specified for all instructional contexts, but must be decided on a case-by-case basis.[22]

Moreover, although it is recommended that each event be presented in a given lesson or unit, their order is not absolute. In fact, much of the differences among instructional methods concerns the decision as to present the information first and follow it by practice, as suggested in the above events sequence, or vice versa, to present the information after practice. In particular, expository instructional strategies are characterized by (1) information presentation, (2) remembering and comprehension tests, (3) practice in applying the rules to examples, and (4) application to problems and real situations. Conversely, discovery instructional strategies are characterized by (1) the opportunity to act and to observe the consequences of one's own actions, (2) testing of the comprehension of cause-effect relations, (3) testing of the understanding of general principles, and (4) application

[21] From a scientific model perspective, a useful analogy is that of electric current polarity, which provokes the flow of electrical current in a circuit.

[22] As early as the 1970s, Rosenshine (2002), conducted a series of studies on the efficacy of class teaching methods. Results showed that the most effective teachers' activities mostly overlapped with Gagné's events of instruction.

to problems and real situations. An example of a discovery instructional strategy is that of the "5E" scientific education instructional model, consisting in the following phases: (1) *Engagement*, (2) *Exploration*, (3) *Explanation*, (4) *Elaboration*, and (5) *Evaluation*.[23] An examination of each phase's activities revealed analogies with Gagné's events of instruction. As typically observed with discovery learning methods, the main difference consisted in the inversion of the information presentation phase (Explanation) with the practice phase (Exploration).

The key aspect characterizing the various approaches is that of sequencing and therefore, the order in which the various events of instruction are presented to students.

From this perspective, simulation is at times viewed—similarly to lab activity—as a type of practice, and therefore, a way to apply and reinforce knowledge acquired through other instructional media. Other times, it is considered a way to present new contents to students. For example, Thomas and Hooper (1991) distinguished between *pure simulation* (i.e., practice only features) and *impure simulation* (i.e., practice and presentation features), and attributed the following instructional roles to simulation:

1. *Experiencing*—setting the cognitive or affective stage for future learning.
2. *Informing*—supplementing or replacing textbooks and lectures to provide initial formal exposure to a topic.
3. *Reinforcing*—strengthening specific learning objectives or consolidating newly acquired knowledge by applying it to a situation similar to one that could be encountered in the real world.
4. *Integrating*—providing students with the opportunity to apply previous learning to new situations and to associate previously unconnected ideas.

The cited authors considered pure simulations to be most useful for experiencing and integrating functions, and impure simulations as being more suited to informing and reinforcing functions. Along the same lines, Brant et al. (1991) investigated whether it is more effective to use simulation before or after lessons. Their participant students receiving the simulation as a framework for understanding prior-to-formal classroom instruction scored significantly higher on an applications post-test than did students using the simulation as an integrating activity following formal instruction. (See Lee 1999 for a meta-analysis on the effectiveness of computer-based simulation, through examination of the relation between pure and hybrid forms of simulation, and between the presentation and practice modes of instructions).

From an instructional design perspective, the progression of one (physical or mental) model to another, which characterizes model-based instruction, can also be viewed in terms of sequencing. For example, Swaak et al. (1996) studied the effect of model progression in a simulation on harmonic oscillation, where the

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[23] The model was developed by the Biological Sciences Curriculum Study, an organization with the aim of improving biology teaching in schools (http://www.bscs.org).

model developed from free oscillation, then to damped oscillation, and lastly, to oscillation with an external force (see Sect. 4.5). They found that model progression was successful in enhancing the students' intuitive knowledge (but not their conceptual knowledge) as compared to an environment without model progression.

Seel and Dinter (1995) studied the effect of presenting a conceptual model (in the form of a well-organized knowledge structure) at the beginning of the learning path in the construction of students' mental models. Their findings confirmed that a conceptual model tailored to students' prior knowledge was directly associated with an increase in learning. Darabi et al. (2010) further investigated the issue of the effect of instructional planning and sequencing on the construction of mental models. They found that "despite the essential role of problem-solving practice for integration and transfer of knowledge and skills, providing novice learners with supportive information before practice can contribute substantially to the progression of a learner's mental model toward an expert-like mental model" (p. 101).

In a presentation of his approach to model-based learning and instruction in science, Clement (2007) noticed teachers' difficulty with pure discovery methods and alternatively proposed a method of student/teacher co-construction of a visual model during large group discussion (see Sect. 5.4). This approach is a form of guided discovery, in which teachers establish the nature and sequence of the activity conducted in class. Specifically, Clement distinguished between the two dimensions of *directing activities* and *generating ideas*: the first is more the teacher's responsibility and the second, the students'. (According to Clement, during experimentation of these methods in class, the teacher directed the activity for approximately 85 % of the time and the students generated approximately 60 % of the ideas emerging.)

Regardless, however, of the strategy adopted, as long as a specific mental model represents a sufficiently plausible explanation for students, they will not be motivated to construct a new one. Equivalently, CLT tells us that the students will not automatically allocate the resources they have available in WM to constructing the mental schema required for learning. It is therefore the teacher's responsibility to set up a sequence of activities to stimulate the need to progress from one mental model to another, and to facilitate the construction of these models. This approach also requires consideration of the role of motivational variables that combine affective and cognitive functioning. A variable of this type is *interest*, which can be defined as a psychological state manifesting itself as "a relatively enduring predisposition to reengage particular contents over time" (Hidi and Renninger 2006, p. 111). Empirical evidence does show that simulation can motivate students' interest in science (National Research Council 2011), but a distinction should be made among different types of interest. A useful reference model for this purpose is Hidi and Renninger's (ibid.), which proposes that interest develops in four phases:

1. *Triggered situational interest*—a psychological state of interest that results from short-term modifications in affective and cognitive processing.

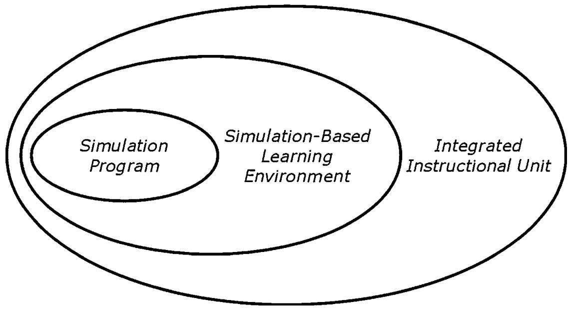

Fig. 5.16 Levels of instructional structure when using simulation

2. *Mantained situational interest*—involves focused attention and persistence over an extended episode in time.
3. *Emerging individual interest*—when students begin to regularly generate their own "curiosity" questions and are characterized by positive feelings.
4. *Well-developed individual interest*—which enables people to sustain long-term constructive and creative endeavors.

The model can help us distinguish between the interest sparked by a given simulation's features such as attention-grabbing images and animations or unexpected information, and other forms of interest that are more significant to learning purposes and are potentially linked to the restructuring of students' schemas and beliefs.

Another research area worthy of investigation is that of students' study strategies, i.e., the repertoires of methods and techniques they apply when using a simulation, or building a simulation model. Examples of these strategies are: brainstorming, taking notes, visually structuring information (e.g., using charts, maps, diagrams, timelines), summarizing, self-questioning, self-monitoring, creating sub-goals, and managing time.

Considering simulation as an activity that can be explicitly linked to, and integrated with other learning activities, broadens the horizon of instructional design from the simulation program or learning environment to that of the instructional unit—i.e., to a series of lessons or learning experiences, rather than single lessons. It is therefore possible to refer to the concept of *integrated instructional units*, which were defined by "*America's Lab Report*" (National Research Council 2006, p. 76) as an instructional sequence integrating laboratory activities with other types of science learning activities, such as lectures, reading, and discussion.[24] The duration of these units can range from several days to several weeks, in agreement with the time students require to meaningfully learn new concepts and practices. For example, as a part of a unit dedicated to the study of astronomical factors causing variations in the temperature between summer and winter, a simulation-based activity could allow for a change in the tilt of the earth's axes, and for virtually measuring the angle with which sunbeams strike the earth in various parts of the globe. This activity could then be integrated with an

[24] The same report also considers simulation as a technology to support learning, which can be integrated with real laboratory experiences making up an instructional sequence.

experiment conducted in class, by using a portable lamp to illuminate sheets of squared paper tilted at various angles to the direction of the light, and by using a felt-tip marker to trace the outline of the illuminated areas. This approach can make it possible to identify and consequently identify analogies to facilitate understanding of what happens when the sun's rays strike the earth's surface from different angles as the seasons change.

Thus, the integrated instructional unit represents the final level of a progression of elements starting from the simulation program (as a technological instrument for manipulating a model) and going to simulation-based learning environments (simulator equipped with instructional support tools), and then to integrated instructional units (simulation only one of the elements involved—not necessarily the main one)—in a sequence of activities designed with a well-defined learning goal (see Fig. 5.16).

Chapter 6
Simulations for Thinking

When the ideas are grasped, the words are forgotten.
(Zhuangzi, XXVI.II)

6.1 Cognitive Partnering

This chapter will examine a topic that (more or less explicitly) emerged in many of the previous pages: the relation between mental simulation and computer-based simulation (Fig. 6.1). What are the similarities and differences between these two types of simulation? How do they interact? How can they be integrated to enhance learning?

A preliminary attempt to answer these questions can be grounded in several general considerations on the relations that exist between humans and computer systems, and specifically, the ways in which these systems can extend human cognition. This view will make it possible to envision learning scenarios with simulations serving as "partners" in developing cognitive processes that lead to conceptual understanding and creativity.

The use of computers to extend human intelligence was a specific field of investigation in educational psychology, especially in terms of the effects of the introduction of microcomputers into schools, which occurred during the 1980s and the early 1990s.[1] Pea (1985), for example, proposed that the computer can be used not only as an "amplifier" of cognition, but also as a "reorganizer of mental functioning". For instance, a word processor can be simply used to more rapidly and precisely create documents and therefore by considering it as an amplification of a typewriter's possibilities. It can conversely be viewed and used as a tool for interactively creating and revising a document's structure. This type of use gives people an opportunity to reorganize their own writing processes and to experiment with different activities during writing. Pea (ibid., p. 174) cited simulation as an example of software that can have dramatic cognitive implications for the reorganization of mental processes—alongside expert systems and knowledge-based

[1] The Apple II home computer was released in 1977 and was the first computer to be used on a broad scale in American secondary schools. IBM responded to the success of Apple II by releasing the IBM PC in 1981. This was the first microcomputer based on an open architecture, which allowed third parties to develop software and hardware for it and other companies to manufacture "PC compatible" clones, igniting the personal computer revolution thereby.

F. Landriscina, *Simulation and Learning*, DOI: 10.1007/978-1-4614-1954-9_6,

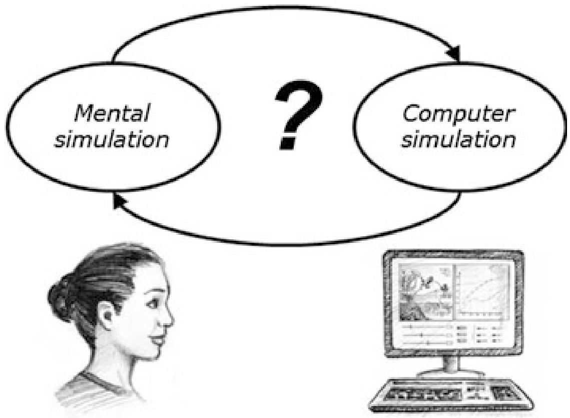

Fig. 6.1 The relation between mental simulation and computer-based simulation

intelligent tutors. (The latter two intelligent technologies were the focus of educational technology research at the time.)

Salomon et al. (1991) distinguished between effects *with* technology, which occur "when people work in partnership with machines" (p. 2), and the effects *of* technology, which occur when "when such partnerships have subsequent cognitive spin-off effects for learners working away from machines" (ibid.). According to this view, a given technology can have two types of effects on students: change in performance *while using the program*, or a *later* change in knowledge or skill when away from the computer. Salomon and Globerson (1987) associated the second type of change with a state of *mindfulness*, which activates non-automatic, controlled mental processes, and therefore mental effort and metacognitive monitoring. They contrasted this mindfulness state with that of *mindlessness*, which is conversely characterized by "blind reliance on the marked structural features of a situation without attention to its unique and novel features" (ibid., p. 4).[2]

The interplay between human cognition and computers is also a key issue in the field of cognitive ergonomics (see Sect. 5.6). Norman (1991) in fact viewed computer programs as an example of *cognitive artifacts*—i.e., artificial devices that "maintain, display, or operate upon information in order to serve a representational function and that affect human cognitive performance" (p. 17). Cognitive artifacts may enhance performance—not by changing a person's capabilities, but the task itself. An example is that of a check-list to monitor tasks calling for many steps and requiring special attention (and therefore tapping a rather high cognitive load). From a "system view"—i.e., the perspective of an observer viewing the total system composed of the elements of person, check-list, and task "from the outside looking in"—the system's overall performance appears to be enhanced, because the person involved is able to do the task more rapidly and with fewer errors than without the check-list. Yet, the check-list does not actually enhance this person's

[2] In a cognitive load perspective (see Sect. 5.6), a state of mindfulness can be compared to a condition in which a student's available working memory resources are currently devoted to the learning task at hand, whereas a mindlessness state refers to a condition of high extraneous cognitive load.

memory: From the "person view" (the user's viewpoint), it only changes the task, from that of remembering the items on the list to the three new tasks of (1) constructing the list (which should be done ahead of time), (2) remembering to consult the list, and (3) reading and checking the items on it. Moreover, in his popular book "Things That Make Us Smart" (1993), Norman distinguished between two general modes of cognition in interacting with a machine:

- *Experiential cognition*—a state of mind in which we perceive, act, and react to events around us effectively and effortlessly (e.g., driving a car, reading a book, having a conversation, playing a video game), and…
- *Reflective cognition*—a state of mind that involves thinking, comparing, and decision-making, and leads to new ideas and creativity (e.g., designing, learning, writing a book).

Both modes are essential for everyday thinking, but each relies on different types of technological support. Reflective cognition is based on the storing of temporary results and the use of those results in further thought processes. This process can be facilitated by external representations that allow us to overcome working memory limitations, for example, in building the chain of reasoning required to understand a system's functioning. This occurs, e.g., when students sketch a diagram of a mechanical system or a map of the cause-effect relations in a simulation model.

From the mid-1990s onwards, the cognitive sciences yielded several new theoretical approaches to representations and mental processes; these were characterized by the idea that cognition is not only a property of the human brain, but necessarily depends on external factors. The more well-known of these approaches are listed here below:

- *distributed cognition* (Hutchins 1995);
- *external cognition* (Scaife and Rogers 1996);
- *extended mind* (Clark and Chalmers 1998).

All these approaches have many points in common and are related in content to a position known in philosophy of mind as "externalism" (Rowlands 2003).

Distributed cognition is a theory developed by Hutchins (1995) on the basis of cognitive ethnography research examining navigation aboard US Navy ships and commercial airline cockpits. The purpose of these studies was to study "cognition in the wild," a term coined by Hutchins to indicate cognition occurring in the everyday natural environment, versus under laboratory conditions. The theory's main tenet is that cognition is constructed from the coordination of both internal and external resources and that the meanings of actions are directly grounded in the context of a given activity.[3]

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[3] A position that has its roots in Vygotsky's sociocultural theory of mind development, which also influenced Cole's cultural psychology and Engeström's activity theory. These approaches in turn focus on the notion of artifacts as culturally constructed mediators of human cognition and behavior (Cole and Engeström 1993).

Hutchins (ibid.) used the example of the "three-scale nomogram", a material artifact used by navigators when attempting to calculate a ship's speed from distance traveled over a specific time period. If the values of any two of the three variables of distance, rate, and time are known, the remaining one can be determined by laying a straightedge on the nomogram, such that it touches the two known values. As a consequence, the straightedge will touch the third scale at the answer value.

The distributed cognition theory emphasizes the fact that the use of these kinds of tools requires the coordination of typically human skills—such as pattern matching, manipulation of objects, and mental simulation—and the material resources to carry out a computation that would otherwise not be possible. Moreover, Hollan et al. (2000) proposed distributed cognition as a foundation for human–computer interaction research.

Scaife and Rogers (1996) examined the cognitive value of external representations by referring to graphical representations, such as pictures, diagrams, animations, and virtual reality environments. Coining the term *external cognition*, they proposed an approach that is based on an analysis of the ways in which the relation between graphical representations and internal representations influence learning and problem solving. A central aspect of external cognition is that of *computational offloading*, i.e.:

- an operation in which a tool is used in conjunction with an external representation to reduce the amount of cognitive effort required to carry out a mental task.

Kirsh and Maglio (1994) conducted a study providing an example of cognitive offloading during computer use by asking participants to play the video game Tetris. In this real-time game, "blocks"—consisting of colored squares called "tetrazoids" or "tetrominos"—fall from a height (the top of the display), and the participant's task is to rotate or move them by using the keyboard to create a horizontal line of blocks with no interruptions. After creating the row, the blocks fall to the bottom of the screen to create new lines. Kirsh and Maglio's (ibid.) findings showed that participants attempting to decide how to rotate or translate a falling block to create a horizontal line prefer to physically maneuver the block on the screen rather than first mentally imagining the movement. The authors calculated that a block's physical rotation through 90° requires approximately 100 ms, plus approximately 200 ms to select the rotate button. Achieving the same result by mental rotation takes approximately 1,000 ms. To account for these findings, Kirsh and Maglio (ibid., p. 514) introduced the idea of *epistemic actions*, i.e., physical actions with the primary purpose of improving cognition by making mental computation easier, faster, and more reliable. (Epistemic actions should be distinguished from *pragmatic actions*, the primary function of which is to bring agents closer their physical goals.) For example, Tetris players' block rotation—and shifting operations are frequently used not only to position a shape ready to fit a slot, but to rapidly determine whether the block and the slot are compatible. Epistemic actions pertaining to a slower time-scale than video games can be observed in many everyday activities such as important-event reminders; time-saving actions, such as organizing the space around us to facilitate the manual location of objects we use daily; and information gathering activities, such as exploring a new house, to decide how best to decorate it.[4]

Lastly, in Clark and Chalmers' (1998) *extended mind* hypothesis, cognitive processes occur not only within the brain, but in some circumstances can also extend across physical and social environments. For example, when using a paper and pen to calculate a complex sum, the objects used (and the actions carried out on them) can also be considered part of the cognitive processes involved, similarly to neural activity in the brain. This extended mind process can occur in those instances in which "the human organism is linked with an external entity in a two-way interaction, creating a coupled system that can be seen as a cognitive system in its own right" (Clark and Chalmers 1998, p. 8).[5]

In brief, all of the approaches to cognition described in the present section (distributed cognition, external cognition, and extended mind) highlight the importance of tool use in manipulating external representations. As Dahlbom and Janlert, the Scandinavian social scientists, effectively summarized in their motto, "just as you cannot do very much carpentry with your bare hands, there is not much thinking you can do with your bare brain" (unpublished manuscript, quoted in Dennett 1996, p. 134).

What simulation consequences can be derived from these studies? It should first be noted that all forms of simulation—physical, analog, and digital—can be considered cognitive artifacts, as (given Norman's definition cited above) they are instruments that allow for the manipulation of representations and impact students' cognitive performance in understanding, decision-making, and problem solving. Simulation programs, however, do present some characteristics that distinguish them from other types of cognitive artifacts. A first difference concerns the type of representations that are involved. The examples described in the literature on the topic typically describe artifacts that are static, material objects with a function linked to the use one makes of them—e.g., paper and pencil use in calculating a mathematical result, figures and diagrams facilitating the resolution of a problem, and calculation instruments such as an abacus or nomogram. With respect to relatively more "immaterial" cognitive artifacts, such as computer programs, the program information and data representations yielded via word processors or

[4] From an anecdotal perspective, the present Author has observed that many people, rather than searching for specific information in their own memory prefer looking it up on the Internet.

[5] This position is less outlandish than might first seem, as it stems from the functionalist viewpoint in philosophy of mind, which states that it is the *functional organization* of a process that determines whether it is cognitive or not. Cognitive processes can therefore be instantiated in a given physical system, as long as this system performs the appropriate functions. It should also be noted, however, that the extended mind hypothesis presumes that it is not phenomenal consciousness (the distinctively subjective character of a conscious experience) that extends beyond the customary boundaries of cognition, but the non-conscious portion of cognitive processes (see Chalmers 2009, p. xiv; Clark 2009, p. 267).

spreadsheets are actually inert, unless of course someone acts upon them by carrying out specific operations to modify them in some desired way (e.g., by writing or modifying a text, inserting numbers, creating formulas, or changing the visualization of a graph).

Simulations, conversely are instruments that allow for the creation and manipulation of a specific type of representations—i.e., dynamic models. Once one of these models is constructed and a simulation run is started, the model unfolds autonomously through time, in a process that includes a potentially unpredictable final state. These aspects render simulation in common with scientific laboratory experiments or observations of natural phenomena.[6]

A further difference between cognitive artifacts as commonly understood, and simulation concerns the mental processes that the latter are (at least theoretically) able to extend beyond the brain and the nature of the "division of labor" between the mind and the program.[7] In fact, researchers in the field essentially consider cognitive artifacts to be cognitive offloading tools that are useful for reducing complexity and improving decisions. Kirsh and Maglio (1994) most clearly articulated this point of view, which holds that the primary function of epistemic actions is to improve cognition by:

- "reducing the memory involved in mental computation, that is, space complexity;
- reducing the number of steps involved in mental computation, that is, time complexity;
- reducing the probability of error of mental computation, that is, unreliability" (p. 514).

Moreover, researchers have mainly focused on investigating fast-paced environments and on tasks that last several seconds at the most, as typically occurs in real time video games or piloting systems (for airplanes or other types of vehicles). These situations are characterized by a tight temporal coupling between internal and external processes and reflect Salomon and Globerson's (1987) *state of mindlessness*, and Norman's (1993) *experiential cognition*, i.e., mental states with the priority of obtaining the right information at the right time and reacting accordingly, as required by the task at hand. A completely different timescale is that considered in the "socially distributed remembering" framework, proposed by Sutton et al. (2010) in the field of the psychology of memory. These authors

[6] Even when simulation reproduces a highly well-known phenomenon, as typically occurs in instructional contexts, its results are not preliminarily known to students; it is therefore analogous to an actual experiment. The analogy holds even more soundly in the scientific research context, where simulation is used as an actual experiment (Morrison 2009), or supports the lab experiment set-up and the interpretation of data generated thereby (Tal 2011).

[7] The division of labor is an economic concept highlighted in Marxist philosophical and social thought, as it indicates the ways in which workers are assigned to various stages in the production process. Activity theory (Engeström 1987) uses the same notion to indicate the division of activities among actors in a socio-technical system.

presented a conception of external and distributed cognition that includes the resources of not only cognitive artifacts but also the functions of collaborative recall and social memory provided by external resources, such as media, cultural institutions, and social networks.

The extended aspect of mind in fast-paced environments is essentially that of the processing capacity of working memory's visual-spatial components. In the socially distributed remembering approach, however, cognition extension refers to the supplementation of long-term memory's information and knowledge storage capacity through the above mentioned external resources. To all effects, this process is accompanied by new forms of social memory enhanced by electronic technologies and in particular, by Internet.[8]

The potential of cognition extension with simulation has conversely received little attention to date.[9] In fact, the only simulation paradigm investigating the relation between computer-based simulation and mental simulation is that of system dynamics (see Sect. 4.11). As early as the 1960s, Jay Forrester, the founder of system dynamics, underscored that main purpose of his new simulation models was not that of reliably reproducing reality, but of rendering explicit—and therefore, sharable—people's mental models. The aim involved was to help people better understand the functioning of an industrial, economic, or social system, and to intervene on it by modifying its behavior in the direction desired. In his seminal book, "Industrial Dynamics", he wrote: "A mental image or a verbal description in English can form a model of corporate organization and its processes. The manager deals continuously with these mental and verbal models of the corporation. They are not the real corporation. They are not necessarily correct. They are models to substitute in our thinking for the real system that is represented." (1961, p. 49).

His acknowledgment of the important role of mental models in decision-making is particularly worthy of note (and far-reaching, considering that it originated in a period still dominated by behaviorism!) More recently, Doyle and Ford (1998, 1999) analyzed and compared the different ways in which the term "mental model" is used in system dynamics, noting the lack of a clear and universally acknowledged definition, and how the approach occasionally tends to confuse mental models (which, by their very nature, are internal and not directly accessible) with paper or computer-based external models, such as causal maps or stock-and-flow diagrams. To facilitate communication among researchers, they defined a dynamic's system mental model as "a relatively enduring and accessible, but limited, internal conceptual representation of an external system (*historical*, *existing* or *projected*) whose structure is *analogous* to the perceived structure of

[8] thanks to which, research on the content(s) of personal memory can be now extended to the contents of global memory, available at any moment, nearly anywhere on the planet.

[9] The media theorist Derrick De Kerchove commented on the topic in his book "The Skin of Culture" (1997), but did so by emphasizing the extension of sensory capacity (e.g., visual, kinaesthetic, tactile) allowed by virtual reality environments, such as flight simulators or multi-user virtual environments.

that system." (1999, p. 414). Moreover, system dynamics is the only simulation paradigm that explicitly uses the tool of mental simulation, defined by Doyle et al. (2001) as:

- "the act of inferring the dynamic consequences of a mental model in one's head without computer assistance" (p. 2).

The above-cited authors described the interrelations among a real system, a mental model of that system, mental simulation, and computer simulation by presenting a highly detailed causal map. Moreover, the chapters of "Road Maps"—a self-study guide developed by the "System Dynamics in Education Project"—present mental simulation exercises with the aim of reinforcing basic concepts such as positive or negative feedback. These exercises require students to mentally simulate the behavior of a simple stock-and-flow model and to trace the trend of one or more variables of the model in a corresponding graph (see, e.g., Whelan 1996). The underlying idea of these exercises is that a strong set of mental simulation skills will enhance students' abilities to validate, debug, and understand dynamic systems and models.

Computer simulation in turn can support and enhance mental simulation. In fact, systems dynamics researchers have frequently highlighted the limits of mental simulation in reliably reproducing the behavior of system characterized by the mutual interaction of many elements, information feedback, and circular causality. Forrester (1968) described these limits as follows: "The human mind is well adapted to building and using models that relate objects in space. Also, the mind is excellent at manipulating models that associate words and ideas. But the unaided human mind, when confronted with modern social and technological systems, is not adequate for constructing and interpreting dynamic models that represent changes through time in complex systems." (p. 3–2).

From this perspective, the purpose of building and simulating system dynamics models is indeed that of enhancing people's mental processes in dealing with time-varying systems. This view therefore does not appear to be very distant from the previously described concepts of distributed cognition and extended mind. Yet, mental process enhancement in this case does not coincide merely with a reduction in the amount of cognitive effort required to carry out a mental task [as in Scaife and Rogers' (1996) external cognition] or, equivalently, of memory resources or of the number of steps involved in a mental computation [as in Kirsh and Maglio's (1994) epistemic actions]. It pertains, rather, what might be a more general limit of the human mind in effectively manipulating the mental model of a dynamic system. As stated by Forrest: "We often draw the wrong conclusions about system behavior, even if we start with a correct model of the separate system relationships. Perhaps this incorrect dynamic interpretation occurs because we solve for system behavior, not by tracing actions and consequences [...], but by drawing conclusions by analogy to past experience." (1968, pp. 3–3). This consideration is not limited to economic and social systems only: The reader will remember (see Chap. 4) that physical or biological systems describable with few variables—such as the pendulum or models of ecosystems with populations of only two species—can also generate complex and unpredictable behavior, which is investigated in disciplines such as chaos theory or fractal geometry.

Thus, our brain shows evidence of being "hard-wired" to effectively simulate situations presenting an effect and a cause that are spatially or temporarily adjacent by linking them in a linear relation (A → B). It runs into trouble, however, when a cause manifests its effect only after a longer time interval (e.g., after the "delays" characterizing models studied in systems dynamics) or when causality becomes circular (A → B → A). Moreover, mental simulation has a strictly qualitative nature, which does not allow for the attainment of quantitatively accurate results or for the exploration of behavior determined by incremental parameter changes. It is therefore not surprising that computer simulation results are frequently said to be "counterintuitive".

As illustrated in the follow sections, the most cognitively important characteristic of (mental or computer) simulation should be sought, not so much in its reproduction of a specific phenomenal instance, but mostly in the categorization and recognition of general patterns of change. It is therefore this aspect that renders both types of simulation applicable to different types of systems.

The interdependence of mental and computerized simulation in formal instructional contexts is still a relatively unexplored field. Yet, one methodologically innovative study was conducted by Monaghan and Clement (1999), who investigated the use of computer simulation to help high school students learn relative motion concepts. Students first interacted with a computer simulation presented in a "predict-observe-explain" format and were then asked to solve post-test problems. The researchers found that computer simulation interaction can also facilitate mental simulation off-line, by helping students learn to solve related target problems. The method of case study protocol analysis was used to examine the students' ability to run mental relative motion simulations on their own, both during and after computer simulation use. This meant observing the indicators Clement (1994) had proposed for mental dynamic imagery research (i.e., depictive hand motions, reference to perceptions, imagery reports) based on the systematic, empirical observations of scientists and experts involved in creative problem-solving tasks.[10] Moreover, in light of the present work the study's findings point to a need for further research on factors influencing the transfer of knowledge and skills gained via simulation to other learning and problem solving contexts.

More formal and automated methods can also be used to assess the ways in which the dynamic aspect of computational models influences changes in students' mental models. For example, Kopainsky et al. (2010) investigated whether software for the automated analysis of verbal protocols can improve the assessment of students' understanding in a system-dynamics-based learning environment.[11]

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[10] The students' off-line use of mental simulation based on their memory of on-line simulation in facilitating the solution of post-test problems is an example of Salomon et al. (1991) "cognitive effect *of* technology", which they distinguished from an "effect *with* technology".

[11] The software used was T-MITOCAR (Pirnay-Dummer and Ifenthaler 2010).

Essentially, when classroom simulation design is based on a careful analysis of the specific learning context, the students' cognitive processes can induce a state of mindfulness (Salomon and Globerson 1987) and of reflective cognition (Norman 1993)—the terrain for mental simulation construction—when interacting with the simulation and later, during other learning activities focused on same or similar content. In learning contexts conversely characterized by an excessively high cognitive load (caused by poor user-interface design, distracting or redundant details, or by an overly difficult learning task), students have a hard time properly structuring their actions. A state of confusion and frustration typically results, leading to limited exploration of the various options available, hindrance in the construction of an adequate mental model of the system and in particular, in the mental simulation of it.

The relation between mental and computerized simulation can therefore be considered a *relation of complementarity* between internal and external resources. In this type of relation, the computer becomes a partner in a larger, but coordinated cognitive system, where each component has a distinct role and cooperates with the other components.[12] This cooperation can manifest itself in the coupling of internal and external simulation on a short time-scale, as in situations requiring students to predict what will happen next and then to compare their predictions with the results shown on the screen. In a model-based learning perspective, the cognitive consonance or dissonance between prediction and simulation can respectively foster the reinforcement, revision, or rejection of a student's initial mental model. This cooperation can also have a more time-distributed effect, as when students rely on their perceptual memory of certain simulations as a framework for visualization, problem solving, or in class discussion. Furthermore, an even stronger relation between mind and computer can be established when students build and test their own computational models. This process provides a greater opportunity to analyze a specific system and develop a conceptual model of it.

All of these cognitive partnering scenarios can be analyzed in light of the new perspective of "learning by system modeling" described in Sect. 5.5.

What remains now to be examined in greater detail, are the similarities and differences between mental—and computer-based simulation and the ways in which they can be integrated to enhance learning.

6.2 Thinking (and Computing) Analogically

This section will examine the relation between mental—and computer simulation from a semiotic perspective, which will then allow us to trace a functional parallelism between these two forms of representation. Due to its unique features, mental

[12] Sutton et al. (2010) defended the idea of a complementarity framework for extended cognition, in opposition to approaches based on the parity or functional equivalence of neural and external components.

simulation will be then characterized as a kind of analog simulation that is augmentable through the use of computer technologies. The successive section will then be dedicated to examining the interaction between mental simulation and language.

Let us begin by referring to some aspects of Peirce's philosophy, as described in Sect. 2.1. The reader will recall that Pierce conceived his triadic model of the sign in an attempt to approach the age-old semantic problem of understanding how a sign can represent something other than itself. His model newly defined a sign in terms of relations among a *sign-vehicle*, an *object*, and an *interpretant* (see Fig. 2.1). Pierce held that an object is a real or imaginary thing, which can be represented by a material sign-vehicle, to produce a further type of a sign—the interpretant—in a person's mind. The material sign is called a "vehicle", because it actually conveys something that is outside of the mind into the mind. This view therefore closely links cognition and semiotics.[13]

Computer simulations are among the most powerful types of sign-vehicles ever designed by humans, because they aim to represent not only a given reality, but also the ways in which this reality might change through time.[14] Moreover, due to its multimodal nature, simulation incorporates other types of signs—symbolic, iconic, indexical—all of which are typically considered in isolation from each other.

It is therefore hypothesized herein that the effect produced in a person's mind—the interpretant—can be that of a simulation, but of a *mental* simulation. Moreover, the situations in which this is more likely to occur are presumably those in which individuals are cognitively engaged by a simulation program and are motivated to invest their own mental resources in understanding the system's functioning or in predicting future events related to the simulated scenario. This approach to simulation is represented in Fig. 6.2 as a variant of the classic "semiotic triangle".

In line with Peirce's triadic theory, the three elements considered—i.e., system, simulation, and mental simulation—influence each other in a way that cannot be reduced to action between pairs of elements, i.e., to a sum of dyadic relations.[15] Specifically, the triangle sides can be considered "pathways" by starting from any of its vertices. In this instance, by moving anti-clockwise, from the vertex at bottom right to the one at the top, the relation between computer simulation and mental simulation can be viewed—from a Vygotskian perspective—as a type of "internalization". In his book "Interaction of Media, Cognition, and Learning" (1979), Gavriel Salomon described in detail the ways in

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[13] See Seel (2012b) for an overview on potentially fruitful relations between the sciences of learning and semiotics.

[14] This peculiarity of representing the future, in ancient times, was exclusively reserved to prophesy or magic.

[15] As illustrated in Chap. 3, reducing the relation between model and reality to a dyadic relation based on logical correspondence or structural isomorphism has been an approach long-used in philosophy of science. The pragmatic approaches described in Sect. 3.4 re-introduced the intentional agent as an essential aspect for the representation relation, but generally focused more on his/her practical purposes than on underlying mental processes.

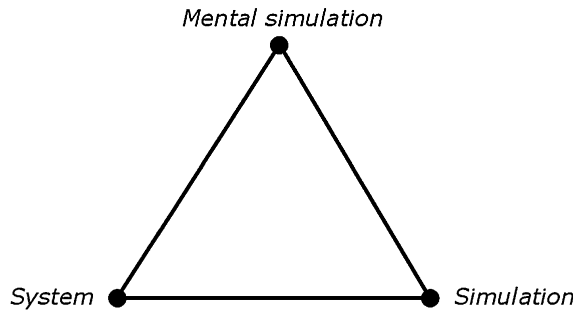

Fig. 6.2 The semiotic triangle of simulation

which the external symbol systems provided by media such as television and computer programs can be internalized to serve as mental tools, and the corresponding educational implications. Similarly, mental simulation can incorporate the symbolic elements provided by computer simulation and can use them as tools for thought. For example, the interactive representations of molecules in the ideal gas or of the gradients of temperature and velocity in the simulation of a fluid can become visual frameworks for conducting mental simulations. They therefore provide a base from which inferences on the examined system's behaviour can be derived or even extended, analogically, to other systems. In turn, these thought processes can lead to a new conception of the system itself (through the mental simulation-to-system pathway). This process in turn changes the way in which the target system is represented (through the system-to simulation pathway), concluding the complete triangle pathway thereby, but concurrently beginning another.[16]

In particular, Salomon observed that to be internalized and used as a mental tool, a symbolic code "requires the preexistence of the mental operations that lead to it" (ibid., p. 133). It is therefore proposed herein that this observation can be interpreted in simulation terms by meaning that, if students are able to internalize the simulation-provided symbolic elements, they must already possess a mental model of the system and be able to simulate it. The semiotic simulation triangle can thus also be represented in terms of models (Fig. 6.3).

According to Seel's model-based learning approach (2003, 2012b), as long as new information can be assimilated into previous knowledge structures, students do not actually need to construct a mental model and to consciously employ their own mental resources in a given simulation. It becomes necessary, however, to construct and simulate a new mental model when the computational model's behavior does not correspond to what is expected.

The following qualitative proportion, which illustrates the relations between four different forms of representation, can be used to compare both versions of the simulation triangle.

$$\text{Mental model} : \text{Mental simulation} = \text{Computational model} : \text{Computer Simulation}$$

[16] Peirce (1907, p. 411) termed this process of meaning creation "semiosis".

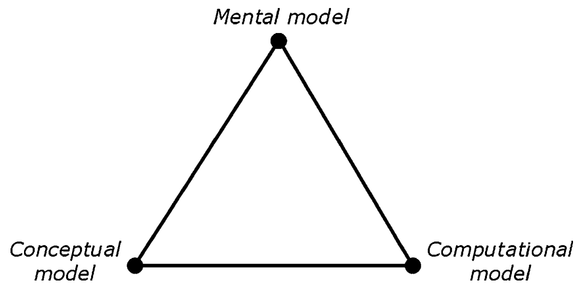

Fig. 6.3 The simulation triangle represented in terms of models

As occurs with all analogies, much can be learned from both the similarities and differences among the above concepts. For example, by starting from the second-to-left concept—i.e., mapping mental simulation to computer simulation—it can be noted that both types of simulation:

- never completely recreate the original experience or phenomenon, but are always partial recreations, which can also contain biases and errors;
- are characterized by a sequence of (computational or mental) models, respectively, that become increasingly adequate to the aim requiring their construction.

Moreover, from a cognitive standpoint, Barsalou's proposal that perceptual simulators in long-term memory can produce infinite simulations in function of a given situation (see Sect. 2.4) can be compared to the computational model's ability to generate a potentially infinite number of quantitatively or qualitatively different simulation runs in function of its various parameter settings. A further correspondence between mental simulation and computer simulation lies in the fact that mental images can be considered a type of mental simulation output, similarly to the images and animations that are frequently the outputs of a computer simulation.

The above proportion, however, is not to be confused with the Mind = Software analogy of classical cognitive science. In fact, coherently with the hypothesis of mind-computer complementarity stated in the previous section, it can be reasonably assumed that the information representation and processing mechanisms involved in the two instances actually differ considerably. For example, one difference between mental and computer simulation concerns the nature of their underlying models. Although mental models and computational models are both runnable and are therefore able to generate a variety of behavior, mental models are usually not clearly defined; they are difficult to communicate to others; and are not always easy to manipulate (Forrester 1968; Norman 1983).

Starting from the far left of the qualitative proportion presented—the relation between mental models and mental simulation—three, progressively complex types of mental models, characterized by the growing complexity of mental simulation, can be identified:

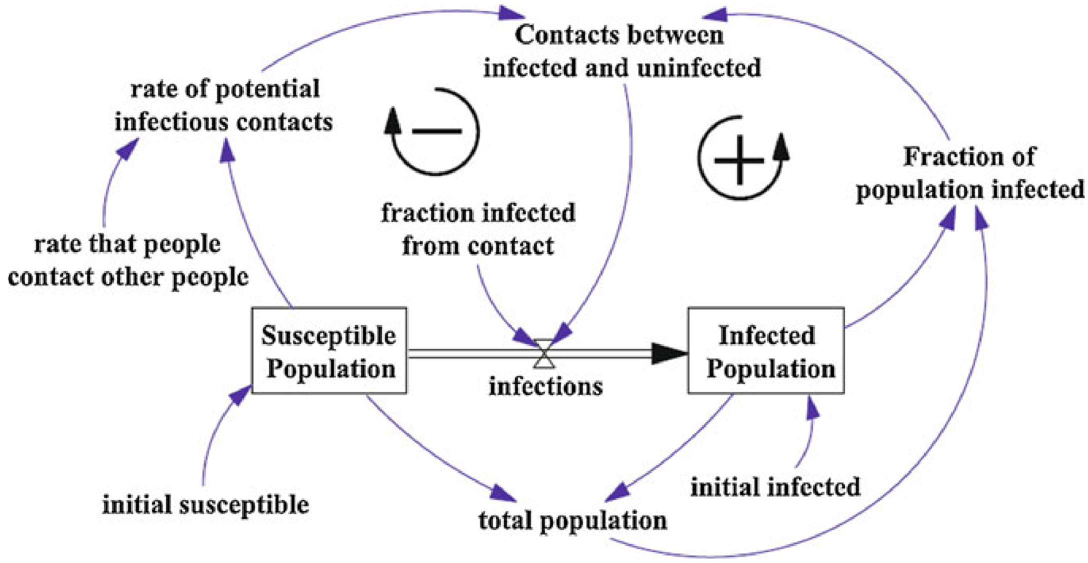

Fig. 6.4 Stock-flow diagram for a simple epidemic model (Dangerfield 2009, p. 9035)

1. *Spatial mental models*—these represent the topological or metric relations among a set of entities; they can be static or can allow for the rearrangement of their elements to explore their possible pattern spaces.[17]
2. *Causal mental models*—these represent the possible cause-effect relations among the elements of a system, but do so on what is still a structural rather than dynamic level, and therefore allow only for inferences on interactions that occur among elements that are local and limited in time.[18]
3. *Dynamic mental models*—these map a succession of system states onto a succession of model states and allow us to simulate the global and time-extended behavior of a system (e.g., imagining a complex course of action, which consists of many distinct steps and their potential consequences).

In fact, it is in constructing and simulating this latter type of mental model (which requires the integration of *structure*, *function* and *behavior*) that humans encounter the most difficulty. This limit has particular relevance in science, given that the dynamic complexity of most natural and artificial systems does not allow them to be captured in a mental model, without the aid of computational models. Consider, for example, a system dynamics model representing the diffusion of an epidemic in a population (Fig. 6.4).

Models of this type are created by (1) spatially arranging the names of the variables defining the system, (2) connecting them with arrows to indicate their cause-and-effect relations, and (3) adding an equation or rule to each relation to specify a given variable's influence on the other. Clearly, the mental construction and running of this type of model would immediately conflict with the limits of the

[17] Similarly as occurs in software for architectural design or molecular graphics.

[18] As occurs in the mental simulation of simple mechanical or hydraulic systems. (see Sect. 2.2).

memory systems involved—limits that would impede the "mind's eye" in following the entire chain of events involved in the phenomenon. Vice versa, the corresponding computational model can run easily even on a personal computer.

Another distinction between mental and computer simulation is related to fundamental differences in the underlying information representation and processing mechanisms. Both empirical evidence and theoretical models from the neurosciences suggest that the brain's computing mechanisms are radically different from those at work in a computer. In fact, there is no evidence that the brain actually executes algorithms, uses formal languages, or has a discrete, digital, architecture (as posited by classical cognitive science). On the contrary, it has been proposed that the human brain is a special kind of analog computer (see Sect. 4.1). It is important to note, however, that analog computation can be defined at different levels of abstraction. In strictly mathematical terms, "the principal distinction between digital and analog computation is that the former operates on discrete representations in discrete steps, while the latter operates on continuous representations by means of continuous processes" (MacLennan 2009, p. 272).

We can better understand the concept of analog representation by comparing two systems frequently used to measure the temperature of a room: a wall thermometer and an electronic temperature sensor linked to a computer. Both systems are physically coupled with the external environment, but are so in different ways. The height of the mercury column in the thermometer varies continuously with room temperature variations: when the temperature goes up, the level of mercury rises in the thermometer and vice versa. Conversely, the computer represents temperature through a series of symbols (the conventional 0–1 patterns) that depend on the computer's programming code.

In his fascinating history of the analog computing field, Small (2001) described how *electronic analog computers* were developed in Britain and in the USA before the invention of the digital computer.[19] In the 1940s, research had revealed that general purpose electronic analog computers were able to simulate any type of dynamic system and to solve nonlinear equations. "Programming" an electronic analog computer meant designing its circuits such that electrical quantities (e.g., voltage, current, conductance) representing the variables under study would obey the same mathematical laws as those of the system to be simulated.[20] Running a simulation therefore meant: (a) configuring the initial state of the circuits (*input*), (b) allowing the simulation to take place until the system reached a stable state (*computation*) and (c) reading the computer's stabilized values (*output*).

[19] They became feasible in the 1940s, after the invention of the *operational amplifier*, i.e., a device able to transform a small input signal in into a much larger output signal. This type of amplifier was called "operational" because it allowed for the development of electronic circuits able to use a continuously variable signal to perform numerous mathematical operations, such as summation, subtraction, multiplication, logarithm, and integration with respect to time.

[20] These laws are typically expressed through ordinary differential equations (ODEs), with time as the independent variable. Yet, analog computers based on *field computation* can also solve partial differential equations (PDEs).

Analog and digital computing technologies co-existed from the end of the Second World War until the late 1960s. Moreover, during the late 1950s and 1960s, a variety of hybrid analog/digital computers were developed, in which a digital computer was typically used to facilitate the control of an analog computer. At the time, a generally acknowledged benefit of analog computers was that of speed, because they operate in a parallel mode and therefore were faster than digital computers, which followed sequential logic, executing one operation at a time thereby. Analog computers, however, were less precise than digital computers, because their circuits are much more susceptible to "noise" than digital circuits are. Moreover, in comparison with the digital computer's general-purpose architecture, analog computers were criticized for being essentially special-purpose and limited to scientific applications only. According to MacLennan (2009), the fact that they operated only with continuous quantities and not with discrete data, as required in business applications, may have been a key reason the computer industry began investing more heavily in digital technology. Indeed, analog computers began to disappear by the early 1970s and were ultimately eclipsed by the digital computer's growing success.

In the mid-1980s, the notion of analog computation made an unexpected return, but in the field of microelectronics, when Carver Mead (a) seminal figure in Silicon Valley) began to explore a new type of neurally inspired computing architecture, called "neuromorphic circuits". These were implement shortly thereafter as very-large-scale integration (VLSI) analog circuits.[21]

In the cognitive sciences, however, the concept of *analogy* more generally indicates any systematic relation between a mental representation or process and a target system (a meaning used several times throughout this book). For example, in the context of the well-known debate on the format of mental images, the "pictorialists" (Shepard and Metzler 1971; Kosslyn 1973, 1980) held that the mind is able to represent information analogically, by maintaining the visuospatial features of visual perception. This view differed from that of the "propositionalists" (Pylyshin 1973), who stated that mental images are based on underlying language-like representations.

Johnson-Laird (1983) characterized mental models as "structural analogues of the world" (p. 165) and therefore in terms of a property that (according to Peirce's sign theory) renders them akin to iconic representations, such as diagrams. Moreover, Gentner and Gentner (1983) pointed out how mental models of complex systems are frequently based on analogical comparisons with a simpler or more familiar system. This situation occurs, for example, when people think of electricity in terms of water flowing through a water system's pipes. Analogical modeling—i.e., reasoning through analogical models—also plays a key role in model-based reasoning and model-based learning, together with other nonformal

[21] Mead's proposal was motivated by the conviction that "the nervous system of even a very simple animal contains computing paradigms that are orders of magnitude more effective than are those found in systems made by humans" (1989, p. xi).

reasoning methods such as visual modeling and simulative modeling (see Sect. 5.3 and 5.4 and references herein).

The heretofore mentioned uses of the term *analogy* in the cognitive sciences do not conflict with the definition of *analog computation* as used in engineering and computer science. Both are based on the notion of *continuity*, because concepts typically used as analogues for reasoning or instruction purposes are nearly always continuous. Examples are: a bathtub's water level used to model CO_2 levels in the atmosphere and elastic body deformation used to model forces in an electromagnetic field).

The idea of the brain being a type of analog computer has been most clearly expressed in the burgeoning field of "dynamical cognitive science"—also called "dynamic cognition theory" (Chemero 2009; Port and van Gelder 1995; Spivey 2008). This line of research uses the language of dynamical systems theory (see Sect. 4.5) to describe cognitive processes. A similarly-inspired approach is pursued in the neurosciences by "cognitive neurodynamics" research (Freeman 2000; Izhikevich 2007; Rabinovich et al. 2006). These dynamical approaches view mental states as continuously changing patterns of activity in brain networks, and thinking processes are equiparated with trajectories in multi-dimensional space. Moreover, mental states are considered to be *metastable*, meaning that they are occupied for some time, but not permanently so and that they may be continuously re-visited, in a roaming motion similarly to as occurs with a chaotic system's states.

When a student or scientist uses a simulation program to study the model of a nonlinear physical system (such as the chaotic pendulum or a fluid in turbulent flow), a rather peculiar scenario develops: A dynamical system (the human mind/brain) is now relying on the intermediation of a digital system (the computer) to try and understand another dynamical system (the model examined). Moreover, when the system being examined is the brain, as occurs, e.g., in dynamical neuronal network simulation, what we actually see is the brain trying to simulate its own processes! Thus, a self-referential scenario develops, which is somehow similar to the one depicted in Escher's famous self-portrait of 1935 (in which the artist observes himself in a reflecting sphere held in his left hand).

Both dynamical cognitive science e cognitive neurodynamics are promising new approaches to cognition and provide the premise for the proposal made herein that mental simulation can be considered a particular type of analog simulation.

Yet, why should humans rely on this type of mental simulation? What are the evolutionary advantages of doing so? As mentioned previously, a strong point of analog simulation acknowledged early on in electronic analog computer research was that of speed; the same benefit can, of course, be ascribed to mental analog simulation. Indeed, our ancestors had to access rapid mental simulation mechanisms in quickly deciding what to do in potentially dangerous situations, and probability of survival was likely a more important criterion than that of precision. Conversely, the computational cost of most simulation algorithms makes them implausible models for real-time reasoning. Moreover, analog computation satisfies the further criteria of *robustness*, *flexibility*, and *adaptability*, which also characterize human cognition (for a description of these criteria and their relevance in a natural computation context, see MacLennan 2009, p. 290).

Another cognitive implication of analog mental simulation is that it is closely related to *qualitative reasoning*. It is well-known that humans frequently reach conclusions about physical or social processes based on very little information, and that the available information is, in most instances, less precise than would be required for purely quantitative reasoning methods. For example, we can deduce what will happen when a sealed container of water is heated from below—even without precise quantitative information about the initial water temperature—or whether a string can push or pull a block to which is attached. These types of reasoning tasks involve *qualitative dynamics* and are usually based on approximations such as considering numerical intervals—e.g., by indicating that a temperature is "somewhere between" 70° and 80° Celsius, or linguistic symbols to represent quantities ("low", "high") or ordinal relations ("larger than", "smaller than"). Cause-effect relations, moreover, can be specified by expressing the influences between two entities (e.g., through the use of verbs, such as "affect", "increase", "decrease"). This aspect of human cognition was thoroughly investigated in several strands of Artificial Intelligence research—e.g., in de Kleer and Brown's (1984) "qualitative physics", Hayes' (1985) "naive physics", and in Forbus' (1984) "qualitative process theory". During those same years, these lines of research also influenced—and at times overlapped with—the knowledge based approach to mental models. As summarized by Gentner (2000): "Mental models reasoning relies on qualitative relations, rather than on quantitative relations. People can reason well about the fact that one quantity is less than another without invoking the precise values of the quantities." (p. 9684). Mental simulation, rather than logical reasoning, was therefore viewed as a means for deriving the type of inferences that qualitative physics requires. Furthermore, Forbus and Gentner (1997) explicitly linked mental simulation to analogical processing, and based on Forbus' qualitative process theory, researchers at Northwestern University developed VMODEL, a visual qualitative modeling environment for middle-school students, which integrates ideas and notations from concept map theory, system dynamics, and argumentation environments (Forbus et al. 2001).

The current section will conclude by drawing a rarely noted conceptual link among *analog*, *digital*, and *mental* simulation, which highlight the importance of analog representation in mental processes involved in simulation-based learning. The link consists in analogies between electronic analog computer controls and a simulation program's controls.

Specifically, electronic analog computers typically have front panels with numerous controls, and in particular, potentiometers are used to set the initial conditions for a calculation or to scale intermediate results by desired constant factors. These potentiometers can be either linear or rotary; the former allows for adjustment of the simulated quantities by moving a slider along a slot, and the latter, by rotating a knob.

Interestingly, the same type of controls—albeit of a virtual nature—is typically present in a simulation program's interface! This is the case of the slider, which is a control with an indicator that can be moved up and down (vertical slider) or right and left (horizontal slider) to alter the value of a given variable (see, for example, Figs. 4.27 and 5.12). In some cases, rotating knobs are present and perfectly mimic their analog homologues.[22] An advantage of the slider over that of an input field is that the indicator position shows a visual indication of its setting. Similar considerations can be made about the interface's output elements, given that continuous curves were once shown on analog computer oscilloscopes as output and are now shown as animated graphs in simulation programs. It therefore seems that the most efficient way for humans interacting with a simulation program in constructing an (obviously) analog mental model of the simulated system is by relying on the intermediation of an analogical interface!

6.3 Simulation and Language

Although mental simulation is essential for a surprisingly wide range of mental capacities and processes, it does not account for many important facets of cognition, and especially those pertaining to the two uniquely human abilities of abstraction and imagination. Moreover, human mental simulation capacity most probably evolved from the need to better coordinate perception and action by iteratively updating an internal model of the world (see Fig. 2.2), and it is therefore highly sensitive to context. This view is reflected in the focus of embodied and grounded cognition theories on situated action, social interaction, and on the role of environment in cognition. Nevertheless, what mostly differentiates human cognition from that of other species is its capacity for abstracting concepts and categories from a given context. This latter ability allows us to imagine situations that are different from the current one, and in particular, situations occurring in the past (*retrodiction*) or which might occur in the future (*prediction*).

Presumably it was a progressive development in human capacity for *constructing, simulating, storing (in long-term memory),* and *modifying* increasingly complex mental models that made it possible for our ancestors of the Upper Paleolithic to think about objects and events that were not physically present. This advance paved the way to the human ability to see things from different perspectives and in different contexts from those in which the original experiences had occurred. In terms of cognitive dynamical science, the mind and the world were initially two "coupled dynamical systems".[23] Yet, with the "decoupling" of mental simulation from the immediate context, humans had a greater opportunity

[22] Similar progress occurred for television sets, where potentiometers were formerly used to control picture brightness, contrast, and color. Nowadays, with digital technologies, they are visualized on the screen as virtual sliders to be regulated by remote control.

[23] A form of coupling that may be figuratively associated with the culturally recurring theme of mankind's initial "Edenic" condition, in which humans lived in an "eternal present" not yet detached from nature and the world around them.

to explain the past, plan the future, and even to imagine things and events of a purely fantastic nature. From a neuropsychological perspective, this change may have depended on the adaptive recruitment of working memory subsystems for the monitoring and manipulation of information about objects in visual and auditory space during perception. In any event, this type of change allowed humans to represent the arrangement of other kinds of information in a more abstract mental space, and in particular, to represent time. This development in cognitive capacity went hand in hand with the need to communicate more effectively the contents of one's own mental simulations to one's companions. By that time, these contents had become more detailed and complex, through symbolic thought and, in particular, through its main form of expression: verbal language.

Indeed, being able to create and understand language allows us not only to communicate complex messages across individuals and across time, but to reason in terms of abstract categories and to creatively combine concepts. In turn this ability involves a greater capacity for mentally simulating the functioning of natural and artificial complex systems, and in particular, in considering a system as being representative of a much vaster class of analogue systems (*generalization*). If mental simulation is actually based on perceptual and motor processes and is therefore fundamentally analogical, what then is its relation to language, which is conversely based on conventional symbols and syntactic structures and is therefore a digital system?

The distinction between *mental simulation* system and *linguistic* system can be viewed in terms of the better-known distinction between *images* and *words*—and therefore, in cognitive terms, between *nonverbal information* and *verbal information*. According to Paivio's (1986) *dual-coding theory*, these two types of information are coded by the human cognitive system in different ways and are processed along separate channels, which are interconnected but independent. Nonverbal information is encoded analogically, i.e., by maintaining similarity with the stimulus originating it, and verbal information, symbolically and thus via conventional symbols. Paivio held that words and images correspond to two types of long-term memory information units, respectively called *imagens* and *logogens*. The two systems do not differ only in the format of their underlying representations (continuous or discrete), but also in the fact that the first type is specialized in parallel processing (of many units simultaneously) and the latter is specialized in sequential processing (of one unit of information at a time). Although Paivio's theory is frequently the theory of reference for researchers and teachers highlighting the differences between verbal and nonverbal systems, the theory actually underscores the *correspondences* that exists between the two systems. For example, we can form a mental image of a tree and then describe it with the word *tree*; or we can hear the word *tree* and then form a corresponding mental image of it. The theory (successfully) predicts that concrete words are remembered more easily than abstract ones, because the verbal system activates the visual system through *referential connections between* logogens and imagens. The distinction between a visual and a verbal system in memory processes is also present in

Baddeley's model of working memory (1992), which posits the existence of two separate subsystems for these two types of information.[24]

Both systems—verbal and nonverbal—are essential to cognition. Although we can say, "a picture is worth a thousand words", it is not always true, because some types of information can be expressed more easily verbally than visually. Try, for example, to visually represent the sentence, "If it rains tomorrow, then we'll have to postpone the game; if not, we'll play". The difficulty in visually representing the informational content here and in other sentences of this type derives from the fact that we use conditional operators, such as *if*, *then*, *else*, *while* to communicate actions and intentions, and the resulting expressions do not have their own visual counterparts.[25]

In fact, to account for these limits in visual representation, Peirce introduced symbols as elements of his existential graph system, together with iconic and spatial elements (see Shin 2002). Similarly, Johnson-Laird (2004) specifically introduced abstract symbols as mental model elements to allow for the representation of propositional connectives such as negation and disjunction in logical reasoning. It is therefore interesting to note—and is likely not a coincidence—that the above-mentioned conditional operators are also constitutive elements of programming languages, which in turn make it possible to build computational models of highly diverse systems.

Theories of embodied and grounded cognition (see Sect. 2.4) which greatly emphasize mental simulation, typically do not place as much attention on the symbolic and syntactic aspects of language. This stance of focusing on sensorimotor processes can be considered a reaction to the overwhelming predominance of these syntactic and symbolic aspects in classical cognitive science, which still identifies proposition-like cognitive structures as being the only type of representation that can possibly underlie knowledge. Yet, coherently with dual coding theory, the empirical evidence accumulating over the years has demonstrated the close link that exists between the mental simulation and linguistic systems. This link is particularly evident in experiments (reviewed in Barsalou 2008a) showing that language can activate mental simulations; for example, to represent the meaning of sentences, readers can construct mental models with spatial properties and can simulate the situation described in texts. These and other experiments (ibid.) have conversely shown that simulations can activate language. For example, people involved in problem-solving tasks frequently activate associated words and syntactic structures to verbalize the solution process, so as to plan their actions

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[24] Both Paivio's dual code theory and Baddeley's model of working memory have strongly influenced cognitive theories of multimedial learning, which developed during the 1990s and in the 2000's (see Sect. 5.6).

[25] An example of this difficulty is the failed attempt to transform the verbal language of programming languages into the visual language of flow diagrams. During the 1980s, nearly all programs had be accompanied by flow diagrams. It was then realized that methods other than visual ones are easier to interpret, such as, e.g., the pseudo-code technique for writing programming instructions that are similar to everyday language (Ware 2008).

and/or to share them with others. Thus, in attempting to understand mental processes it is important to highlight the *interaction* between the simulation and linguistic systems.

In fact, to account for the richness and complexity of the two systems' interactions, Barsalou (2008b) broadly extended his initial "perceptual symbols systems" approach to cognition. In this new and broader view, he proposed that symbolic operations result not from simulation alone, but also from language-simulation interactions. He specifically stated that "symbolic capabilities could have increased dramatically once language evolved to control the simulation system in humans. Adding language increased the ability of the simulation system to represent non-present situations (past, future, counterfactual). Adding language increased the ability to reference introspective states, thereby increasing the ability to represent abstract concepts and perform metacognition. Adding language increased the ability to coordinate simulations between agents, yielding more powerful forms of social organization." (ibid. pp. 36–37).

Yet, what exactly did Barsalou mean in his reference to "linguistic system"? Although linguistic research focused on the deep syntactic structure of language until the mid-1990s, another concept has been developing for some time now, which underscores the importance of statistical regularities in linguistic surface structure (Burgess and Lund 1997; Landauer and Dumais 1997). This point of view derives in particular from the success of algorithms able to extract the meaning from a text based on statistical computations of the correlations among words, the contexts in which they appear, and by the similarity between these of algorithms and human cognitive processes. A well-known example of this type of approach is that of the latent semantic analysis (LSA) algorithm, which uses large text corpora to compute semantic similarities among concepts (Landauer and Dumais 1997; Landauer et al. 1998). It is interesting to note that none of the knowledge extracted by this method derives directly from perceptual information about the body or the physical world. For example, the meaning of the word *dove* is entirely derived from its associations with words like *bird*, *pigeon*, *white*, *feather*, and *peace*. This approach to symbolic cognition is therefore quite the opposite of embodied cognition! How then might we conciliate these two viewpoints?

The *language and situated simulation (LASS) theory* of conceptual processing (Barsalou et al. 2008) proposes a mechanism dedicated to the interaction between simulation and language. The theory proposes that the linguistic system and the simulation system both initially become active, but that word activation peaks before simulation activation. If the linguistic forms generated as inferences thereby suffice to produce accurate performance, there is no need for executive processes to shift attention to the simulation system as an alternative information source. When the linguistic system conversely stops being useful, simulation will begin to dominate conscious, deliberate cognition. In LASS theory, linguistic system- and simulation system activation are respectively associated with *superficial verbal processing* and *deep conceptual processing*. For everyday decision making processes and planning- and problem solving tasks, the theory posits a complex series of interactions among the two systems, during which they become active simultaneously at many points in time, and do so in varying proportions.

The two levels of processing described in LASS theory can also be linked to Schwartz and Black's (1996) observations on the use of mental simulation (see Sect. 2.2). The two researchers proposed, in fact, that people use mental simulation in novel situations for which they have no rule available or when their rules are inadequate, and that, vice versa, they rely on the application of verbal rules (e.g., the "parity rule" for determining the motions of linked gears in a mechanical system, which states that "if there are an odd number of gears connected, then the first will go in the same direction as the last"). According to Ritchie (2008), people also apply a similar strategy to figurative language comprehension (see Sect. 2.5), in that idioms are sometimes superficially processed as *lexical units*—i.e., by tapping information contained in the linguistic system—and other times as *metaphors*—i.e., via activation of the simulation system.

Other theoretical frameworks similar to LASS, which propose that peak activation of the linguistic system is reached before peak activation of the simulation system, are Louwerse and Jeuniaux's (2008, 2010) symbol interdependency hypothesis and Lynott and Connell's (2010) *embodied conceptual combination (ECCo)* model. The symbol interdependency hypothesis focuses on language comprehension, and the authors have experimentally investigated the conditions under which embodiment and linguistic factors determine performance in semantic judgments for words. Their findings support the view that conceptual processing is both linguistic and embodied. The researchers proposed a mechanism based on symbolic cognition in the early stages of comprehension, to allow for the rapid creation of an approximate representation (*shallow language processing*), and on embodied cognition in subsequent stages, to allow for the creation of a complete situation model (*deep language processing*). They also proposed that the relation between these two types of cognition is made possible by the fact that language encodes perceptual information.

The ECCo model (Lynott and Connell 2010) conversely focuses primarily on the processes involved in creating a new concept from the combination of two already-known concepts, as frequently occurs in everyday spoken and written language. The model is based on a representation of knowledge that incorporates linguistic statistical information and situated simulation. The main idea underlying the model is that, "linguistic information guides or facilitates the simulation process, but the new concept created during conceptual combination is fundamentally a situated, simulated entity." (*ibid.* p.1).

The findings from all of these studies strongly suggest that the simulation- and linguistic systems are tightly integrated and mutually reinforcing, such that they can be considered "partial reflections" of each other. Their relation is therefore complementary and dynamic (see Fig. 6.5).

As illustrated here below, the linguistic system can also serve similar functions in simulation-based learning. In fact, verbal information plays a key role in all the steps of a simulation-based learning pathway. To trigger students' interest, teachers typically begin a simulation-based learning activity by verbally describing

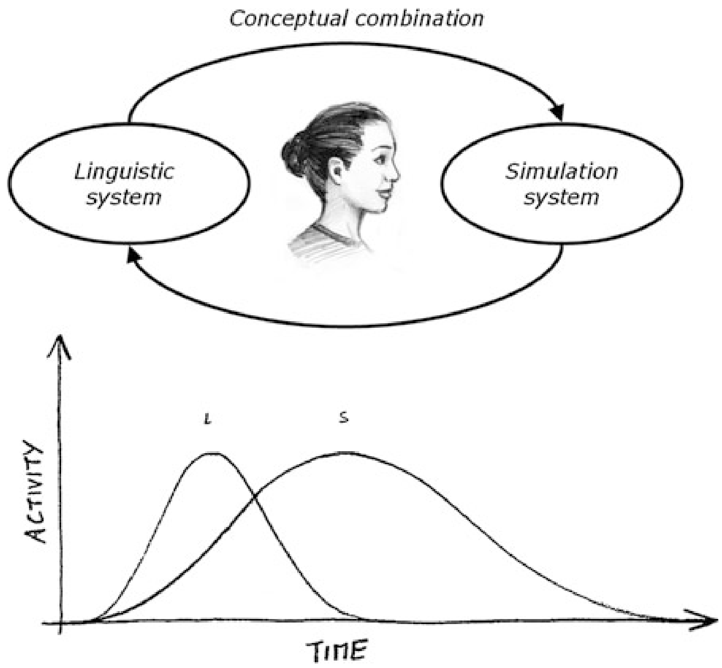

Fig. 6.5 The simulation-linguistic system relation

the system under study to the class and the simulation's goal, contributing thereby to the definition of the students' initial conceptual model (M_0). During the intermediate phases, questions and discussions will be required to progressively refine the students' initial model and to arrive at a target, teacher-student agreed-upon model (M_T). At the end of the learning pathway, the quantitative behavior revealed by the simulation of the target model will be synthesized and summarized in qualitative descriptions—typically in the form of verbal rules ("The molecules move faster as temperature increases, and slower as temperature decreases") or narrations ("When the number of prey began to grow, the number of predators, who found more food available, also increased, but, after some time the prey began to run out").

Language can support simulation-based learning in many other ways. For example, it can be used by both teachers and students:

- *to guide* the exploration of an simulation-based learning environment (e.g., to focus attention on various user interface features);
- *to control* the simulation (e.g., to decide which variables to modify, to try different strategies);
- *to facilitate* student understanding of the underlying conceptual model (e.g., to link the model's structure with the behavior observed).

From a cognitive load perspective, language is the main instrument of instructional techniques aimed at:

- *reducing intrinsic cognitive load* (e.g., through pre-training or worked-out simulation examples);

- *facilitating schema construction* (e.g., through self-explanations or reciprocal learning).

Nonetheless, in some instances, students may not feel it is necessary to fully dedicate their mental resources to the construction of and during simulation of a dynamic mental model. They may therefore opt to use language as a "shortcut" to more rapidly achieve the expected learning outcomes. For example, in a reciprocal learning situation, one of the two students involved may superficially adhere to a conclusion reached by his/her companion and may memorize it without any further effort to understand it. (This is a social conformity effect, more frequently observed in large group settings). Similarly, students may passively listen to a teacher-provided explanation of a simulation outcome and may accept it by going no further than a merely linguistic level of processing. They may therefore end up constructing a static vs. dynamic mental model.

The observation that some learning tasks can result in words being processed only through their connections with other words, and not necessarily at the deeper conceptual level of mental simulation (Barsalou et al. 2008) can also account for the previously mentioned mixed research findings on the instructional effectiveness of simulation (see Sect. 5.7). When students rely only on verbal rules such as "if… then", their information processing will be superficial. Moreover, assuming that the simulation has activated a deep level of processing will result in an efficacy "overestimation" error of the simulation as an instructional method.[26]

If the outcomes of a complex simulation can be summarized with only a few rules, why not directly teach these rules (e.g., by using direct instruction methods such as worked examples or drill-and-practice tutorials)? Well, in some instances…this can actually be the best strategy! Specifically, if the learning task is to remember an empirical law (such as the ideal gas law [$PV = RT$] or Ohm's law [$I = V/R$]), mathematical or verbal descriptions with additional memorization practice should suffice. Conversely, simulation may be a better strategy when the learning task is that of understanding the microscopic origins of observed regularities or of solving complex problems.

More generally, the answer is that rules learned merely linguistically are generally too rigid for application to a variety of different situations. If they are to generalize any knowledge acquired, students must first construct flexible mental models and then must be able to simulate them and modify them, as necessary, when facing new situations requiring their modification or substitution of initially learned rules.

Another instance in which the simulation system must necessarily accompany the linguistic one is in the learning of new concepts that derive from the creative combination of existing concepts (Lynott and Connell 2010). In these cases, direct

[26] An error that in part accounts for the "hype" (exaggerated statements actually not supported by solid scientific evidence) occasionally encountered in the promotion of simulation as an educational technology.

instruction methods—which are conversely ideal for constructing an initial knowledge base—are no longer the most recommended.

The use of superficial linguistic strategies can be highly effective in producing accurate performance, but may also be somewhat devoid of meaning. One way to re-instill meaning in language is through the use of narratives. The function of narrative—in its oral and written forms—has always been that of representing and communicating time-extended events and the introspective states that accompany them. As the reader will remember (see Sect. 2.4), Barsalou (2008a) held that simulators for representing abstract concepts are indeed developed by capturing the perceptual features of events and states of this type. Abstraction therefore goes hand in hand with the typically human capacity for telling stories.[27]

Craig et al. (2002) have illustrated the interplay between perceptual simulations and narratives in analogical problem solving and provided evidence that perceptual factors can be manipulated via narratives in the form of short stories. Storytelling as a way to understand and communicate the behavior of complex systems has been mostly studied by researchers and practitioners in the field of system dynamics. System dynamics-based microworlds are frequently presented in the form of stories in which a student or manager must take on the role of a character (in the simulation) and must make decisions causing the story to evolve towards one outcome vs. another. For example, Senge's (1990) *systems archetypes* are "elaborate structures that recur in our personal and work lives again and again" (p. 92), which we can begin to construct once the building blocks of the system dynamics method have been learned.[28] Systems archetypes can be seen as exemplar stories, which different Division managers can see reflected in their own experiences: "Just as in literature there are common themes and recurring plot lines that get recast with different characters and settings, a relatively small number of these archetypes are common to a very large variety of management situations." (ibid., p. 94).

In the final analysis, the affinity between simulation and narration is due to the fact that stories are a way to transmit time-related knowledge in more dynamic form than allowed for by simple verbal rules.[29]

Consideration of the simulation-linguistic system relation can yield some helpful indications for approaching simulation-based learning in a way that integrates and balances the perceptual and motor components of instruction with

[27] Baddeley (2000) added a component to his initial working memory model—the "episodic buffer"—which has the function of integrating visual, spatial, and verbal information from the other subsystems to create coherent and storable episodic memories that can be consciously retrieved from long-term memory.

[28] Senge listed the following archetypes in his book "The Fifth Discipline": Balancing process with delay, Limits to growth, Shifting the burden, Eroding goals, Escalation, Success to the successful, Tragedy of the commons, Fixes that fail, Growth and underinvestment. Although originally conceived for organizational learning, the same archetypes can be applied in other fields, such as ecology and the social sciences.

[29] Narrations have the power to "bifurcate" into a series of alternative branches, similarly to the bifurcations of a nonlinear dynamical system, as suggestively illustrated by the author Jorge Luis Borges in his 1941 story of "The Garden of Forking Paths".

verbal components. In this approach, we must firstly consider that *both* cognitive systems of simulation and language can be activated by *two types of* input:

- *experiential input*—and therefore from sensory stimulation (visual, auditory, tactile, kinesthetic) or from physical activities;
- *verbal input*—and thus from explanations provided by teachers, textbooks, discussions, and/or by stories.

In other words, the simulation system can be activated by sensory experiences and by verbal information. (Motor simulations of functional actions can be triggered by either a perceived object or by its name). Analogously, the linguistic system can be activated by words, but also by images. In fact, a word can activate other words through semantic or phonetic associations, just as the image of an object can activate the name of that object. Teachers should therefore avoid establishing a superficial correspondence between experiential and active learning on one hand and between verbal input and direct instructions on the other. Specifically, they should avoid the a priori favoring of one type of input over another in function of one of two main strategies (see the discussion in Sect. 5.7 on the limits of dichotomously conceptualizing instructional strategies). The challenge for educators and instructional designers, rather, is to *integrate* both types of input in function of the specific instructional context and to take more recent cognitive science models into account. These latter models essentially describe an activation alternation between the two systems, in function of a given task's characteristics (Barsalou et al. 2008; Louwerse and Jeuniaux 2008, 2010; Lynott and Connell 2010).

This means that teachers using verbal input should initially rely on simple and straightforward language (to facilitate the students' creation of an initial, approximated mental model), which should then be followed by words and phrases/expressions to guide and facilitate the students' mental simulation process. This second phase is therefore focused on minimizing the *shortcut effect*, which occurs when students limit themselves to using readily accessible verbal strategies (such as "if… then" rules).

The field of cognitive linguistics can offer an important contribution in this regard, as it investigates the relation that exists between figurative language and mental simulation (Gibbs 2006b; Matlock 2004; Ritchie 2008).[30] In particular (see Sect. 2.5), researchers in this field have proposed the concept of image-schemas as non-linguistic abstract structures emerging from sensorimotor experiences, and serving as source domains for many conceptual metaphors. Embodied simulations based on image-schemas can allow students to understand verbally described

[30] Somewhat surprisingly, cognitive linguistics and instructional science have, for the most part, developed along completely separate lines of research. From an instructional perspective, notable exceptions are Hestenes' (2010) modeling theory for mathematics and science education and Fuch's (2007, 2010) approach to the teaching of thermal physics. In cognitive linguistics, Lakoff and Núñez (2000) investigated the conceptual metaphors underlying mathematics and consequently proposed modifications to mathematics education.

abstract entities as if they were concrete objects.[31] Moreover, in instructional situations such as these, narratives can greatly enhance the simulation-inducing effect of language. Craig Nersessian and Catrambone (2002) hypothesized that "if readers generate perceptual simulations to represent events described in a story, the image-schematic structure embedded in those simulations might depend to a large extent on how the story is written, from what perspective, for example, and in what context." (p. 178). They tested this hypothesis by presenting undergraduate students with different versions of stories derived from Gick and Holyoak's (1980) "fortress story",[32] and found some supporting evidence that a particular image-schema—the *convergent-force* image-schema—can increase the probability that the story is used to construct a mental simulation of the problem, facilitating its solution thereby.

In brief, and in conclusion, two observations linked to the ideas proposed in the preceding two sections can be formulated here below:

- when students use their mental simulation capacity to explore a computer simulation and to understand the represented phenomena, the two types of simulation influence each other, creating a cognitive partnering situation thereby (see Sect. 6.1);
- due to constructive interaction between the linguistic and simulation systems, mental simulation can be characterized as a type of "linguistically programmed analog simulation". It can therefore be conceived as being based on a type of hybrid analog/symbolic computation—a proposal requiring further exploration in cognitive science research (see Sect. 6.2).

[31] As for mental simulation in general, simulations of this type are not necessarily activated each time a student hears a metaphorical phrase, but presumably only when the learning task requires that a specific metaphor phrase be used for inferences.

[32] A "classic" used in many Cognitive Science studies as an example of the difficulty of analogically transfering one problem's solution to another domain. The story concerns an army's attempt to conquer a fort with access roads planted with landmines. The problem's structure is similar to that of a problem requiring a doctor to use radiaton to destroy a malignant tumour without damaging the surrounding tissues. Although the two problems are structurally analogous, Gick and Holyoak (ibid.) found that only 30 % of participants reading the fortress story were able to transfer their knowledge of the solution to the tumor problem.

Chapter 7
Simulation-Based Instruction

Imagination has given us the steam engine, the telephone, the talking-machine, and the automobile, for these things had to be dreamed of before they became realities.
L. Frank Baum, Introduction to *The Lost Princess of Oz* (1917)

7.1 Content and Process

Throughout this book, we have focused on the cognitive processes underlying simulation use and dynamic model building and, in particular on several processes that are crucial to learning (e.g., creating analogies and metaphors, generating inferences, reorganizing mental models and schemas). The present section will conversely examine an aspect of instructional simulation not yet directly discussed herein and, that is, *what* to teach via simulation.

Simulation is actually used for many different instructional purposes such as

- teaching specific knowledge (e.g., Newton's laws of motion, the kinetic theory of gases, the principles of photosynthesis, knowledge of subject-specific skills and techniques);
- *developing general thinking skills* (e.g., critical thinking skills, problem-solving skills, scientific thinking skills);
- *increasing students' interest in science* (e.g., motivation to learn science, using scientific language, apply scientific knowledge to everyday situations/life).

How then might teachers orient among such a variety of applications? The approach proposed in the present section is to identify specific types of learning outcomes students are more likely to achieve through simulation and which pertain to science education. The approach is therefore aimed at

- helping educators align learning objectives, instruction, and assessment;
- making simulations an integral part of school curricula;
- supporting educators in their decisions as to when and how to use simulation in a specific context.[1]

Firstly, teachers attempting to clearly define a given learning objective should carefully consider two of the more general aspects of learning objectives:

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[1] The instructional use of simulation requires time and resources; it is therefore important for teachers and educators to verify whether it is actually justified for a given instructional situation or whether other instructional technologies and/or methods are more effective in achieving the same learning objectives.

F. Landriscina, *Simulation and Learning*, DOI: 10.1007/978-1-4614-1954-9_7,

1. the *knowledge* students must acquire/produce; and
2. the level of *cognitive performance* required thereby.

Anderson and Krathwhol (2001) introduced a learning objective model that considers both elements and can be readily applied to simulation-based instruction. The model consists of a two-dimensional framework deriving from a revision of Bloom's (1956) original taxonomy of educational objectives. This taxonomy was subdivided into six student cognitive performance levels:

1. *Knowledge*
2. *Comprehension*
3. *Application*
4. *Analysis*
5. *Synthesis*
6. *Evaluation.*

In the model's revised version, the level names appear in their verb forms, which refer to categories of cognitive processes, that is, thinking skills students must use in a learning task; moreover, the last two level positions are inverted. The categories are therefore as follows:

1. *Remember*
2. *Understand*
3. *Apply*
4. *Analyze*
5. *Evaluate*
6. *Create.*

Together, these categories make up the model's *Cognitive Process Dimension*. Specific cognitive processes are described for each category (e.g., *Recognizing*, and *Recalling*, are the *Remember* category processes). The second dimension of the model is the *Knowledge Dimension* and is subdivided into the following knowledge types:

A. *Factual knowledge*
B. *Conceptual knowledge*
C. *Procedural knowledge*
D. *Metacognitive knowledge.*

Each of the knowledge types is in turn subdivided into further subtypes (e.g., the *Factual knowledge* subtypes are *knowledge of terminology* and *knowledge of specific details and elements*). Factual and conceptual knowledge combined correspond to what is termed *declarative knowledge* (traditionally defined as knowing *that* vs. procedural knowledge, which refers to knowing *how*).

For teachers writing up learning objectives, the model dimensions, respectively, coincide with the *verbal part* and the *nominal part* of a well-written objective statement, as illustrated by the following learning objective example:

Table 7.1 The taxonomy table (adapted from Anderson and Krathwhol 2001, p. 28)

The knowledge dimension	The cognitive process dimension					
	1. Remember	2. Understand	3. Apply	4. Analyze	5. Evaluate	6. Create
A. Factual knowledge						
B. Conceptual knowledge		*x*				
C. Procedural knowledge						
D. Metacognitive knowledge						

The *x* marks a B2-type instructional objective (see example in the text)

- Students will be able to explain in their own words which astronomical factors determine temperature variation from summer to winter.

The verbal part of the objective—*to explain* [*in their own words*]—represents the cognitive process category, and the nominal part—*the astronomical factors that determine temperature variation from summer to winter*—represents the type of knowledge to be acquired.

A two-dimensional visual representation of Anderson and Krathwhol's framework yields the *Taxonomy Table*, the rows and columns of which can be used to classify the objectives, activities, and assessments of a given course or unit (see Table 7.1). For example, the learning objective example reported above is the "understand conceptual knowledge" type and can therefore be placed in the B2 cell of the table.

Learning objectives related to remember or understand, simple forms of knowledge can be taught effectively with reception-based methods (which do not necessarily mean rote memorization!). Conversely, learning objectives linked to understand, analyze, evaluate, and create, therefore, to more complex forms of knowledge, can respectfully and progressively benefit from discovery-based methods, including those based on simulation. In fact, simulation-based learning activities corresponding to the three topmost categories of the cognitive process dimension can be rather easily imagined and are similar to the examples presented in the present book. Some examples are shown in Table 7.2 (the listed objectives' various conditions and criteria have been omitted here for reasons of simplicity).

An important advantage of using the taxonomy table is because it ensures that objectives, activities, and assessments are targeted to the same type of knowledge and cognitive performance. When this occurs, these three elements are "aligned" with each other and can be placed in the same table cell.

Once more in reference to the astronomical learning objective example, one option could be to design a simulation that allows students to visualize and modify the Sun's and Earth's relative positions throughout the solar year, and to measure the correspondingly different inclination with which the Sun's rays strike the Earth's surface in different areas on the globe. Figure 7.1 shows a simulation of this type (in this instance, no moveable numerical levers are present, but students can directly manipulate either the Earth's axis or a protractor to make

Table 7.2 Examples of higher-order learning objectives that can be taught with the help of simulation models

Cognitive process	Learning objective
Understand	Understand the molecular mechanism of phase transition between solid and liquid states in a crystalline solid
Analyze	Analyze how the length and initial angle of a pendulum concur to determine the pendulum's oscillation amplitude
Evaluate	Evaluate the effects of different management strategies in limiting the diffusion of an epidemic
Create	Create a stock-and-flow model of two bodies in thermal contact

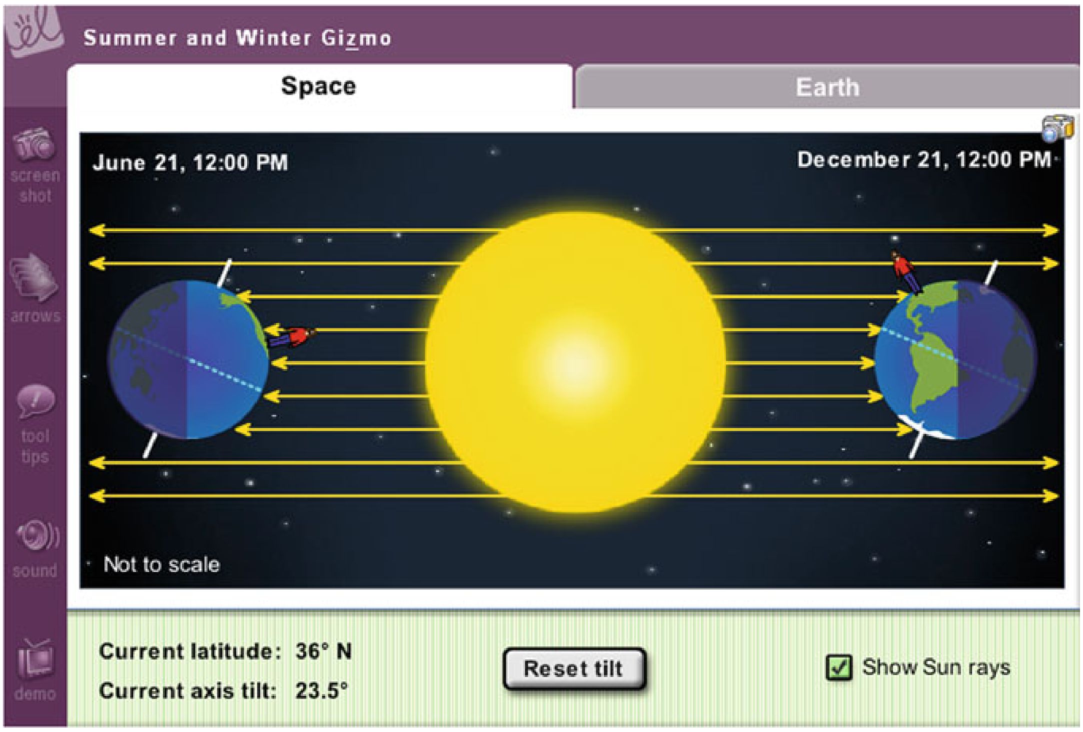

Fig. 7.1 A summer and winter simulation. Image courtesy of ExploreLearning Gizmos™. *Web site* http://www.ExploreLearning.com

measurements). A learning activity aligned with its objective—and, therefore, of the B2 type—might in this instance consist in the following simulation task:

- *Observe the degree of tilt of the Earth's axis and the way in which the sun's rays strike the Earth's surface at different angles in June and in December.*

An assessment item that is aligned with the objective and with the activity proposed might consist in showing students a still picture from the simulation and in asking them:

- *What season and day of the year is it for the man in the picture*?

Simulation can also be used to teach procedural knowledge. Consider, for example, "virtual laboratories" that are usually developed to integrate or potentially replace the traditional, hands-on laboratory experience requiring the physical handling of materials and tools.

In Anderson and Krathwhol's revisited taxonomy of instructional objectives, knowledge and cognitive processes are intrinsically linked, as the two essential parts of a learning objective, and should therefore not be considered in isolation. Conversely, over the past decades, an approach based on the idea that general thinking skills acquisition is more important for learning than that of specific knowledge has gained a great deal of ground in the instructional sciences. An example of this view can be observed in the diffusion of "higher-order thinking" programs, which were launched in the mid-1980s in schools in the United States, and which promoted a shift from *acquiring knowledge* to *learning to think* (Lipman 1991; Resnick 1987). The movement was motivated by the conviction that current economic and social changes require more complex reasoning abilities than those of the past did. These skills are more difficult to acquire, but are utilizable in various contexts, and are thus more easily transferrable to the workplace. Student acquisition of higher-order thinking skills therefore became a national goal, and teachers were encouraged to foster and assess the development of these skills in the classroom.[2]

Yet, what exactly are these skills? How can they be precisely defined? Some studies (e.g., Lewis and Smith 1993) consider them simply as the equivalent of, or similar to the topmost three levels of Bloom's taxonomy of instructional objectives (i.e., *Analysis, Synthesis, Evaluation*). Other views include different types of skills, including *critical thinking skills* (Ennis 1985; Lipman 1991; Paul 1992), *problem-solving skills* (Hayes 1989), and *scientific thinking skills* (Kuhn 2005).

The proponents of programs aimed at teaching higher-order thinking skills contrast these programs with other, more traditional school activities and nearly always describe the latter as "an accumulation of facts," "the superficial memorization of bits of information," "the mere absorption of knowledge," and the like. In these programs, domain-specific knowledge is seen as a necessary condition for developing the thinking skills students will be required to demonstrate, but the main instructional emphasis is on skills that transcend specific school subjects and are therefore generalizable across different contexts.

It is important to note that computer simulation has been frequently considered as a valuable approach to building and enhancing *all* of these types of skills. For example

[2] Methodologically, the development of higher-order skills was included in the instructional repertoire and goals of the then-developing constructivist pedagogy.

- Steed (1992) argued that, by authoring system dynamics simulations, students are forced into higher levels of thinking, including predicting, analyzing, and justifying;
- Rivers and Vockell (1987) investigated and proposed the use of computer simulations to stimulate critical thinking;
- Kuhn (2005) used simulations with dichotomous variables (i.e., that can take on only one of two possible values at a time) as a method to study the control of variables as a form of scientific inquiry.
- Jonassen (2004) focused on the ways in which system dynamics–based modeling tools can support complex problem solving.

This positive view of simulation is mainly based on its potential to develop capacities such as analyzing situations, stating hypotheses, considering alternative points of view, making decisions, and solving problems—that is, skills frequently associated with higher-order thinking.

Yet, however fascinating the idea of "learning to think" might appear, a note of caution is required. As early as the late 1980s, Crow (1989) warned that "research has shown that transferability is somewhat limited, that is, developing critical thinking within the confines of a biology course does not mean that this skill will be transferred to other disciplines or other situations" (p. 116). Similarly, Bailin (2002), argued against considering thinking processes as separate from knowledge, stating that "it makes no sense to refer to a process of interpreting which remains constant regardless of subject matter. Rather, what is involved in and even meant by interpreting varies with the context, and this difference is connected with the different kinds of knowledge and understanding necessary for successful completion of the particular task" (p. 366). According to Willingham (2007), the evidence that students can learn a set of critical thinking skills to be employed in any circumstance is actually quite poor. He maintains that programs teaching these kinds of skills are mostly ineffective, because thinking processes are intrinsically intertwined with the content of thought itself.

Similar considerations can be made about programs teaching problem-solving skills. In the early days of cognitive science, the goal of research on problem solving was to identify general-purpose strategies to be applied to a variety of problems (Newell and Simon 1972). A body of research on problem solving, however, showed that no single solution process can be devised to apply to different domains, and that the differences between AI and human problem solving are far greater than their similarities. Cognitive scientists have observed that domain knowledge plays a key role in problem solving, as it guides solvers in focusing their attention on problem aspects that are crucial to determining the solution (for a research overview, see Novick and Bassok 2005). Similarly, expert–novice research has shown that familiarity with that problem domain-specific content plays a more important role in solving a given problem than general problem-solving strategies do, because students' problem representation criteria improve as their knowledge becomes more richly structured (Schoenfeld and Herrmann 1982). As Bruer (1993) highlighted, expertise depends "on highly organized, domain-specific knowledge that can arise only after extensive experience and practice in the domain. Strategies can help us process knowledge, but first we have to have the knowledge to process" (p. 15).

The higher-order thinking skills receiving the most science educator's and teacher's focuses are undoubtedly those of *scientific thinking skills*, especially in the context of inquiry-based learning. Scientific thinking has been frequently characterized in terms of the cognitive abilities scientists [supposedly] use when reasoning on scientific problems. For example, in a study examining the use of a "microcomputer-based laboratory," Friedler et al. (1990) considered scientific reasoning to include the following abilities:

(a) Define a scientific problem
(b) State a hypothesis
(c) Design an experiment
(d) Observe, collect, analyze, and interpret data
(e) Apply the results
(f) Make predictions on the basis of the results.

These types of abilities essentially overlap with the "five-step model" of the scientific method, which can be stated as follows:

1. Define the problem
2. Make observations/gather information
3. Form a hypothesis
4. Test the hypothesis
5. Draw conclusions.

Multistep lists of this type (the five steps are sometimes extended to six, by adding a final reporting and communication of results step) can be found in many science textbooks and educational web sites. They are also frequently presented to students as a procedure to follow in a nearly algorithmic sense, for example, with lists represented in the form of flow diagrams, so as to give the idea of a computer algorithm, and to emphasize the cyclic aspect of hypothesis testing and revision. With its resemblance to laboratory experiments, simulation has oft been considered a way to teach scientific thinking skills as exemplified by the five-step method.

Yet, do scientists actually use this step-by-step method? The concept of a single scientific method, composed of rigorously and unambiguously defined steps, has no correspondence in either Philosophy or the History of Science (Bauer 1994; Chalmers 1999). The notion can be therefore considered an idealization (if not a misconception!) of the nature of scientific enterprise. According to McComas (1998), the idea of a general and universal scientific method, composed of steps such as those listed above, is a "myth of science," which remains pervasive, however, among students and teachers alike. The steps do reflect the way in which scientific results are presented for publications in research journals, but not the process of scientific discovery as it actually occurs.

As illustrated by Rudolph (2005) in his analysis of the historical origins of the five-step method in American schools, the origins of this conception of science can be traced back to ideas formulated in the early twentieth century by the American philosopher and educator John Dewey (1910, 1938). Until then, the dominant concept in science instruction in the United States had been that of the "laboratory method of instruction," based on a list of precisely described laboratory exercises, which underscored the need for precision of execution and quantitative measurement. Conversely, Dewey's proposal was to describe the scientific method in *psychological terms*. In *How We Think* (1910), he described "a complete act of thought" as a mental process made up of the following five steps: "(1) a felt difficulty, (2) its location and definition, (3) suggestion of possible solution, (4) development by reasoning of the bearings of the suggestion; (5) further observation and experiment leading to its acceptance or rejection; that is, the conclusion of belief or disbelief" (p. 72). In this new framework, the main function of experiments was not that of learning how to use an apparatus, as in the laboratory method, but to corroborate, or verify, a conjectural idea. The focus on the process of knowledge construction rapidly garnered favor among the leading science educators of the time, and the five-step approach became the foundation of the "scientific method" as taught to high school students. As highlighted by Rudolph (ibid.), however, the need to adapt Dewey's psychological schema to the demands of a rapidly increasing student population resulted in the same steps being interpreted as a rigid formula with standard lists of projects—and thus, in a process differing little from the previously taught laboratory method!

Procedural descriptions of science must therefore overcome their current limits, and specifically, (a) they do not give students a factual account of scientific practice; (b) students may follow the procedure's steps mechanically and uncritically; and (c) these descriptions risk portraying a cold and unexciting view of science, which can discourage student interest and motivation in studying science or in pursuing a scientific career.

Proponents of inquiry-based learning do acknowledge these problems, and two solutions proposed have been those of emphasizing the recursive and nonlinear nature of the inquiry process (Stripling 2003) and of describing scientific inquiry more generally, in terms of higher-order thinking processes, such as those of critical thinking and problem solving (Kuhn 2005).

Yet, referring to critical thinking or problem solving as the key components of science education results in the same problems discussed above, in terms of programs for teaching these skills, and, in particular, the risk of underestimating the role of domain-specific knowledge. As observed by Crow (1989), "In many of these instances, the entire course or program is devoted to the development of critical thinking. Science content merely serves as the background for the skill development" (p. 115).

Approaches to science education based on the development of higher-order thinking skills are also frequently accompanied by a view of science as a systematic enterprise prominently based on logical, convergent, and disciplined thinking processes. The appeal to think critically is almost invariably associated with that of thinking logically. Yet, research on the cognitive basis of science offers an image of the scientific mind that is far more varied and complex (for a review of studies, see Dunbar and Fugelsang 2005). Firstly, a more recent general consensus is that scientific thinking relies on the same cognitive mechanisms all humans use and is not a different type of thinking at all. Moreover, alongside traditional lines of research (e.g., on problem solving, hypothesis testing, and logical deduction), the current focus is on *causal thinking*, *analogy*, and *conceptual change*. In this context of renewed interest in the aspects of creativity and imagination of scientific thinking, Clement's (2008) and Nersessian's (2002, 2008) research on non-formal reasoning and model-based reasoning are particularly promising, as they underscore the role of mental imagery and simulative reasoning in science (see Sect. 5.3).

The considerations presented in this section allow us to conclude that instructional approaches based on the development of higher-order thinking skills pertain, at best, to only a partial account of scientific enterprise. In a similar vein, primarily considering simulation as a way to develop students' higher-order thinking skills—such as the ones involved in critical thinking, problem solving, and scientific thinking—may not be the most effective system for exploring this learning method's true potential. In fact, all of the activities related to simulation building or using (see Sect. 5.1) rely heavily on the student's background knowledge of the domain being explored. Process-based approaches to simulation may therefore undervalue the role of simulation in the situations that are the most frequently encountered in schools, in which the objective is to acquire a subject matter's specific contents and skills.

The view of simulation as merely an instrument for developing higher-order thinking skills is one reason its diffusion in schools and universities has remained rather scarce to date.[3]

If we are to overcome the limits of a purely process-based view of simulation, an approach is needed to more effectively integrate knowledge with the processes concurrently acting upon it. In an integrated approach of this type, knowledge of a given domain should not necessarily be equiparated with information to be memorized.

In this regard, Anderson and Krathwhol's (2001) model of learning objectives (see the beginning of the present section) allows for the frequently cited requirement of moving beyond the simple presentation of facts, by moving from factual knowledge—which contains "the basic elements students must know if

[3] This is particularly evident in the case of the system dynamics simulation paradigm: despite the great potential of this method for modeling and simulating all kinds of systems, the tendency to consider it mostly as an instrument for developing "systems thinking skills" (Forrester 1996; Richmond 1993), and to focus on large-scale and highly complex problems only, is one of the reasons it is little used as an instrument to teach the standard science curriculum. Researchers at the Creative Learning Exchange organization (http://www.clexchange.org/) have recently undertaken an effort to more closely link system dynamics to educational standards. See also, Fisher (2001) for an integration of system dynamics with mathematical education standards.

they are to be acquainted with the discipline or to solve any of the problems in it" (p. 45)—to conceptual knowledge, procedural knowledge, and metacognitive knowledge. Furthermore, conceptual knowledge need not comprise an undifferentiated category, because it includes knowledge of:

- classifications and categories
- principles and generalizations
- theories, models, and structures.

Students' conceptual knowledge therefore includes all the schemas, mental models, and theories that they have developed up to a given moment in time. The next section will examine the issue of the ways in which simulation can support the construction of such a rich and complex body of knowledge.

7.2 Crosscutting Concepts

The previous section argued that simulation-based learning activities or units should be based on both the knowledge to be acquired and the students' cognitive performance levels. It also highlighted how simulation can be used as a tool for understanding (as well for analyzing, evaluating, and creating) conceptual knowledge. The present section will address two related issues, that is, the types of scientific concepts that are best suited to be taught through simulation, and how simulation can improve students' understanding of these concepts, when compared to other teaching methods.

A first point underscored here is that conceptual knowledge should not be viewed exclusively as subject-matter content. Most science education experts agree that the accelerating pace of science makes it impossible to teach all the ideas related to a given discipline in a school or university curriculum's limited time frame. Moreover, science is increasingly characterized by a blurring of the boundaries between traditionally separated disciplines (and between "pure" and "applied" science). This situation poses educators and teachers with the challenge of adopting an increasingly interdisciplinary approach to science education.

Several recently published science education standards and benchmarks have acknowledged the role of conceptual knowledge in establishing connections between various disciplines (e.g., the American Association for the Advancement of Science 1993; the College Board 2009; the National Research Council 1996, 2012; these are examined more closely here below in terms of their content standards). One point made in all of these publications is that instruction should focus on a small number of conceptual themes that can find applications across different domains of science. Rutherford and Ahlgren (1990) made the first recommendation of this kind in their influential book, "Science for All Americans," by stating that "Some important themes pervade science, mathematics, and technology and appear over and over again, whether we are looking at an ancient civilization, the human body, or a comet. They are ideas that transcend disciplinary boundaries and prove fruitful in explanation, in theory, in observation, and in design” (p. 165). The authors called these ideas *common themes* and presented four main ones in their book:

- Systems
- Models
- Constancy and change
- Scale

The Benchmarks for Science Literacy (AAAS 1995) produced standards for the same four themes, for grades 2–12, and the National Science Education Standards (NRC 1996) proposed the content category “Unifying concepts and processes in science” to provide connections between scientific disciplines. These concepts and processes include

- Systems, order, and organization
- Evidence, models, and explanation
- Change, constancy, and measurement
- Evolution and equilibrium
- Form and function.

The Science College Board Standards for College Success (College Board 2009) confirmed the emphasis on conceptual knowledge by proposing the following unifying concepts:

1. Evolution
2. Scale
3. Equilibrium
4. Matter and Energy
5. Interaction
6. Form and Function
7. Models as Explanations, Evidence, and Representations.

The College Board Standards also used the term “scientific practices” to indicate “a rich set of integrated processes and ways of thinking that support the development of a conceptual understanding of scientific concepts” (p. 18).

It is important to note that common themes and unifying concepts such as the ones cited above should not be considered as being substitutes for discipline-specific concepts (e.g., concepts from the physical, life, and earth sciences), but as complementary to them (e.g., the concept of equilibrium may find applications in the physics of evaporation–condensation, as well in photosynthesis or in the water cycle). Moreover, students need to work with these concepts over a period of years rather than weeks or months.

The Framework for K-12 Science Education (NRC 2012) is a report highlighting the role a limited set of concepts can have in connecting knowledge from various disciplines into a coherent scientific view of the world. The report is framed around three dimensions:

- Scientific and engineering practices
- Crosscutting concepts
- Core ideas in the science disciplines.

The first dimension describes "(a) the major practices that scientists employ as they investigate and build models and theories about the world and (b) a key set of engineering practices that engineers use as they design and build systems" (ibid., p. 30).[4] The second dimension focuses on conceptual knowledge, and in particular on the following *crosscutting concepts*:

1. Patterns
2. Cause and effect: Mechanism and explanation
3. Scale, proportion, and quantity
4. Systems and system models
5. Energy and matter: Flows, cycles, and conservation
6. Structure and function
7. Stability and change.

These concepts clearly summarize the other publications' common themes and unifying concepts, whereas the "core ideas" are discipline-specific concepts, grouped into four major domains: the physical sciences; the life sciences; the earth and space sciences; and engineering, technology, and applications of science.

The interdisciplinary approach to science, which informed all of the above-described standards and benchmarks, is also a distinctive feature of simulation, in which a relatively small number of computational models can be applied to a wide range of phenomena, on different scales, and in seemingly unrelated disciplines.

From a History of Science perspective, interdisciplinarity was a goal of cybernetics from its very beginning. The later fragmentation of cybernetics into a series of increasingly specialized disciplines (e.g., computer science, artificial intelligence, systems science, cognitive science) occurred toward the end of the 1970s and has since slowed down the search for a unitary conceptual framework for human/natural/artificial system interaction. The purpose of studying abstract organization principles in different types of systems was re-launched in the late 1980 and in the 1990s in the contexts of dynamical systems, cellular automata, adaptive complex systems, and artificial life—all of which largely rely on simulation as an innovative research tool/methodology (see references, Chap. 4).

The versatility of computational models in describing a wide range of systems has its origin in the versatility of equation-based mathematical models overall. Ordinary differential equations (ODEs) and partial differential equations (PDEs) can be viewed as *computational templates*, that is, equations that can be used in a variety of situations and contexts. For example, the ODE governing the simple harmonic oscillator originated in the physical sciences and has applications in molecular and cell biology, where it describes the rate at which mRNA produces

[4] Note how this description focuses on "practices" (versus "skills"), as the Science College Board Standards do; note also the consideration accorded to engineering alongside pure science.

proteins in a cell. It also has neuroscience applications, as noise-driven harmonic oscillators can model rhythmic neural activity in the central nervous system.

An advantage of simulations is that they allow teachers to introduce advanced mathematical and scientific concepts through numerical experiments rather than via equations. In this way, qualitative trends can be demonstrated without having to laboriously go through each step required to solve an equation (and in situations presenting unsolvable or a complete lack of equations!).

The reader might notice that the crosscutting concepts listed in the Framework for K-12 Science Education can be effectively exemplified and made intelligible through the instructional use of simulation. Some examples are given below.

7.2.1 Patterns

Patterns are all around us—in nature, for example, in the venation of a leaf or the structure of a snowflake. They are also ubiquitous in all forms of art, from painting and architecture, to music and dance. Patterns are also ubiquitous in cognition, for example

- In the visual system, patterns (simple combinations of lines and colors) are a form of information that mediates between low-level visual features and meaningful objects.
- Perceptual learning—the ability to identify similarities and differences in stimuli—is a form of pattern recognition.
- Expert performance in various fields is largely based on the ability to identify meaningful patterns in a given situation or problem.

Simulation can dynamically represent pattern formation in natural and artificial systems, through the use of computational models based on numerical solution of PDEs (e.g., reaction–diffusion equations) or on cellular automata: it therefore supports the ability to think in patterns. These two specific types of models allow scientists to simulate phenomena ranging from the arrangement of stripes on a zebra coat to the spiral shapes of galaxies. They also facilitate investigation of pattern formation mechanisms in highly idealized systems (as in, for example, Conway's Game of Life). Moreover, these dynamically generated patterns can be classified into distinct universality classes, as in the instance of Wolfram's one-dimensional cellular automata.

According to studies examining the relation between *perceptual learning* and *conceptual learning* (Goldstone Landy and Son 2008), simulations that represent abstract scientific principles via easily understandable visual patterns can have important instructional applications. In particular, these types of simulations allow students to ground their knowledge of symbolic abstractions and to simultaneously transfer it analogically from one learning context to another.

Another important advantage of simulation is that it allows for the representation of *patterns of change*, which are common to different systems. One example is the logistic, or “S-shaped” curve, which appears as an output in the simulation of physical, biological, or social models. These simulations render easily evident the idea that quantities as diverse as the concentration of reactants and products in a chemical reaction, the size of a population, or the number of customers of a new product can actually all show the same pattern of change, which consists in a phase of rapid growth, followed by a diminished growth phase, and ultimately, one in which the curve asymptotically approaches a constant value. Significantly, the perceived similarity can be linked to an underlying common mechanism and namely that in which two processes compete for some critical resource (this mechanism can be most clearly viewed in the causal maps and stocks-and-flows diagrams of system dynamics models).

7.2.2 Cause and Effect: Mechanism and Explanation

Overall, scientists are interested in searching for causal mechanisms, that is, event chains leading from a cause to an effect. Hence, a key component of scientific thinking is that of being able to develop causal mechanism models. Mechanisms in general have a distinguishing qualitative nature that differ from the quantitative nature of statistical data models, as the latter are used to determine the degree of covariation between a cause and an effect.[5]

Simulations designed for understanding the ways in which different systems work are mostly based on causal models, for example

- Large-scale climate prediction simulations are used to investigate the oceans' effect on climate.
- Simulations in the fields of molecular and cell biology are aimed at isolating and understanding the mechanisms that regulate the functioning of biological systems.
- Brain network simulations are used to explain cognition in terms of underlying neural mechanisms, such as neuronal oscillations and synaptic plasticity.

In fact, as Bechtel and Abrahamsen (2005) pointed out, a *mechanistic explanation*—that is, one accounting for a system's behavior in terms of the functions performed by its component parts—is a widely used modeling strategy in science. Simulation can therefore serve to stimulate students to develop forms of scientific thinking that are more akin to those of scientists.

One aspect of causal reasoning that is seldom considered in science is that of “circular causality.” Teachers and textbook generally focus on linear

[5] The covariation of *A* and *B* is not, in and of itself, a criterion for stating that *A causes B*. It may be that a third factor *C causes* both *A* and *B* and that *A* and *B* covary only, as in the case of “spurious correlation.” Other instances are those in which *B causes A* but *A* does not *causes B* (reverse causation), or in which *A* and *B* are both *causes* of each other (e.g., the variations of pressure and temperature in an ideal gas).

cause-and-effect relations—that is, relations of the form *A causes B, B causes C, C causes D*, …—whereas many phenomena imply a *circular* relation—that is, *A causes B, B causes C,* and *C causes A*. As previously underscored (see Sect. 6.1), our own mental processes have a hard time following a circular chain of events, most probably due to basic limitations in the working memory system. Simulation programs do not present these limits and can therefore extend our capacity to deal with circular causality.

The simplest way of modeling circular causality is via feedback. In fact, any simulation models aimed at explaining goal-directed behavior and self-organization in complex systems focus on the role of feedback in these processes. In particular, feedback loops visually represent the relations between variables in system dynamics models and also in the diagrams used in the modeling and simulation of biological cells (e.g., compare Fig. 4.26 with 4.31). One aspect of causality that is also frequently underscored in system dynamics modeling is that a system's behavior may be determined by internal rather than external causes. This endogenous point of view does not imply that a given system is closed to the exchange of matter, energy, or information with the environment, but that external factors only serve to trigger the system's behavior and that the latter mainly derives from the system's internal structure.

7.2.3 Scale, Proportion, and Quantity

Science describes many natural phenomena on an enormous variety of space and timescales, ranging from the subatomic level of elementary particles to the cosmological level of galaxy clusters. Moreover, different descriptional levels not only characterize different fields of inquiry, but can also be observed within the same field. An interesting example is that of thermal physics, in which heat-related phenomena are studied from both the *macro* perspective of thermodynamics and the *micro* one of statistical mechanics. (The terms "macro" and "micro" will be used herein to indicate, respectively, a level of description consisting in the representation of entities and properties that are available to the senses, and, vice versa, a level of description for which this is not possible).[6]

The teaching and learning of phenomena at different scales is usually based on multiple representations, which are aimed at providing students with opportunities to construct appropriate mental models of the phenomena under study. These representations, however, are either frequently static (e.g., scale models, diagrams) or of a highly symbolic nature (e.g., mathematical formulas). They may consequently fail to capture the dynamic dimension of the phenomena they intend to represent and/or may not allow students to ground their conceptual understanding

[6] The terms "microscopic" and "submicroscopic" are sometimes used to respectively indicate a portion of the world that can be seen under magnification, as with an optical or electron microscope, and a portion which, conversely, is so small that cannot be directly seen with any instrument.

in perceptual and motor processes. Students can therefore find it difficult to link different types of representations at different levels.

The above-mentioned drawbacks of multilevel representation can be obviated through the instructional use of simulation. For example, Wilensky and Resnick (1999) proposed an agent-based approach, to support students' understanding of the concept of "emergent levels" in complex systems. They designed simulations for explaining pressure and temperature in an ideal gas, in terms of a system made of "particles in a box" or, similarly, the aggregation of amoebas into slime mold cells, or predator–prey interactions in population model. In fact, in all of these systems, objects and phenomena emerge (i.e., originate spontaneously) from simple interactions between homogenous elements.

The same emergent level-based perspective was adopted by Sengupta and Wilensky (2009) in NetLogo Investigations in Electromagnetism (NIELS), a curriculum of multiagent-based computational models. The models represent phenomena such as electric current and resistance as emerging from simple interactions between electrons and other charges in a circuit.

The Molecular Workbench is a simulation-based learning environment developed by the Concord Consortium (Xie and Pallant 2011) and is based on the molecular modeling paradigm (see Sect. 4.8) and on quantum mechanics calculations. The basic idea of the Molecular Workbench is to render the invisible world of atoms and molecules, and the dynamic phenomena occurring in that world, visible for students. The learning environment is structured around a series of lessons that are based on one or more simulations and form a guided learning space. As with the agent-based modeling paradigm, the Molecular Workbench allows students to interpret many basic concepts on a macro-scale (e.g., heat transfer, diffusion, osmosis, phase transitions) by referring to micro-scale processes. But it also highlights "first principles," in the form of foundational scientific laws, such as the first and second laws of thermodynamics, and the law of momentum conservation.[7]

All of these projects point to simulation as an effective strategy when the learning objective is to understand the microscopic origins of observed macroscopic regularities. Accordingly, by connecting dynamic representations at the macro- and micro-levels, students learn which concepts are meaningful at a specific scale level.

7.2.4 Systems and System Models

Emphasis on systems and models is a recurring theme in all of the standards and benchmarks cited in the present section, reflecting a current general consensus on

[7] The Molecular Workbench creators use these and other laws as test cases to ensure the validity of the computational engine underlying the simulation program.

the importance of models and model building in science thereby. The modeling and simulation process, as described from various perspectives in this book's previous chapters, comprises many aspects of scientific modeling in general. The phases of the process (see Sect. 4.3) are common to various disciplines, application areas, and simulation paradigms. Moreover, simulation-based learning is a form of model-based learning, in that it is based on a progression of mental models. Thus, simulation building (or even simple discussion of the models underlying different simulation programs) can be an effective way for students to familiarize with the concepts and methods of model-based science.

7.2.5 Energy and Matter: Flows, Cycles, and Conservation

The concepts of energy and matter are equally the most common ones in science and the most difficult ones for students to understand. Energy and matter are always part of a system, but can also transfer into or out of the system, or from one of its component parts to the others—a process that is of great relevance in natural systems and in engineering. Indeed, a specification frequently missing from educational contexts is that both energy and matter can be described in alternative ways and therefore represented through alternative models.

The main concern of educators and teachers is frequently that of teaching elementary and middle schools students that matter is made of small particles (atoms and molecules), which goes against the common sense notion of matter being a continuous substance. Children are consequently instilled with the idea that the world they perceive with their senses is—from a scientific perspective—a kind of "illusion," and the macro-level of reality is explained by referring to the micro-level only (see the above paragraph on scale, proportion, and quantity).

Although simulation can be a perfect window on the otherwise invisible world of atom and molecules, it can also be a window to another and equally relevant view of the world, which plays, however, only a minor role in traditional curriculums: the view of continuum physics (see Sect. 4.7).

Continuum physics describes both the macroscopic physical world around us and phenomena occurring at the interface between the macroscopic and microscopic worlds.[8] The field has many applications in science and engineering (e.g., materials science, geophysics, astrophysics, construction science, thermal engineering, and nanotechnology), where researchers must grapple with a multitude of aspects that characterize real solids, liquids, and gases. The modeling approach used in continuum physics is based on the notion of *continuum body*, that

[8] It is based on a theoretical approach—*continuum mechanics*—which was introduced as a branch of classical mechanics during the nineteenth century by the French mathematician Augustin-Louis Cauchy. (Many of his theorems in the field of infinitesimal calculus were conceived in the context of continuum mechanics). It was then reorganized upon rigorous mathematical foundations in the twentieth century by Clifford Truesdell.

is, a body (solid or fluid) assumed to be infinitely subdividable. This continuity hypothesis makes it possible to identify the *material points* of a body as the *geometrical points* in a region of space and to define a continuous *density function* within this region.

Continuum physics examines the collective behavior of many atoms or molecules, but without the need to explicitly compute the motion of every particle in a system. Of course, this approach is an approximation based on the separation of scales between microscopic structure and the phenomenon of interest, but it is also a very useful one. Moreover, a similar approximation underlies the use of continuum functions in calculus—as when differential equations are used to describe the aggregate behavior of systems composed of a great number of discrete elements.[9]

The germane point from an instructional perspective is that the notion of continuity, used as a modeling strategy in continuum physics, is in accordance with the intuitive notions of matter and energy used by laypersons and scientists alike, and with the related mental processes of analogical reasoning, visualization, and mental simulation (Sect. 5.3).

One reason continuum physics has been excluded from traditional science curricula, however, lies in its complex mathematical methods—studied in advanced university courses only. Yet, simulation itself can be a valuable tool to overcome this limitation, and to introduce these types of models to students and teachers at nearly any educational level, with no need to master the underlying mathematical formalisms.

This type of continuum physics-based approach is used in Energy2D (Xie 2012), an interactive, visual simulation program developed by the Concord Consortium, which models heat transfer mechanisms (i.e., conduction, convection, and radiation). The program's computational engine is based on the numerical solution of the heat equation and on the Navier–Stokes equation. The modeled systems pertain to the fields of thermal engineering, earth science, and fluid dynamics and are visualized through information visualization methods that are derived from simulation-based engineering and science (see Fig. 4.11).

The system dynamics simulation paradigm is well suited to a continuum physics-based approach to science education. For example, Fuchs (2010) used system dynamics as a method to teach a unified approach to physical processes (see Table 4.5). The system dynamics' modeling metaphor of stocks-and-flows perfectly matches the conceptual model underlying Fuchs's theory in which processes are represented "as the result of the *storage and flow of fluidlike quantities*" (ibid., p. 26).[10] The next section will also refer to Energy2D and Fuch's models, due to their implications from an embodied cognitive science perspective.

[9] It fact, Chaucy's theorems of infinitesimal calculus were developed in the context of continuum mechanics. The same holds for "tensor calculus," which was originally developed for calculating stresses acting within a deformable body and has since found applications in many other fields, including Maxwell's theory of electromagnetism and Einstein's relativity theory.

7.2.6 Structure and Function

The relation between structure and function is an issue that cuts across different disciplines. As underscored in the Framework for K-12 Science Education: "The functioning of natural and built systems alike depends on the shapes and relationships of certain key parts as well as on the properties of the materials from which they are made" (NRC 2012, p. 96).

The term "structure" frequently refers to a static organization of parts, as in an architectural model (the etymology of the term is linked to "construction").[11] In fact, in science programs students are often asked to learn the content (i.e., the elements and relations) of hierarchical structures, which are usually represented in the form of tree diagrams (e.g., the classification of living organisms, or the cladograms of phylogenetics). Nevertheless, all natural structures are also *dynamic* patterns, which may appear static, however, only due to the timescale on which they occur (as is apparent, for example, in time lapse videos of plants growing). Moreover, a substantial difference between natural and artificial systems, which also has educational implications, is that an artificial system's structure and the functioning of its parts are established by a designer. In natural systems, conversely, they are the result of biological evolution processes.

Simulation can help students explore different kinds of dynamic structures. Indeed, most simulation modeling activities have the key goal of connecting structure and behavior. Specifically, simulation facilitates students' understanding of a conceptual model by linking a model's structure with observed behavior. For example, system dynamics modeling consists in visually representing a system's causal structure and using equations and rules to describe the functional relations between the model's elements. Similarly, in cellular modeling and simulation, different kinds of modeling and diagramming techniques have been developed to represent the structure of a cell in terms of its subsystems and the functional connections that exist among them.

Simulation can also be well suited for teaching the basic principles of self-organization and in particular, the key role of *nonlinearity* in self-organizing processes. Indeed, students of any age level may be surprised to discover the ways in which stable structures can emerge from nonlinear dynamical systems without explicitly external intervention.

Students are often required to explain structure by referring to function and vice versa, to explain function by referring to structure. Although in some instances this

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[10] Fuch's approach conceptually derives from the "Karlsruhe Physics Course," in which "extensive" or "substance-like" physical quantities play the role of basic concepts. These quantities are mass, energy, electric charge, amount of substance, momentum, angular momentum, and entropy. (The course material is available at: http://www.physikdidaktik.uni-karlsruhe.de/index_en.html).

[11] In the National Science Education Standards and the Science College Board Standards for College Success, the term "form" is used in place of "structure"—a choice that highlights a focus on natural forms, as opposed to man-made structures.

is a relatively simple task, in others it is impossible without the aid of simulation. For example, the structure of a fir tree needle can be easily linked to its function—to let falling snow slide off of it and not accumulate on the tree's branches—and the function of a gear in a mechanical system can be understood by the way in which it is connected with the other gears.[12] Yet, it may be difficult or impossible to identify the function of a computational model's component solely on the basis of the model's structure and equations, without explicitly simulating the model.[13]

The interplay between structure and function is most evident and has been most widely investigated in modern network theory (Canright 2009). The field originated from studies on graph theory conducted in the 1990 and 2000s and has since found applications in a variety of fields, similarly to as occurred with research on fractals in the 1980s.

The "Seven Bridges of Königsberg" problem (Sect. 3.2) showed us how graph theory can yield an abstract representation of the notion of structure, which allows different kinds of systems and problems to be modeled as vertices connected by edges. Yet, although their relevance to mathematical research and engineering applications, classical graphs are not very useful for understanding the dynamic nature of real networks encountered in nature or in human societies, because they are static structures. Conversely, *small-world networks* (Watts and Strogatz 1998) and *scale-free networks* (Barabasi and Albert 1999) are dynamic structures, in the sense that they can increase the number of their nodes and links over time: As a network grows, it is subjected to constant topology changes, which can in turn alter the network's function. Moreover, the *states* of these nodes can change, giving rise thereby to complex dynamical phenomena, such that a change in a node can induce a change in other node states. Thus, networks can support the same kinds of phenomena that generally characterize nonlinear dynamical systems, including self-organization and synchronization in node activity.

Simulation can be used to teach the basic notions of network theory, as well some of its more advanced applications, and the process of moving from simple paper-and-pencil network representations to computational models is relatively easy. Students, moreover, tend to find network theory applications very interesting, because they range from the social network relations between members of a group to the structure of the Internet.

[12] Student comprehension in both instances may rely on mental simulation.

[13] In the system dynamics modeling method, it is frequently stated that a system's behavior can be explained in terms of its structure, but this statement is based on the premise that only simulation use allows for this type of explanation, because the model would remain otherwise opaque.

7.2.7 Stability and Change

The interplay between stability and change is a key aspect of dynamical systems, which comprise simple physical systems as well as entire human societies. The most simple type of stability refers to the commonly shared meaning of the term—that is, *static equilibrium*, in where there is no system change (e.g., a ladder leaning on a wall). A different type of stability is that characterized by *dynamic equilibrium*, in which the system's form does not change, even if its material composition does. Some examples are whirlpools in a stream, a tornado's funnel-shaped cloud, or the Great Red Spot on Jupiter. A dynamically stable situation can also consist in a repeating pattern of cyclic change, as in the motion of a satellite around a planet. A more complex type of stability is that of *homeostasis*, in which a system (typically a living organism) maintains some properties constant, in function of its own internal regulation mechanisms (e.g., the physiological mechanism of blood glucose concentration regulation). The concept of homeostasis is also at the origin of the concept of closed-loop regulation in control systems (a well-known example is the thermostat) and, consequently, of the feedback concept in cybernetics.

Simulation can be an effective means for introducing students to all of the above-described concepts of stability; it can be especially helpful when shifting from static to dynamic equilibrium concepts. We previously discussed an educational simulation example (Fig. 5.13) that models the mechanism of dynamic equilibrium through the analogy of water in a bathtub, the level of which may remain constant with steady quantities of water moving, respectively, in and out of the bathtub. This concept can be generalized to any system characterized by a continuous exchange of matter or of energy with the external environment and in which the entering flow equals the outgoing.

Simulations of physical systems in dynamic equilibrium with their environments can allow students to vary the parameters determining the equilibrium, and to analogically transfer these examples to more realistic and complex situations (e.g., the water cycle, the composition of the atmosphere, the monetary dynamic equilibrium of a nation's economy). Students can also grasp the idea that a system may be stable within a certain range of conditions only and may conversely become unstable when the conditions change. Lastly, they can learn about the crucial role of feedback in determining a system's stability (e.g., by exploring the roles of reinforcing loops in causing the system's growth or decay and of balancing loops in leading a system to stability).

Moreover, simulation can convey the notion that *instability* is not… such a bad thing after all! This idea may come as a surprise for students, because the term "unstable" frequently has negative connotations in everyday language, meaning "not firmly fixed," "unpredictable," or even denoting a person with emotional instability. Conversely, the simulation of nonlinear dynamical systems demonstrates that instability can be a source of variety and innovation, because a system "at the edge of instability" can switch spontaneously into a variety of new and potentially innovative states. Thus, instability can serve a useful role in many situations. Moreover, the study of dynamical systems can enrich a student's view of stability and change with other concepts such as "metastability" and "multi-stability," which are currently the focus of research endeavors in many scientific areas, from gene regulation to neurodynamics (e.g., see Freyer et al. 2012).

The crosscutting concepts listed in the Framework for K-12 Education, which were examined in the present section from the point of view of simulation-based instruction, are not independent from each other, but are *interrelated* in many ways—for example, *patterns are a kind of structure; the flow of energy and matter in and out of an open system can give rise to stable structures; change may imply mechanisms at different scales; dynamical models rely on circular cause-and-effect relation*, etc. Students can very effectively explore these concepts and their interrelations by using simulation.

7.3 A Grounded Cognition Perspective on Simulation

We now come to the question of, "How might simulation be used to effectively teach the unifying concepts highlighted by science educators?" A first step in answering this question is to investigate *the contents* of the mental representations developed by students when using a simulation program or build a simulation model. As described previously (Sect. 5.5), simulation-based learning can be characterized as a progression of mental models, beginning with a student's initial model of an examined system and developing into a target conceptual model—presumably the same one underlying the simulation's computational model. Moreover, to arrive at the target model, students must first develop *their own* intermediate conceptual models, which are mental models expressed as cognitive artifacts (e.g., descriptions, drawings, maps, equations). Essentially, conceptual models serve to bridge the world of the mind with the world of computers and programs (Fig. 7.2).

From a grounded cognition perspective, knowing a concept means being able to mentally simulate it, which entails the ability to

- construct an adequate mental model of the concept and run the corresponding mental simulations;
- revise a mental model when confronted with empirical evidence of its inadequacy.

Conversely, any difficulties in concept comprehension and conceptual change frequently pertain to

- lack of domain-specific knowledge (essential for constructing and simulating an adequate mental model);
- high extraneous cognitive load (which exceeds the available working memory capacity);

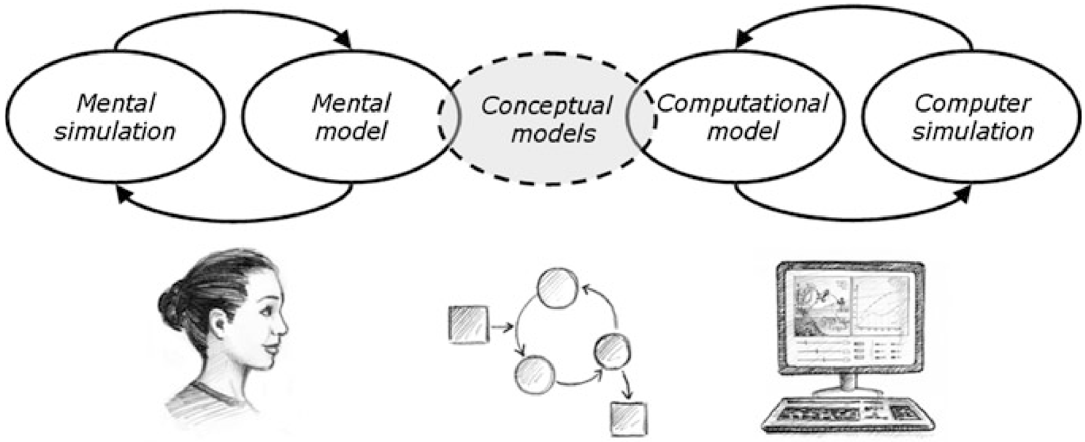

Fig. 7.2 The mediating role of conceptual models

Table 7.3 Levels of analysis of concept understanding

Level	Cognitive task	Instructional method
1	Recognize occurrences of the concept, discriminate	Providing concept name, definition, examples, and non-examples
2	Identify relations with other concepts	Concept maps
3	Mentally simulate the concept	Grounded and embodied instruction

- difficulty in grounding the new knowledge in an embodied sensorimotor experience;
- difficulty in comparing the outcomes of mental simulation with contrary empirical evidence.

The interplay of mental and computer simulation, however, can increase the effectiveness of concept learning and can obviate the above-listed problems.

Concept comprehension can be examined at different levels of analysis (Table 7.3). Traditionally, it has mostly been identified with the ability to recognize the instances of a concept and to differentiate it from other similar concepts. From a teaching perspective, this view corresponds to the technique of giving students a concept's *name*, *definition*, *examples*, and *non-examples.*[14] An additional level of complexity is that of representing relations between concepts, as in the *concept map* method (Novak 1991). Although concept maps are an effective way for students to represent and organize knowledge, they do not allow the meaning of a given concept to be grounded in sensorimotor experience. For instance, students will unlikely learn the concept of magnetism exclusively by knowing its relations with other concepts and without having first-hand experience of, or having imagined the effect of, a magnetic field. Thus, a third level of concept understanding is required, that is, that of mental simulation, which is based on sensorimotor experience.

[14] Also, the method advocated in classical instructional design (Clark 2008).

According to Black (2010), three steps are involved in grounded and embodied learning:

1. Have a perceptually grounded experience
2. Learn to imagine the perceptually grounded experience
3. Imagine the experience when learning from symbolic materials.

For example, Chan and Black (2006) found that graphic computer simulations of a roller coaster, which also involve movement and animation, can effectively help 5th and 6th grade students to learn and understand the functional relations between potential energy and kinetic energy. A related line of research develops *haptic augmented simulations*—that is, simulations based on emerging tactile feedback technologies allowing forces, vibrations, and/or motions to be felt by students (Hallman et al. 2009; Han 2011). These simulations make it possible to go beyond the usual visual and auditory "channels," and actually "touch" phenomena, such as intermolecular, magnetic, and mechanical forces (Park et al. 2011).

Grounded and embodied instruction should not be limited to physical manipulation, because cognition can be grounded in many ways, not only through bodily states. In fact, according to the recent developments in the cognitive sciences reviewed in Sect. 6.3, conceptual processing involves a continuous interaction between mental simulation and language. The notion of image-schemas can help us shed light on the nature of this interaction: On the one hand, image-schemas are non-linguistic abstract structures emerging from sensorimotor experiences, and they are not directly available to consciousness; on the other hand, they support language understanding by serving as source domains for many conceptual metaphors. For example, Mandler (2008) used the term "conceptual primitives" to indicate aspects of spatial information that are used to form early global concepts in infants (e.g., animal, vehicle, plant, furniture), and she highlighted image-schemas as a possible format for these spatial descriptions. In Mandler's view, conceptual primitives are the outputs of an attentive mechanism (*Perceptual Meaning Analysis*), which identifies patterns in perceptual data and re-describes them in a reduced and re-coded form that is suitable for use in the limited capacity system of conscious conceptualization.

Thus, image-schemas allow students to understand abstract mathematical and scientific concepts as if they were concrete objects. Specifically, the verbal or visual description of a concept can activate an image-schema, which in turn can activate a mental simulation. The same holds for concept-related experiences involving motor action, tactile, and kinesthetic input (see examples below in this section). It is not an automatic process, however. A student can rely on deep conceptual processing (associated with the simulation system) or on superficial verbal processing (associated with the linguistic system), in function of a given learning context.

To facilitate the mental simulation-based process of concept understanding, the following instructional design guidelines are proposed:

1. Imagine the experiential and verbal input that can be associated with the concept's comprehension.
2. Identify the relative conceptual metaphors and image-schemas underlying this input.
3. Devise and design instructional activities that can facilitate mental simulation of the concept (on the basis of the target conceptual metaphors and image-schemas).

An example of these guidelines could be that of how to teach the concept of *temperature field*: We begin by noticing that temperature is usually considered a global property of a system; for example, people usually refer to the temperature of a building, a liquid, or the human body. This notion, however, holds only for the temperature of a system that is uniform in space, and many real-world situations do not present systems in this condition. For example, the temperature in a house can vary continuously from ceiling to basement, and that of a lake, from bottom to surface. The phenomenon of point-to-point temperature variation therefore requires reference to the concept of temperature field, which is defined as:

- the set of temperature values at all points in a given space at a given instant.

The temperature field is a physical quantity that can be measured by moving a thermometer to different points within a system. Moreover, a temperature field can also change in time, as when cold air rushes into a house when a window is opened in winter, or when the water used as a coolant in a power plant is returned to the natural environment at a higher temperature. Thus, two conditions pertaining to this concept can be distinguished: (1) steady-state (or static) temperature field, and (2) unsteady-state (or dynamic) temperature field.

Let us now try to imagine what experiential and verbal input might be associated with the temperature field concept. In the first instance, we can refer to the sense of *thermoception*, which is based on receptors in the skin that codes changes in temperature within the physiological range: by touching a metal bar slightly heated at one extremity, we can sense temperature differences at various points of the bar.

With reference to the visual system, we can notice that certain colors are usually associated with the sensation of "hot" and others with that of "cold." In fact, in graphics and design, color (a purely visual phenomenon) is characterized in terms of temperature. Red, orange, and yellow are generally considered "warm" colors, and blue, violet, and green are called "cold" colors.[15] It therefore comes as no surprise that in the practice of scientific visualization, temperature fields are usually represented through *temperature gradient maps*, in which color varies

[15] From an embodied cognition perspective, this mapping between temperature and color is based on our interactions with physical objects (e.g., a red hot iron, the blue of water in a swimming pool), and on bodily experiences of an interoceptive nature (e.g., flushing red with fever).

from *red* (areas with higher temperatures) to *blue* (areas with lower ones), and using all the intermediate colors ranging between.[16]

Temperature gradient maps are extensively used in the fields of astrophysics, physical geography, and thermal engineering. In these maps, a two-dimensional temperature field is represented by means of a family of *isotherms*, each of which connects all points having the same temperature (the distance between isotherms being inversely proportional to the temperature gradient). Moreover, an analogous type of color representation has also been extended to phenomena not involving temperature, such as the *velocity field* in a fluid or the *neural field* in a population of neurons.

Based on the above-described type of sensory input, we can consider that a simulation based on the use of gradients in a temperature map will enhance students' understanding of the temperature field concept. Indeed, the isotherm method of representation is used in the Energy2D simulation program (Xie 2012) to teach students about the mechanisms of heat transfer. Specifically, an Energy2D model shows the difference between *convection* and *conduction* (Fig. 7.3) by showing a heater at the bottom of the screen, which warms a chamber of air and a solid of equal size. The air and the solid are separated from each other by a thermal insulator, but they are not insulated from the rest of the environment. During the simulation, heat propagation through the two materials is vividly represented by turbulent and hot currents in the air chamber and by slow changes in the solid's colors. The heater's temperature is set at a constant value of 30 °C. Initially ($t = 0$ s), both the represented air temperature ($T1$) and that of the solid ($T2$) are shown to be 0 °C. After only a few seconds, however, temperature increases in the air chamber much more rapidly than it does in the solid (e.g., for $t = 1.5$ s, $T1 = 12.9$ °C, and $T2 = 1.1$ °C). Moreover, the heat in the air chamber is visibly more uniformly distributed than in the solid, because it is rapidly transported by the turbulent air currents into different parts of the chamber, whereas the heat in the solid slowly rises upward from the bottom of the material.

Table 7.4 lists several image-schemas that can be activated by the above-described simulation.

The linguistic system also presents many associations between temperature variation and emotional states. For instance, the conceptual metaphor EMOTIONS ARE TEMPERATURE (Lakoff 1987) is grounded in sensations of heat and cold, as in the following phrases: "I vividly remember having a heated discussion with my boss"; "He is a cold person"; "The thought chilled him"; "She received a warm welcome." Moreover, it is also a primary metaphor (Grady 1997) that emerges directly from correlations between bodily experiences and subjective emotional states.

[16] This type of representation has become familiar for many of us, thanks to the use of infrared thermography images (in which thermal imaging cameras detect radiation in the infrared range of the electromagnetic spectrum and produce images called "thermograms").

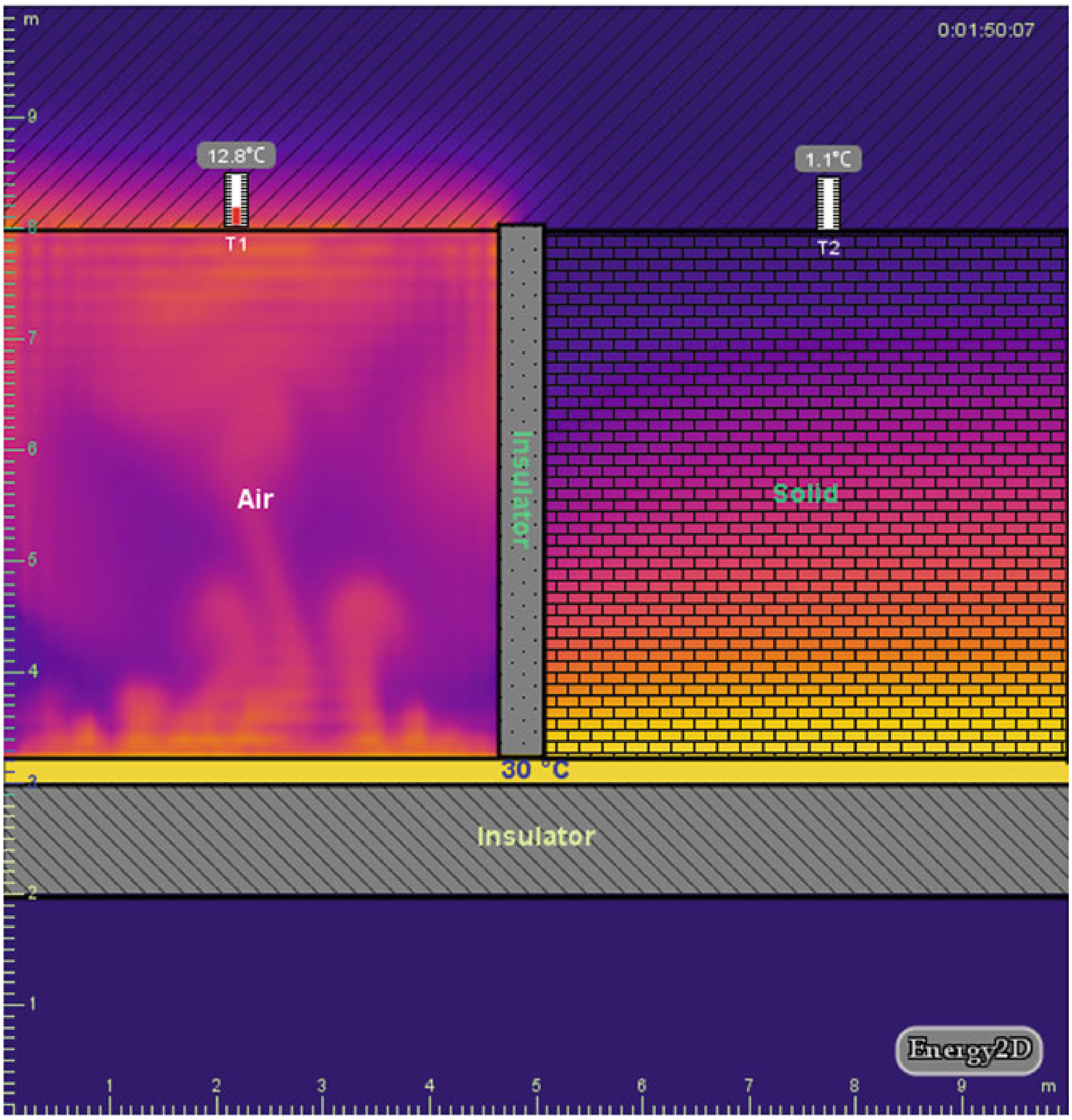

Fig. 7.3 A model that shows the difference between natural convection and conduction. Image from a simulation conducted with the Energy2D simulation program, courtesy of the Concord Consortium. *Web site* http://energy.concord.org/energy2d

Table 7.4 Levels of analysis of concept understanding

Image-schema	Group	Indicator
IN–OUT	CONTAINMENT	Heat appears to spread out from its SOURCE (the heater), like a dense fluid spreads out from its CONTAINER
FORCE	FORCE	The difference in temperature between the heater and the rest of the system acts as the driving force of the heat transfer process
RESISTANCE	FORCE	The air chamber and the solid appear to oppose the heat's movement, which would otherwise be instantaneous
EQUILIBRIUM	BALANCE	The process moves toward a state of equilibrium, in which the temperature remains constant in time, in all parts of the system

Teachers can tap the power of these associations with devise instructional activities that emotionally engage students and simultaneously facilitate the activation of image-schemas emerging from the interaction of students' preexisting mental representations and new knowledge. As described in Sect. 6.3, the use of narratives can greatly enhance this process.

In his research on physics teaching, Fuchs (2007, 2010) identified what he calls "force dynamic gestalts," that is, perceptual gestalts that have the three aspects of (a) *quantity* (size), (b) *intensity* (quality), and (c) *force* or *power* (forms of causation). He maintains that these aspects are rooted in image-schemas that are projected metaphorically onto an examined phenomenon. He proposed a thermal physics example, in which the aspect of quantity may related to what in everyday language is called *heat;* the aspect of intensity, to *temperature*; and that of power, to *temperature difference*.

Fuchs's approach to physics education, based on image-schemas and dynamical models, is perfectly in line with Clement's research on non-formal reasoning (Sect. 5.3). Clement (2008) proposes that teachers encourage and develop students' *natural reasoning processes*, because "it is essential that we not destroy the student's natural ability to use imageable mental models, model-based reasoning, and intuition-based grounding for new meanings in science" (2008, p. 567).

The reader may have noticed (with perhaps some consternation) that the image of heat as a substance is similar, if not equivalent, to the "caloric theory of heat," which dominated thermodynamics in the eighteenth and nineteenth century. As is well known, Sadi Carnot used this theory to derive the thermodynamic cycle named after him. The caloric theory of heat was later superseded, however, by Rudolf Clausius' mechanical theory of heat, and the latter became the basis of the kinetic theory of the ideal gas. Thus, among educators, the caloric theory of heat is considered a typical and pernicious example of scientific misconception—one that the students continue to hold onto, notwithstanding teacher's efforts to teach them a purely atomistic view of nature.

Fuchs recently (2010) proposed the rather elegant solution of considering "entropy" as the scientific equivalent of what is intuitively called "heat" in everyday language. In fact, entropy "is the fundamental thermal property that is stored in bodies (to make them warm, melt them, expand them…), flows from system to system, and is produced in irreversible processes" (p. 124). His specification therefore allows what commonly appears to be a student's misconception to conversely become a valid imagery source.[17]

Moreover, the emphasis on temperature difference as the thermal driving force (Fig. 7.4) allows teachers and students to make a series of analogical connections with other physical (e.g., gravitational, hydraulic, and electrical) phenomena. (see Table 4.5, for a comparison of different physical processes along this view).

[17] We are focusing on this specific topic here, as it illustrates the fact that teaching a scientific concept may require not only innovative instructional methods, but also a more accurate re-examination of the concept itself, from historical and epistemological perspectives.

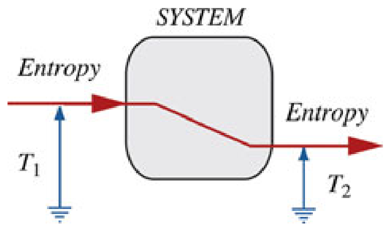

Fig. 7.4 Symbolic representation of a temperature difference as the thermal driving force of a flow of entropy (from Fuchs 2010, p. 124)

A helpful image for introducing these connections is that of a waterfall with power being proportional to its water flow and to the height from which the water falls.

At this point, the reader might easily imagine various kinds of instructional activities that could facilitate a deep conceptual understanding of the temperature field notion.[18] We shall limit ourselves herein to highlighting the opportunities a new type of sensor interface provides by allowing for the conduction of *mixed-reality experiments*.

Mixed-reality applications are currently being developed as an extension of the Energy2D simulation program and greatly extend the currently available range of simulation possibilities (Xie 2012). These applications are based on the use of surface temperature sensors connected to tablet computers. In a typical experimental situation, a sensor measures the ambient temperature, and other sensors are placed on the edges of the computer display. By bringing warm or cold objects to the edges of the display, students can view the temperature field on the screen, represented in the form of a color gradient map that changes in real time with the ambient temperature variations.

These kinds of experiments are called "mixed-reality labs," as they can be categorized somewhere between the purely virtual experiments of computer simulation and traditional laboratory experiments. From a learning-by-system-modeling perspective (Seel 2012a), the activities that students conduct in these laboratories allow them to more rapidly construct and simulate their mental models and to immediately compare the mental simulation outcomes with the empirically available information. Moreover, on a micro-scale, this process constitutes a kind of "epistemic cycle," which will be discussed further in the next section.

7.4 The Epistemic Cycle

Given that this book is about models, it is only natural to conclude it by presenting …a model! The one presented in this section is termed the *Epistemic Cycle* (Landriscina 2009a, b), which focuses on the ways in which students acquire knowledge through simulation in an instructional context (see the flow diagram in Fig. 7.5).

[18] Assuming that, for every specific instructional context, the other simulation design aspects examined heretofore would be equally considered, including cognitive load effects (Sect. 5.6), instructional method (Sect. 5.7), and learning goals definition (Sect. 7.1).

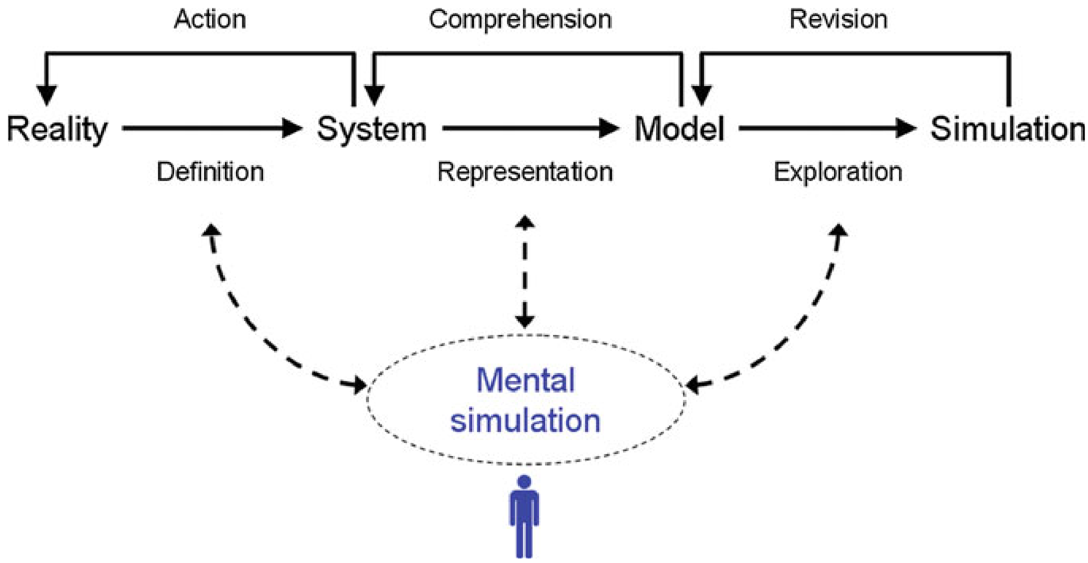

Fig. 7.5 The epistemic cycle (based on Landriscina 2009a, b)

The model comprises four main simulation-related concepts, which have also been clearly outlined in the previous pages, and namely

- Reality
- System
- Model
- Simulation.

The model assumes that each concept can manifest itself in the form of physical objects (e.g., as an observed part of the world) and/or of epistemic artifacts (e.g., a conceptual model). The inter-concept relations involved therein are modeled in terms of epistemic processes, represented by arrows connecting the concept names. Combined, these eight processes compose a cycle, which in its turn is subdivided into three subcycles (feedback loops):

- The Reality-System Loop
- The System-Model Loop
- The Model-Simulation Loop.

Mental simulation completes the model and is considered to be a mechanism that is tapped in all the represented mental processes making up the model. Each of these processes is examined here below in terms of some specific simulation-based learning issues. (These descriptions are kept brief, as this book has already covered these issues in various ways. The following indications therefore serve as a blueprint for further investigation).

From Reality to System (The system definition process)

Defining a system means creating a conceptual boundary between a part of the world and the other parts that surround it. This act can be related to figure-ground organization in visual perception: As with optical illusions, the system's boundary can be a purely subjective one (e.g., the borders of Kanisza's triangle); or the system itself and what lies outside of it can compete for attention (e.g., the well-known image of a vase and two human face profiles).

Moreover, it can be difficult to define the boundary of a system when a part of it remains invisible. For example, we usually conceive the Sun as a sphere, but if we also consider an essential part of it, the heliosphere (the bubble of charged particles created in space by the solar wind), the overall system becomes much larger, because it extends, indeed, as far outward as Pluto's orbit. Another issue related to system definition arises when observer and system cannot be separated, and the result of an observation depends upon their interaction (e.g., for phenomena at the quantum scale, or in participant-observation in the social sciences).

Lastly, an important system-related notion is that of the *observation interval*, that is, the time interval in which one is able to observe the system. During this interval, a given system can remain essentially the same, or it can undergo dramatic changes, as occurs for geological or evolutionary systems, in which the original system transforms into a completely different one (e.g., a caterpillar metamorphosing into a butterfly).

From an epistemic perspective, it is important to underscore that what is usually a system is already, in and of itself, a *representation* of reality (see Sect. 3.1 for a review of some of the philosophical issues involved in the reality-representation distinction). The passage/shift from reality to system requires that choices be made about what should be included and what should be excluded from the system; it is therefore subject to abstractions and idealizations. In fact, "real" systems (e.g., the liquid in a container) are frequently distinguished from "model" or "ideal" systems (e.g., a collection of rigid spheres, the motion of which is governed by Newton's second law of motion). It is important to note that both kinds of systems can be the topic of scientific investigation: a real system can be studied through observation and laboratory experiments and an imaginary system, through mental or computer simulation (which, respectively, correspond to scientists' *thought* and *numerical experiments*).

Overall, the criteria for defining a system are always of a pragmatic nature (see Sects. 3.4 and 3.6). As pointed out by Ashby (1952), "every material object contains no less than an infinity of variables and therefore of possible systems" (p. 39). The decision as to what elements should be selected to be part of the system also depend on what actions will be conducted on it, and defining a system and intervening on it are two closely intertwined processes (making up the epistemic cycle's reality-system loop). Scientists and engineers typically select and study the facts that pertain to some main theory or project that is already given. Hence, observing which elements an individual or group decides to include in a system and what to leave out of it can yield significant information as to their purposes and goals.

From System to Model (The representation process)

Modeling a system means representing it through a series of increasingly complex models in which the description of the system's composition and structure is followed by increasingly detailed descriptions of its functioning. During this process, moreover, a model can in turn serve as a system for a further model—for example, the rigid spheres model of a liquid becomes, in and of itself, the system to be modeled and simulated.

The modeling strategies simulation designers choose are frequently those dictated by curricular models or software tools that are currently available. Yet, consideration of only one strategy should be avoided: A given modeling strategy is one way to understand a specific system and thinking that there is only one correct model means that there is only one correct way to understand the world! For example, in simulations using continuum physics methods to model a liquid, students are asked to consider what is called a "representative elementary volume" of a liquid—that is, the smallest part of a liquid that maintains the macroscopic properties of the liquid as a whole—and are not asked to focus on microscopic particles. A comparison, however, of the two types of models would allow students to ask "What is the true nature of a liquid?". In attempting to respond to this question, the idea that *both* particles and elementary volumes are mathematical abstractions would become more easily understandable.

In fact, scientists can select one type of model over another, in function of the phenomena they are investigating and their research goals. For example, one model may be best suited for studying the transition between the liquid and gaseous states; another, for studying the compressibility of a liquid; and still another, for describing its motion. Thus, the comparison of different modeling approaches can provide valuable insights into a better understanding of the system under study.[19]

A final aspect to underscore is that some models can function not only as tools for investigating an original system, but also as research objects in their own right, by "substituting" themselves with the reality they originally were intended to represent.

From Model to Simulation (The exploration process)

The distinctive characteristic of a dynamic model is its ability to reveal system behavior that would otherwise be impossible to predict and/or explain. In the absence of complex dynamical effects (e.g., nonlinear effects), simple behavior can be simulated mentally or by using paper and pencil. For example, the concept of "analytically solvable equation" refers to an instance in which an individual (in principle) can carry out all operations required to solve an equation. Yet, if the system goes beyond a given complexity threshold, computer simulation becomes an indispensable cognitive partner (Sect. 6.1). Simulation also makes it possible to extend the original system's observation interval, by extending it into the past or into the future.

[19] Lautrup (2011) notes that "Although continuum physics is always an approximation to the underlying discrete atomic level, this is not the end of the story. At a deeper level it turns out that matter is best described by another continuum formalism, relativistic quantum field theory, in which the discrete particles—electrons, protons, neutrons, nuclei, atoms and everything else—arise as quantum excitations in the fields. […] It appears that we do not know, and perhaps will never know, whether matter at its deepest level is truly continuous or truly discrete." (p. 10).

Using a simulation to explore a model's behavior implies a "suspension of disbelief" that is akin to our understanding of literature, theater, and cinema, because one must temporarily suspend judgment as to the simulation's plausibility, and experience it as if it were real thereby. When compared to artistic fiction, however, simulation involves the further epistemic step of comparing events in the simulated world with those of the real world.

The main risk involved in designing simulations is that of simulation "opacity," that is, not rendering the simulation's hypotheses and underlying rules explicit. For example, a simulation game can represent thousands of scenarios and situations, but may not show the "rules" that were originally built into the game by those who created it. Then, when game players observe events that occur as a consequence of their choices, they tend to attribute the system with rules that may coincide with those that are actually present, but may also be only the result of their own mental models: They can therefore reach partial conclusions, which they assume, however, to be irrefutable truths.

From Simulation to Model (The model revision process)

Observing and analyzing the results of a simulation allows its creators to critically reflect on the underlying model and to modify it accordingly. The modeling and simulation, in fact, provides many verification and validation methods to test a model's structure and behavior.[20] This approach yields information on how the model can be improved and rendered more credible, and it can then be used to draw valid inferences about the system under investigation.

This model revision process is a form of hypothesis testing, because the conceptual model underlying a simulation is essentially a collection of hypotheses concerning its related system. In this view, therefore, hypotheses are not merely linguistic statements to be corroborated or falsified by a test on observable data, but make up the components of an explanatory model.

The construction and revision of a simulation model also mirrors the cyclic process of mental model construction and revision as described in the model-based reasoning and model-based learning and teaching (Sects. 5.3, 5.4) of the present book. In particular, modeling software can shorten the construction-revision cycle by allowing us to rapidly modify a computational model and to observe the consequences of these changes, in real time.

Moreover, simulations frequently yield unexpected results when they represent complex systems, potentially producing *cognitive dissonance* in students thereby. This phenomenon facilitates cognitive schema accommodation—a process that is essential for learning scientific concepts.

From Model to System (The system comprehension process)

Using the above-described procedures to improve a model makes it possible to achieve an ever deeper understanding of the structure and functioning mechanism of the originally examined system. Specifically, comprehending a system can

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[20] Schwaninger and Groesser (2009) conducted a review of these methods. See also Robinson (2004).

mean different things—for example, explaining observed phenomena, measuring some property of the system, and gaining insights into the system's potential future behavior. One type of comprehension that is particularly amenable to simulation is to deconstruct a system into its component parts and operations and then re-assemble it by using the variables of a computational model.[21]

A key aspect of the comprehension process is that it can lead to a new view of the system itself. In fact, if a model does not turn out to be sufficiently credible for the purposes intended, it will be necessary to re-examine some specific feature of the system and/or to introduce new features not previously considered. For example, a physical system may have been initially considered only in terms of local interactions between its composing particles, but simulation may fail to reproduce phenomena that also depend on field effects. New models, however, can include these effects. Similarly, a social system might be considered only in terms of the local interactions of autonomous agents, but this view may fail to generate social phenomena that depend on macroscopic properties, such as norms, roles, and cultures. Models based on second-order emergent properties (Sect. 4.10) can directly map the connection between macro- and micro-levels of description.

Significantly, system-level conceptualization changes frequently require that different scientific or philosophical positions be considered (e.g., atomism/holism, subjectivism/structuralism). These are ways, in and of themselves, to conceptualize the world in terms of systems.

From System to Reality (The action on reality process)

By returning from system to reality, we close the epistemic cycle. A better understanding of the system makes it possible to return to reality by observing it from a new and fresh perspective. It also allows it to be modified in function of a specific goal. Overlooking this last step leads to the risk of dropping Arianna's thread, when returning to the real world, and remaining confined in the circularity of the relation between model and simulation. Moreover, a new perspective of the system itself could also be the starting point of a new modeling and simulation process, in which—as with all cyclic models—the end is also the beginning.

In scientific enterprise, the practice of reflecting on a simulated system has frequently led to new experiments. Moreover, simulation models can serve as blueprints for the construction of many real objects (e.g., vehicles, commercial products, industrial plants, molecular medicines). Indeed, in the future, they will play the same role in the construction of synthetic organisms. Let us also not forget that simulation has become a tool to guide policy and management decisions.

Science fiction literature and movies propose future scenarios showing ever thinner and "fuzzy" lines between the real and virtual worlds (in an ever-increasing degree of confusion that has been fueled in the recent years by video game constructors). Not surprisingly then, the epistemological status of simulation

[21] Bechtel and Abrahamsen (2010) termed the strategy of modeling a system with ordinary differential equations *dynamic mechanistic explanation*. This strategy should not be confused with the philosophical notion of *mechanism*, which implies the belief that living things are like man-made machines or artifacts.

is evolving from that of imitating reality to being a *hyperreality* and, therefore, simulation that tries to make the real coincide with its model.

From an instructional perspective, it is important to underscore here that the knowledge developed through simulation-based learning is not a substitute for the experience itself. On a broader scale, it is crucial to remain alert to the environmental, social, and ethical implications of applying a simulation's outcomes to real problems involving individuals and communities.

Considering the epistemic cycle in its entirety, we can conclude that simulation as a knowledge method—reveals to us something, not only about the system being simulated, but also the *epistemic relation* between *observer* and *system*. Thus, in ultimate analysis, simulation tells us about our relationship to a reality that still yet remains beyond the grasp of our models, in the immediateness of its very presence.

Appendix
Simulation Resources

Equation-Based Modeling

1. Java based applets

PhET (Physics Education Technology)

- http://phet.colorado.edu/

Physlets

- http://webphysics.davidson.edu/Applets/Applets.html

Interactivate

- http://www.shodor.org/interactivate/

Open Source Physics

- http://www.compadre.org/osp/index.cfm

MyPhysicsLab

- http://www.myphysicslab.com

2. Online simulations

ExploreLearning Gizmos™

- http://www.explorelearning.com/

WISE 4

- http://wise4.berkeley.edu/webapp/index.html

Energy2D

- http://energy.concord.org/energy2d/

F. Landriscina, *Simulation and Learning*, DOI: 10.1007/978-1-4614-1954-9,

3. Modeling software

SimQuest

- http://www.simquest.nl/

Modellus

- http://modellus.fct.unl.pt

Interactive Physics

- http://www.design-simulation.com/ip/index.php

Molecular Dynamics

The Molecular Workbench

- http://mw.concord.org/modeler/

Virtual Molecular Dynamics Laboratory

- http://polymer.bu.edu/vmdl/index.html

Folding@home. Distributed Computing

- http://folding.stanford.edu/English/Main

Epidemiological Modeling

STEM (Spatiotemporal Epidemiological Modeler)

- http://www.eclipse.org/stem/

GLEaMviz Simulator

- http://www.gleamviz.org/

Agent-Based Modeling

NetLogo

- http://ccl.northwestern.edu/netlogo/

The Repast suite

- http://repast.sourceforge.net/

AnyLogic (XJ Technologies)

- http://www.xjtek.com.com

Cellular automata simulation of the Ising model

- http://physics.ucsc.edu/~peter/ising/ising.html

PercoVIS software

- http://amath.colorado.edu/student/larremore/PercoVIS.html

Percepts and Concepts Laboratory

- http://cognitrn.psych.indiana.edu/

System Dynamics

1. Examples and models

Road Maps. A Guide to Learning System Dynamics

- http://clexchange.org/curriculum/roadmaps.asp

Strategy Dynamics

- http://www.strategydynamics.com/microworlds/

Forio Online Simulations

- http://forio.com/

2. Modeling software

STELLA® and iThink® (isee systems)

- http://www.iseesystems.com

Vensim (Ventana Systems)

- http://www.vensim.com

AnyLogic (XJ Technologies)

- http://www.xjtek.com.com

PowerSim Studio (Powersim Software)

- http://ww.powersim.com

Simulate™ (Forio Online Simulations)

- http://ww.powersim.com

Cellular Modeling and Simulation

The CellML Project

- http://www.cellml.org/

The E-Cell Projec

- http://www.e-cell.org/ecell/

V-Cell. The Virtual Cell

- http://vcell.org/

PyDSTool. Dynamical systems modeling, simulation and analysis environment

- http://www.ni.gsu.edu/~rclewley/PyDSTool/FrontPage.html

Systems Modeling and Design

VMODEL Software (Qualitative modeling)

- http://www.qrg.northwestern.edu/software/software_index.html

MathWorks Simulink

- http://www.mathworks.com/products/simulink/index.html/

Maplesoft MapleSim

- http://www.maplesoft.com/products/maplesim/

Wolfram SystemModeler

- http://www.wolfram.com/system-modeler/

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