Characterizing the Application of Computer Simulations in Education: Instructional Criteria

Jos J. A. van Berkum, Hans Hijne, Ton de Jong, Wouter R. van Joolingen, and Melanie Njoo

15.1 INTRODUCTION

When discussing the use of computer simulations in instruction, and defining ways to include computer simulations in instructional environments, it is necessary to say exactly what we mean by instructional use of computer simulations. As argued elsewhere (de Jong, 1991b), computer simulations in an instructional context can be characterized in terms of four aspects: simulation models, learning goals, learning processes, and learner activity. This chapter provides an outline of each of these characteristics. It draws upon (and originally preceded) more detailed work reported in a special issue on computer simulations in an instructional context (de Jong, 1991a).

15.2 GENERAL CLASSIFICATION OF MODELS

15.2.1 Introduction

The first and most salient characteristic of simulations is that they hide models of domains. In this section a general classification of such models will be given. A more elaborate version of the discussion of characteristics of models is presented in van Joolingen & de Jong (1991).

We define a model as a representation (of a system) created in order to be able to experiment with it through simulation. Such a system can be physical, artificial, or hypothetical.

15.2.2 Quantitative Versus Qualitative Models

A model is a representation of a part of the real world or of some hypothetical system. Often, a complex system is represented as a less complex symbolic system, in order to obtain information, and/or make predictions about the real system. There are numerous ways to represent real systems in models. Therefore, a classification of these different representations is needed.

The first distinction to be made is between qualitative and quantitative models. In the latter type the model entities are represented by numbers and
the relations between them are expressed in mathematical relations. For qualitative models the relations between entities are given in terms of propositions, which can be of a less restricted type than the mathematical relations of quantitative models. The propositions of qualitative models must of course be of a kind that makes simulation possible, i.e., they must give an unambiguous rule set to determine the behavior of the model.

Both qualitative and quantitative models represent the real system by means of a state, which contains all information about the current properties of the system and a set of rules, which determine the development of the state.

15.2.3 Quantitative Models

The model entities in quantitative models are variables. Variables can be dependent or independent. Dependent variables are those that can be calculated from the independent ones (except for their initial conditions). Independent variables are not under control of the model relations.

Variables can be continuous or discrete, depending on the values they can take. Continuous variables can take all values (sometimes between certain boundaries), whereas discrete variables can only take values from a discrete (countable) set.

These considerations lead to a classification into four model types: continuous-continuous, continuous-discrete, discrete-continuous, discrete-discrete. The first term applies to the dependent variables, the second to the independent variables. It appears that the nature of the model is determined more by the continuity of the dependent variables than by the independent ones. Therefore, a classification into continuous and discrete models is mainly used, where the continuity of the dependent variables is the only criterion.

Next to continuous and discrete models a mixed type is also found, which contains both discrete and continuous variables, and in which continuous variables can change at certain points in a discontinuous way. In practice, most models of sufficiently complex systems will be mixed. The "pure" types only occur as small models or as submodels of larger systems (i.e., models of a subsystem).

Another classification criterion is the appearance of time as an independent variable. Models in which time occurs (explicitly or implicitly) as an independent variable are called dynamic, otherwise a model is static. This criterion will prove to be important when the model is to be manipulated.

15.2.4 Qualitative Models

In qualitative models the relations between model concepts are not numeric but propositional. This means that the model state is described in terms of a set of propositions. Based on the types of propositions that are used, two types of qualitative modeling can be distinguished: quality-based and abstraction-based modeling (Fishwick, 1989a, b). In the first type of model quan-
itative aspects of a system are described qualitatively (e.g., “The voltage is oscillating”). The second type of model uses propositions about non-quantitative properties of a system (like “the switch is closed”).

In qualitative modeling and simulation the calculation of the development of the state is a more complex issue. Here, quite often techniques from artificial intelligence are used to enable this.

15.2.5 Interaction and Scenarios

Another important aspect of simulations is one of timing, where timing does not apply to the model time but to the sequence in which the input variables are supplied to the model and the output variables can be retrieved. The sequence of providing input and getting output will be called the interaction process. The interaction determines in which order the model elements can be manipulated. The interaction process can be influenced by certain factors, such as internal characteristics of the underlying model or the instructional strategy used. When the interaction itself is a learning goal it will be called a procedure (operation) or skill.

A related topic concerns who will perform the actions in order to address the different model elements. This can be the learner, the tutorial system, or any other, simulated or real, person or system. This means that the learner will be assigned a role. The combination of process description and role assignment will be called the scenario, following Reigeluth & Schwartz (1989).

15.3 LEARNING GOALS FOR SIMULATIONS

15.3.1 Introduction

The aim of this section is to provide a taxonomy of simulation learning goals. Its theoretical justification and a further elaboration of it can be found in van Berkum & de Jong (1991). After some brief remarks on the concept of a learning goal, we will describe three dimensions on which learning goals can be characterized, followed by a few examples and qualifying remarks.

15.3.2 The Concept of a “Learning Goal”

First of all, our approach to learning goals is a cognitive one. This means that goals will be classified according to dimensions of the knowledge involved, rather than the ultimate behavioral performance that this knowledge allows for. Since behavioral performance and the supporting knowledge structures are very much related, this is obviously a matter of emphasis, and not of strict separation.

Second, the taxonomy will only deal with terminal learning goals, that is, with what a learner knows as a consequence of using a simulation. We are not concerned with intermediate learning goals while using the simulation, such as
"knowing prerequisite principle X" or "having mastered prerequisite procedure Y" (although these "enabling objectives" could in principle be classified in the same way as terminal goals). Neither do we deal with learning processes thought to be instrumental for a particular learning result, such as "verifying the correctness of principle X" or "rehearsing procedure Y." Such processes have been addressed in Goodyear et al. (1991). Similarly, our learning goal concept does not include momentary (sub)goals of the instructor in the course of instruction, such as "get sufficient learner attention" or "find misconception held by the learner."

Finally, the proposed taxonomy does not specify who actually entertains certain learning goals. Both the learner and the instructional agent can refer to learning goals in terms of the present classification; such goals may then suitably be called learner or instructional goals, respectively.

### 15.3.3 A Classification of Simulation Learning Goals

Learning goals can be classified according to the subject-matter domain from which they are derived. However, knowledge to be learned in different domains can have some interesting things in common; interesting in that these can determine the optimal nature of the simulation and its instructional environment in important respects. For instance, learning how government spending affects the inflation rate is in a way similar to learning how the heart rate affects blood pressure, since both involve the learning of a relational principle. The acquisition of these two principles will probably benefit from a similar type of instructional environment, while the learning of procedures for operating a system will probably require a different type of instructional environment.

Each specific learning goal can be classified along three dimensions:

1. The kind of knowledge to be learned may be conceptual or operational. **Conceptual knowledge** is knowledge of principles, concepts, and facts related to the (class of) system(s) being simulated; examples are the power law of practice in psychology, the concept of acceleration, or the function of a specific system component. **Operational knowledge** is knowledge about sequences of cognitive and/or noncognitive operations (procedures) that can be applied to the (class of) simulated system(s); examples are how to perform a titration, how to handle a nuclear power station emergency, or how to deal with a traffic intersection.

2. Knowledge can be encoded in a declarative or a compiled representational format. **Declarative knowledge** is represented in a format that is relatively easy to acquire, that makes the knowledge relatively easy to report upon, that makes the knowledge of potential use in an unlimited number of problem contexts, and that requires interpretation in order to use it in a task. **Compiled knowledge**, on the other hand, is represented in a format that is only obtained after using the knowledge in a problem-solving context, that makes the
knowledge hard to report upon, that restricts its potential use to a limited number of contexts, and that can be used in a more automatic, effortless way.

3. Finally, the target knowledge may vary in scope. Domain-specific knowledge is specific to the simulation domain at hand, such as device and troubleshooting knowledge for a particular piece of radar equipment. Generic knowledge is not specific to the simulation domain at hand, but extends to other domains as well; examples are general troubleshooting or problem-solving heuristics which can be used for different types of equipment, or even for dynamic and deterministic systems in general.

Without presenting the arguments here, the above dimensions are taken to be orthogonal, that is, specifying independent aspects of a learning goal. If one bisects the two more continuous dimensions of representation and scope, the taxonomy can be depicted as a three-dimensional matrix (Figure 15.1). A few examples may illustrate the use of this matrix, or "goal cube." As a first one, imagine a course in general systems theory, in which the learners interact with three simulations from different domains (say, electronics, economics, and biology), in order to acquire an explicit understanding of a negative feedback relation between dynamic system variables. This learning goal involves knowledge of a relation (conceptual knowledge), which is not specific to the three domains employed (relatively generic), and which should be easily accessible for verbal reporting and used in different contexts (declarative representation).

As a second example, take a simulation training course in which nuclear power station operators should learn how to react to cooling system failure in a quick and automatic way, and without making any mistakes due to stress, panic, etc. Such a learning goal involves knowledge of a normative sequence of actions (operational knowledge), which is specific to the system being

![Figure 15.1](image)

Figure 15.1 Classification of simulation learning goals with respect to knowledge category, knowledge scope, and knowledge representation.
simulated (domain-specific), and which supports fast, robust, and automatic performance at system failure time (compiled representation).

A final example may be the use of a highly complex simulation of the human physiological system in order to train students in medical diagnosis, and particularly in the "immediate" recognition of complex symptom patterns among many potential disease cues. Here, the learning goal involves knowledge of common relations between symptoms (conceptual knowledge), which is only valid for the human system (domain-specific), and which supports relatively automatic pattern matching performance (compiled representation).

The proposed classification needs to be qualified in several ways. First of all, it is important to emphasize that most simulations probably involve more than one type of learning goal. Consider for example a simulated electronics device which is used for learning about particular electronics principles as well as about relatively generic troubleshooting procedures. This means that more than one cell in the above matrix can be addressed by the same educational simulation. Of course, some learning goals may be more explicitly aimed for, while others may be regarded as interesting side effects, or may even be ignored altogether.

Furthermore, not all cells will be equally relevant in the general context of simulation learning. It remains to be seen, for instance, whether the use of simulation for acquiring declarative operational knowledge has any great advantage over other methods of instruction.

Finally, applying the above taxonomy to "real life" curricular situations will not always be very straightforward. Any particular cluster of performance aimed for in simulation learning may rely on both conceptual and operational knowledge, part of which may be domain-specific, and part of which may be relatively generic. Likewise, a performance cluster may rely on knowledge which is partly represented in declarative format, and partly stored in a more compiled way. The fact that it may be difficult to disentangle all this in "real life" is probably more an indication of life’s complexity than of taxonomical validity.

15.3.4 Learning about Knowledge Acquisition

The learning goals covered by the above taxonomy all involve knowledge about particular simulation domains (or classes of simulation domains). However, we have ignored a very plausible class of simulation learning goals, which address the process of knowledge acquisition itself. Consider, for instance, using a simulation to teach people how to efficiently obtain and validate knowledge about a system through experimentation. To some extent, this will involve relatively generic knowledge of system's structure and function (conceptual knowledge), and of how to deal with systems (operational knowledge). To a large extent, however, learning about knowledge acquisition is learning about one's own cognitive processes and products (metacognitive knowledge).
It is not entirely obvious how to extend the above, domain-oriented taxonomy in order to accommodate such learning goals. One may well imagine a second, similar cube for the classification of metacognitive learning goals (related to the process of knowledge acquisition in exploratory learning environments). The argument would be that learning about knowledge acquisition processes (1) can involve both conceptual knowledge (e.g., the relation between theory, hypothesis, and prediction) and operational knowledge (e.g., how to test an hypothesis), (2) can be represented in a relatively declarative or compiled way, and (3) can be more or less specific to the simulation domain at hand. While these are speculative statements, they are not at all inconceivable. For the time being, the class of metacognitive learning goals related to knowledge acquisition will be considered as a homogeneous class in addition to the above matrix.

15.4 LEARNING PROCESSES IN EXPLORATORY LEARNING ENVIRONMENTS

Learning with simulations is viewed as essentially exploration based. An understanding of the learning processes that are implicated in learning with computer simulations is fundamental to a better comprehension of computer simulations in an instructional context. In Goodyear et al. (1991) an inventory and a description scheme of simulation learning processes are presented. This section gives a schematic overview of simulation learning processes.

We define learning processes as cognitive transactions of the learner that are meant to transform information into knowledge. This specification is based on the information-processing approach and differentiates learning processes from learning goals, instructional processes, and learner activity.

The inventory of simulation learning processes is based upon general views of exploratory learning, discovery learning, problem solving, and induction (e.g., Ausubel, Novak, & Hanesian, 1978; Anderson, 1985; Michalski, 1987; Klahr & Dunbar, 1988) and research which is directly concerned with learning from computer simulations (e.g., Hille, 1980; Reimann, 1989; Rivers & Vockell, 1987; Lavoie & Good, 1988; Njoo & de Jong, 1991a, b).

The views on learning in general, and learning in an exploratory environment, show great similarities and constitute a general framework for the description scheme of simulation learning processes. The similarities are in the active, constructive, and goal-oriented character of the learning processes. The learner has to formulate general rules of definite principles, preferred procedures, or higher order skills and has to discover these rules by her- or himself. The general idea is that this active, constructive attitude of the learner encourages meaningful incorporation of information into the learner's cognitive structure. The goal-oriented aspect is most strongly recognized in the problem-solving approach but can also be found in the other approaches. One difference can be noted between discovery learning and inductive learning. One of the ways in which inductive learning can be accomplished is by
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Figure 15.2 Description scheme of simulation learning processes.

observation. In this way inductive learning does not necessarily require physical activity of the learner. So, discovery learning always implies an active involvement of the learner whereas inductive learning can be the result of "physically passive" processes.

The present scheme is only intended as a preliminary inventory of simulation learning processes. Refinement, based on results of ongoing and following studies (e.g., Njoo & de Jong, 1991c), is foreseen. Furthermore, the scheme is not prescriptive but has a descriptive character; it does not prescribe a normative sequence of learning processes.

The scheme has a multilayered structure of learning phases and processes. The phases represent a combination of learning processes which can be characterized as one class of operations. Additionally, the phases and processes in the scheme have an iterative character, which means that specific processes can be repeated throughout the study process.

On the first level the scheme consists of four phases: orientation, hypothesis generation, test, and evaluation. These phases resemble a cycle that is generally perceived as the method of scientific inquiry. Several of the phases are mentioned in the discovery and inductive approach (Ausubel, Novak, & Hanesian, 1978; Anderson, 1985; Michalski, 1987; Klahr & Dunbar, 1988; Hille, 1980; Reimann, 1989; Lavoie & Good, 1988). A schematic overview of phases and processes is given in Figure 15.2.

15.5 LEARNER ACTIVITY AND SIMULATIONS

One important aspect of discovery learning, as was also stressed in section 15.4, is that the learners are active. The purpose of the present section is to provide an overview of possible types of learner activity in simulation
learning environments. Learner activity is defined as the "physical" actions a learner can take when interacting with the simulation. This issue can be approached from two directions: the model/simulation, including the scenario, or the interface. Learner activity is to be distinguished from learner control which refers to the control the learner has over the whole instructional environment (e.g., the instructional strategy followed) (see de Hoog, de Jong, & de Vries, 1993).

In this section we take the model/simulation perspective as a central viewpoint. This means that we will describe all the possible types of activity the learner principally can engage in when interacting with a simulation. Some of these activities are more central to the interaction process (e.g., choosing variables and variable values) whereas others are more peripheral (e.g., choosing settings that facilitate data interpretation such as turning on/off a grid).

We can distinguish between several kinds of learner activity. These can be grouped, according to the part of the simulation that is addressed when the learner activity comes into play.

First, a learner may be able to define experimental settings or environments. Simulation can often be seen as performing experiments with a model. Therefore the "experimental settings" must be defined. During this type of learner activity the model and its environmental parameters can be affected. Possible types of these definitions are:

• **Setting environmental qualities.** This means that learners may set values of (independent) variables and parameters in the model. For example, the learner may define the temperature at which the experiment must take place by altering the value of the associated parameters.

• **Defining initial conditions for the experiment.** The difference between this item and the previous one is that the environmental qualities remain constant in time whereas the variables that are set as initial conditions will be subject to change during the simulation. For example in an economics simulation the amount of money each person owns can be defined at the start of the simulation.

• **Selecting and composing experimental "equipment."** Blocks representing equipment or domain elements can be linked together in order to perform a certain experiment. An example might be connecting an engine to a transporting mechanism in order to experiment with several types of those mechanisms to see which is the most efficient.

• **Building an experimental subject.** The difference with the previous learner activity is that now the building block cannot be regarded as a complete model. For instance, a resistor cannot be simulated as such. A resistor is always specified in terms of its behavior in an electrical circuit.

The second major type of learner activity is activity associated with the interaction process (see section 15.2) and navigation:

• **Deciding on the next step to take in the interaction process.** This next step may for example be to perform an experiment, analyze data, make smaller
alterations in the simulation experiment, etc. This kind of learner activity is especially important when we look at simulations that have a procedure as their instructional objective (for a discussion of scenarios and roles see van Jooleijn & de Jong, 1991).

A third type of learner activity is concerned with collecting data from the simulation, accessing the output variables of the model:

- **Attaching measuring instruments to the simulated experiments.** This means the learner has to decide where to collect data, but also how to collect them. This means choosing the appropriate measuring instrument.³

A fourth type of learner activity applies to the choice of data presentation, addressing the user interface:

- **Direct choice of a certain kind of presentation.** There is some overlap with the attaching of measurement instruments. It is important to note that the current item is not concerned with the choice of which variable to represent but only with how to display it. Another point is that measurement instruments are only concerned with output variables, but input variables can also be represented on the screen.

- **Manipulating the presentation.** This is additional to the previous item. When the type of data presentation is fixed, by the learning environment or by the learner, the precise form of presentation, e.g., the choice of axes of a graph or the layout of a table, can be determined. This type of activity is independent from the previous one: freedom in one does not necessarily imply freedom in the other. On the one hand the data presentation may be fixed but the format can be free; on the other hand there can be a free choice between several types of representations, with each representation having a fixed format.

Finally, the learner can have control over the simulation that does not directly affect variables and parameters, nor the scenario, but is carried out by providing boundary conditions to the simulation. We will term this metacontrol and distinguish:

- **Control over pace and direction of simulation process.** This means that the learner can control simulation time. This can mean that simulation time can be started and stopped by the user. Also, control over the pace of simulation time can be possible (e.g., for processes that are too fast or too slow to make real-time observation feasible). Finally, it may be possible to invert the direction of simulation time, i.e., going backwards in time.

- **Putting constraints on the simulation.** This can be important for certain specific problems. Examples of constraints are: "keep a specific variable between two boundary values" (or exactly on one value) or "make sure that at \( t = t_f \) a certain variable reaches a certain value." The simulation must adapt values of (other) variables and parameters in order to achieve the given goal.
NOTES

This chapter is a slightly modified reprint of a paper that appeared in *Education & Computing* 6 (1991), 231–239, under the title "Aspects of computer simulations in an instructional context." As the original paper was part of a special issue, modifications were made to make this reprint a self-contained chapter. The work presented was part of the SAFE (SIMULATE) project. SAFE (SIMULATE) was an R&D project partially funded by the CEC under contract P7001 (D1014) within the Exploratory Action of the DELTA programme. The work of SAFE (SIMULATE) is now continued in the SMISLE (System for Multimedia Integrated Simulation Learning Environment) project partially sponsored by the CEC in the DELTA main phase programme. For more information on the SMISLE project contact Ton de Jong, Faculty of Educational Science and Technology, University of Twente, P.O. Box 217, 7500 AE Enschede, The Netherlands. Email: jong@elte.utwente.nl.

Authors are listed alphabetically. Jos van Berkum is responsible for Section 15.3, Wouter van Jooken and Ton de Jong for Sections 15.2 and 15.5, and Melanie Njoo and Hans Hiune for Section 15.4.

1. The term real system is used for all modeled systems whether physical, artificial, or hypothetical (abstract).

2. In describing these aspects we take a broad view, which means that we do not take into account prescriptions from instructional strategies and the interface for offering possible restrictions on learner activity.

3. The measuring instruments are, of course, simulated as well. The term "measuring instrument" must be understood in the widest possible sense, as an apparatus or method suitable for the retrieval of information from the observed situation.

REFERENCES


