Aspects of computer simulations in an instructional context

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Computer simulations in an instructional context can be characterized according to four aspects (themes): simulation models, learning goals, learning processes and learner activity. The present paper provides an outline of these four themes.

The main classification criterion for simulation models is quantitative vs. qualitative models. For quantitative models a further subdivision can be made by classifying the independent and dependent variables as continuous or discrete. A second criterion is whether one of the independent variables is time, thus distinguishing dynamic and static models. Qualitative models on the other hand use propositions about non-quantitative properties of a system or they describe qualitative aspects in a qualitative way. Related to the underlying model is the interaction with it. When this interaction has a normative counterpart in the real world we call it a procedure.

The second theme of learning with computer simulation concerns learning goals. A learning goal is principally classified along three dimensions, which specify different aspects of the knowledge involved. The first dimension, knowledge category, indicates that a learning goal can address principles, concepts and/or facts (conceptual knowledge) or procedures (performance sequences). The second dimension, knowledge representation, captures the fact that knowledge can be represented in a more declarative (articulate, explicit), or in a more compiled (implicit) format, each one having its own advantages and drawbacks. The third dimension, knowledge scope, involves the learning goal's relation with the simulation domain; knowledge can be specific to a particular domain, or generalizable over classes of domains (generic). A more or less separate type of learning goal refers to knowledge acquisition skills that are pertinent to learning in an exploratory environment.

Learning processes constitute the third theme. Learning processes are defined as cognitive actions of the learner. Learning processes can be classified using a multilevel scheme. The first (highest) of these levels gives four main categories: orientation, hypothesis generation, testing and evaluation. Examples of more specific processes are model exploration and output interpretation.

The fourth theme of learning with computer simulations is learner activity. Learner activity is defined as the 'physical' interaction of the learner with the simulations (as opposed to the mental interaction that was described in the learning processes). Five main categories of learner activity are distinguished: defining experimental settings (variables, parameters etc.), interaction process choices (deciding a next step), collecting data, choice of data presentation and metacognition over the simulation.

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. For this we defined four themes: simulation models, learning goals, learning processes and learner activity (see de Jong, this volume). These themes will structure our discussion of components of Intelligent Simulation Learning Environments (or ISLEs as we call them).

The present article provides a (summarizing) outline of these themes and serves as an organizer for the reader. Each theme will receive full discussion in the paper that deals with the design component to which the theme is most closely related.

2. General classification of models

2.1. Introduction

The first and most salient characteristic of simul-
tions is that they hide models of domains.
In this section a general classification of such models will be given. This section serves as a background for the following papers where, for the various design components of an Intelligent Simulation Learning Environment (ISLE) the relation with the underlying model will be described. A more elaborate version of the discussion of characteristics of models is presented in Van Joolingen and de Jong (this volume).

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.

2.2. Quantitative vs. 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 behaviour 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.

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.

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 modelling can be distinguished: quality-based and abstraction-based modelling (Fishwick, 1989a,b).
In the first type of model quantitative 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 modelling 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.

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 and Schwartz (1989).

3. Learning goals for simulations

3.1. Introduction.

The aim of the present section is to provide a taxonomy of simulation learning goals. Its justification can be found in van Berkum and de Jong (this volume), and the present section merely presents the proposed taxonomy itself. In order to avoid unnecessary overlap, it will be a concise presentation, and readers are referred to van Berkum and de Jong (this volume) for further elaboration.

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.

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 behavioural performance that this knowledge allows for. Since behavioural performance and the supporting knowledge structures are very much related, this is obviously a matter of emphasis, and not of strict separation.

Secondly, the taxonomy will only deal with terminal learning goals, that is, 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 will be addressed in Goodyear et al. (this volume). Similarly, our learning goal concept does not include goal 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.

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 Fitts' 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 1).

![Figure 1 Classification of simulation learning goals with respect to knowledge category, knowledge scope, and knowledge representation.](image-url)

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 use 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 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.

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 systems 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 (a) can involve both conceptual knowledge (e.g. the relation between theory, hypothesis, and prediction) and operational knowledge (e.g. how to test an hypothesis), (b) can be represented in a relatively declarative or compiled way, and (c) 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.
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. (this volume) an inventory and a description scheme of simulation learning processes will be presented. The present 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/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 observation. In this way inductive learning does not necessarily require physical activ-

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Figure 2 Description scheme of simulation learning processes.
ity 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 (for example 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 multi-layered 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 2.

5. Learner activity and simulations

One important aspect of discovery learning, as was also stressed in Section 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 learners has over the whole instructional environment (e.g. the instructional strategy followed) (see De Hoog et al., this volume).

In the present 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.

\[1\] 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.
• 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 experi-
  ment 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 can not be
  regarded as a complete model. For instance, a resistor cannot be simulated as such. A resistor
  is always specified in terms of its behaviour in an electrical circuit.

The second major type of learner activity is activity associated with the interaction process (see Section
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
  Joolingen and de Jong, this volume, Section 5).

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.\footnote{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.}

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 lay-out 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. in for processes that are too fast or too slow to make real-time observation feas-
  ible). Finally, it may be possible to invert the direction of simulation time, i.e. going back-
  wards in time.
• Putting constraints on the simulation.
  This can be important for certain specific problems. Examples of constraints are: 'keep a spec-
  ific variable between two boundary values' (or
exactly on one value) or 'make sure that at \( t = t \)
a certain variable reaches a certain value'. The
simulation must adapt values of (other) variables
and parameters in order to achieve the given
goal.

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