Learning from rediscovering system dynamics models

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ABSTRACT

This article deals with learning from the exploration of system dynamics models. System dynamics modeling intends to improve judgment and decision, but is very time consuming. Model-based interactive learning environments allow saving time, but critics doubt the effectiveness for deep learning. The question is if there is a third way in-between. Relevant examples from system dynamics are analyzed to identify the key activities that trigger learning; they are organized as a structured exploration process, making learners ask relevant questions, obtain valid responses and correctly interpret them. Based upon this, a process for guided rediscovery is proposed together with guidelines for the functional properties of a "systemic exploratory". Guided rediscovery enables non-specialists to gain relevant insights into dynamically complex situations and is a tool for decision policy design.

Key-words: System dynamics, Interactive learning environment, Modeling, Model exploration, Discovery learning

RÉSUMÉ

Cet article traite de l'apprentissage tiré de l'exploration des modèles de dynamique des systèmes. Dans cette discipline, la modélisation cherche à améliorer le jugement et la décision, mais la modélisation demande un temps important. Si bien les environnements interactifs d'apprentissage basés sur ces modèles permettent d'économiser du temps, il y a des doutes concernant la profondeur des apprentissages qu'ils permettent. Surgit la question d'un possible compromis entre ces deux positions qui permet d'atteindre des apprentissages profonds sans investir un temps important. Des exemples révélateurs de la discipline permettent d'identifier des activités-clé pour l'apprentissage. Sur cette base, une procédure structurée de « redécouverte guidée » est proposé comme compromis faisable et satisfaisant, permettant une exploration pertinente en posant des questions, en faisant des expériences afin d'obtenir des réponses et en les interprétant correctement. La procédure est présentée ensemble avec des propriétés fonctionnelles d'un « exploratoire systémique ». Ainsi, des non-spécialistes peuvent découvrir des « insights » concernant des situations complexes qui aident à améliorer les politiques de décision.

Mots-clés : Dynamique des systèmes, Environnement interactif d'apprentissage, Modélisation, Exploration, Apprentissage par découverte

1. INTRODUCTION

A model is a reduced, simplified version of an object or a phenomenon, and it may be built with varying purposes. One of the main goals of system dynamics modeling is to trigger deep learning, often referred to as conceptual change. In its original version, the process of *modeling* was supposed to lead to important insights into how a causal structure drives behavior over time. However, the proliferation of easy-to-use computer interfaces and software has made it possible to produce models and build simulation games that intend to purvey such insights from interacting with readymade *models*. Proponents of this approach argue that full scale modeling requires previous learning of modeling technique and a time-consuming work process; at the same time, orthodox dynamicists hold that only this effort leads to worthwhile insights.

Our question in this inquiry is: *can there be a third way, which requires less time and previous knowledge than modeling but still yields conceptual change?* This article proposes that it is indeed possible inside system dynamics, and its argument is based upon elements taken from various pieces of work inside the field. Analysis of these examples leads to a prototypical process of "guided rediscovery" as a means to reduce the amount of time and prior knowledge required, yet still produce conceptual change.

The article is organized in the following way. We start with a brief presentation of "modeling as learning", which is typical for system dynamics modeling. The following section analyzes the typical activities users perform during the modeling process and during the use of an ILE with respect to their learning effects. The subsequent section uses this to look at typical system dynamics products that were intended to foster learning. Based upon these comparisons, in the fourth section a process of guided rediscovery is proposed in order to incorporate the most relevant learning effects of modeling into the exploration of a model. The fifth section discusses the learning types such environments should be expected to support, in order to call for further research in this area.

2. "MODELING AS LEARNING" IN SYSTEM DYNAMICS

2.1. Decision policy design supported by modeling and simulation

In the modern society, many decisions are taken inside complex and dynamic social systems like business firms and non-profit or governmental organizations. In such systems, interacting feedback processes govern behavior: the information available about the situation frames the decision, and (upon implementation) the decision changes the situation. Even though decision makers may have some influence, frequently such systems resist change and display unintended side effects (Sterman, 2002).

One means for improving human judgment and decision under such conditions is system dynamics (Forrester, 2007). It is based upon the premise that in social systems (where decision making occurs), closed feedback loops are pervasive: virtually any decision one can take affects entities that in some way influence the situation in which this decision is taken. It follows that in any relevant situation decisions will have many effects in different parts of the system. The dynamic complexity of

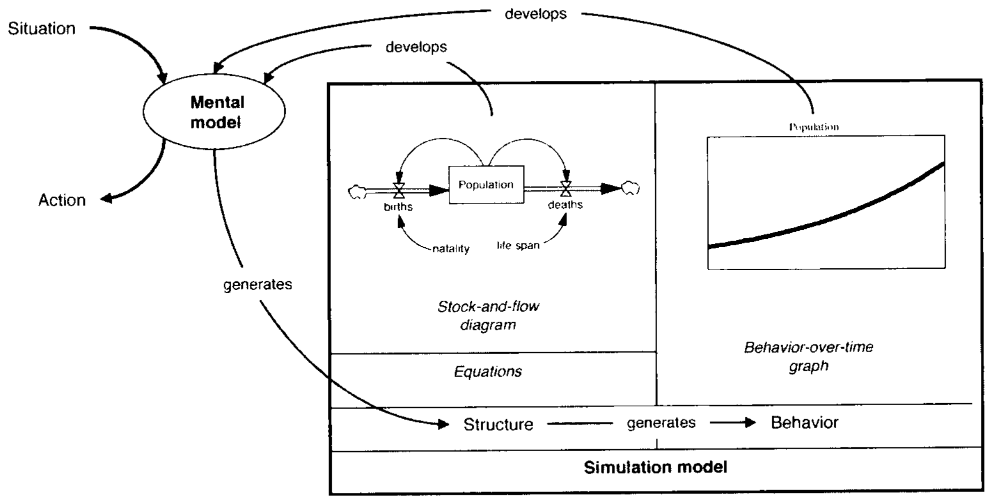


Figure 1. Modeling for learning.

models with feedback loops makes it hard to intuitively infer the behavior. However, a sound comprehension is the base of efficient action, so there is need for help. According to system dynamics, computer simulation is this help for developing the comprehension and also as a way to test possible decision policies in a low-risk setting.

The decision maker's mental model frames which information is taken into account and how (Doyle and Ford, 1998, 1999); mapping the structure of the situation is one channel for developing the mental model (Figure 1). Then, simulation is used to coherently derive behavior from this structure; the "surprises" that arise during simulation help to surface erroneous ideas and allegedly lead to "insights" that further develop the mental model (Mass, 1991). Simulation is necessary because – just like the systems they strive to represent –, system dynamics models are complex constructs with three different levels of description (Forrester, 1969). The most detailed level would be the variables and their connections with neighboring variables: each variable represents some part of the modeled situation; there also is some kind of behavioral rule (equation) that represents how this variable depends on the preceding ones. The next level is the feedback loop, which has a behavior of its own, emerging from the individual variables' behaviors. The highest level is the whole model: its structure is the superposition of all the feedback loops and its behavior emerges from their interactions.

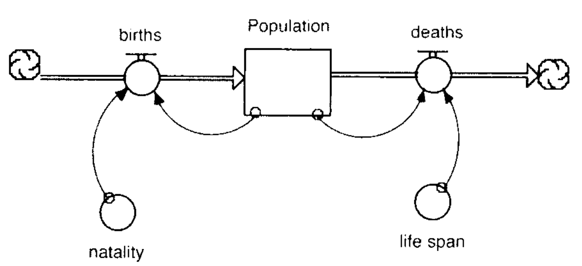
Additionally, if the real world is the only source for probing and improving mental models -where experiments cannot be conducted- then a computational representation of the mental model of the situation may allow for such experimentation and provide an avenue for improving the mental model (Sterman, 2000).

2.2. Developing simulation models versus using them

In conceptual terms, system dynamics posits that one can represent the entities in such systems as accumulations and flows -frequently with nonlinear and delayed relationships amongst them- from which feedback loops emerge (Lane, 2008). Much importance is given to representing only the information that decision makers do have and take into account, as well as the way they actually use this information (Sterman, 2000). In this aspect, system dynamics has a commonality with naturalistic decision making (Todd and Gigerenzer, 2001). However, rather than searching to develop scientific theories of human decision making, system dynamics strives to improve policy makers' mental models – even though some threads of research may come close to each other. For instance, in the "stock and flow thinking" studies (Booth-Sweeny and Sterman, 2000, 2007; Cronin and Gonzalvez, 2007), pattern matching heuristics have found to be important. Still, this research concerns itself with how such heuristics turn out to be deceptive rather than 'fast and frugal' (Todd and Gigerenzer, 2001).

Even though "causal loop diagrams" – the diagram technique used at the level of feedback loops – are intuitive to use, the benefit of such diagrams comes from simulating their behaviors, which requires executable equations to be developed; this means the modeler has to create a set of finite difference equations. The mathematical requirements of this task are high, and so system dynamics has remained a field for specialists from its start in the late '50s until the mid '80, when the first personal computers with a graphical user interface appeared on the market. This reduced the complexity of modeling because it allowed non-specialist users to develop the model structure by diagramming, like shown in figure 2.

In the figure, the diagram represents a population where births (depending on population size and natality) augment population and deaths (depending on population size and life span) reduce population. This can readily be seen from the diagram, which shields the user from the computational details included in the equations. It is easier to conceptualize this when it is presented as a diagram, rather than directly in the form of the equations.



This diagram expresses:
- *births* add to *Population*
- *deaths* reduce *Population*
- *Population* influences *births*
- *Population* influences *deaths*
- *natality* influences *births*
- *life span* influences *deaths*

implies (and hides)

*Population(t) = Population(t - dt) + (births - deaths) * dt*
INIT Population = **100** {individuals}
*births = Population*natality* {individuals/year}
deaths = Population/life_span {individuals/year}
life_span = **70** {years}
natality = **0.1** {%}

The variables for each equation are automatically derived from the diagram. The modeler has to specify initial values for stocks, mathematical operators and parameter values (printed fat).

Figure 2. Diagram and equations.

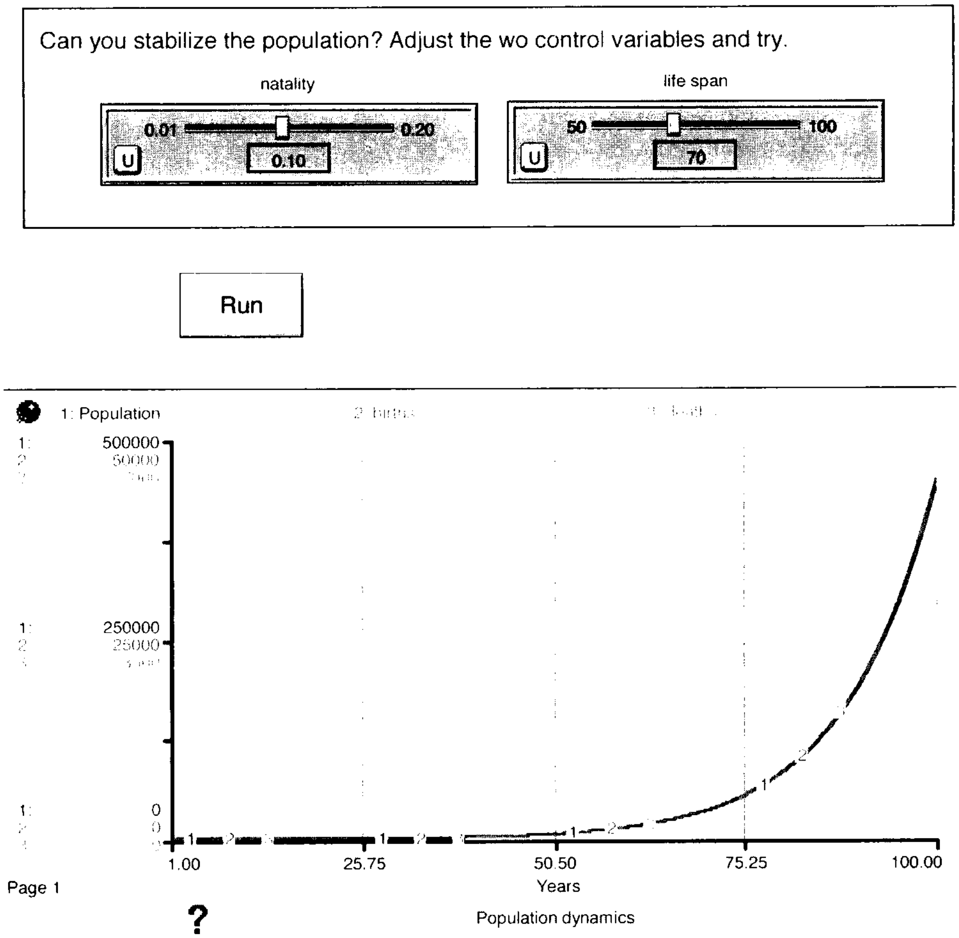


Figure 3. Gaming interface.

Soon afterwards, some system dynamics software packages also allowed users to create simulation interfaces that shield the user from even the diagram representation of the simulation model. Then it became possible to encapsulate these models in simulators to make them available to others who had not taken part in the modeling process.

In figure 3, the two parameters can be adjusted by the user who then can run the simulation and see the population's behavior on a graph pad. Now it is not even necessary to read the diagram in order to interact with the model.

If it is possible to "transfer" learning and important insights to other people, much time could be saved with these interfaces, since "using" a model is faster and simpler than "producing" one. The underlying hope was that one could trigger enduring change in mental models by making simulations available in this way (Morecroft, 1994). From early on, in contrast to this shielded approach, it was seen as essential that the model must be transparent and open to modifications (Davidsen, 1994). Some authors reported from "model-supported case studies"

(Graham *et al.*, 1994), others spoke of a "management-flight-simulator" approach (Bakken *et al.*, 1994). Over the following years, many such simulators have been developed under different names. Some were called "microworld" - borrowed from the community around Seymour Papert, the father of LOGO (Papert, 1993). Already at this time, problems with computer-based learning environments were acknowledged and mitigation strategies proposed (Isaacs and Senge, 1991). Important topics for designing such artifacts have been identified (Grössler, 2004). In an attempt to establish a taxonomy, Maier and Grössler (2002) proposed the term "interactive learning environment" (ILE), which we will use here.

While these developments were taking place, skeptics have argued that what is learned during the process of modeling cannot be learned by simply interacting with a predetermined model (Forrester, 1985). Firstly, there is no such thing as a truly finished model, and any product like a book (or, for our purpose, an ILE) is "only a snapshot in time and catch[es] but a single step in a continuously evolving set of ideas about a social system. [...]The very nature of such a book tends to mislead the reader into feeling that there is greater commitment to the precise structure than is in fact true." Thus, work based upon a model the way it is at a given moment in its evolution could never yield more than the understanding the modelers had built up until that moment. Forrester wrote that "rather than stressing the single-model concept, it appears that we should stress the process of modeling as a continuing companion to, and tool for, the improvement of judgment and human decision making."

Forrester (2007) maintains that any simplification that takes away the mental effort of modeling would endanger the main goal of system dynamics (p.363), which he describes this way:

> "Through an appropriate simulation model, one should know the structure causing the problem, should know how the problem is created, should have discovered a high-leverage policy that will alter behavior, should understand the reasons why the low-leverage policies will fail, should be able to explain how strongly defended policies within the system are actually the cause of troubles, and should be able to argue for better alternative policies. Everything that one says should fit into a totally consistent story, which is possible when built on insightful computer simulations."

2.3. Rediscovery as a compromise between developing and using a simulation model

There may be good reasons *not* to engage into modeling, the most obvious being the time required to learn modeling and the time required to develop one model up to being able to "enter a complex dynamic situation and aspire to be the only person present who can talk about the issues for 20 minutes without contradicting oneself" (Forrester, 2007:363). Also, learning goals may be less ambitious: one may wish to awaken a sense of problem in a wide non specialist public by publishing a non technical book. Or, one might desire to make students of economics understand the economy as a dynamic system without studying system dynamics. Or the goal might be to help a management team develop an approximate understanding of the problem and one recommendable solution strategy.

However, if we seek to achieve the high staked goal of conceptual change, observe that modeling is a means (not an end in itself) and that one simulation model (if it is appropriate) can suffice. We will now inquire relevant examples of learning-oriented system dynamics work, in order to design the process of "guided rediscovery" in the subsequent sections, as a possibility to find a third way, in-between full-blown modeling and simple simulation use..

3. ACTIVITIES AND LEARNING IN SYSTEM DYNAMICS AND ILES

3.1. Model explorers need external structure

Most ILEs are based on a simulation model that contains generic structures, and exposure to them is intended to foster the generation of mental structures (Maier and Grössler, 2002); users are supposed to infer the characteristics of the model underlying the simulation (de Jong and van Joolingen, 1998; van Joolingen, 1999) by a discovery process which is strikingly similar to system dynamics modeling (Table 1).

Learners have to move across two spaces: a hypothesis space and an experiment space. The hypothesis space is the set of all possible rules describing the studied phenomenon. The experiment space is the set of all possible experiments. Several different problem areas have been found in relation to the way in which learners traverse these spaces:

- Hypothesis generation may be hindered by not knowing what a hypothesis is, by not being able to adapt an hypothesis to data and by being led by considerations that do not help to find the right principles;
- The design of experiments may be hindered by the confirmation bias (searching data that confirms a hypothesis rather than the contrary), inconclusive experiments (that do not help to refute false hypothesis), inefficient experimentation and the desire to achieve good results (rather than testing hypothesis).
- The interpretation of data may be hindered by wishful misinterpretation and difficulties at interpreting graphs.
- Weak regulative capabilities usually lead to poor learning results.

Inside the domain of system dynamics-based learning environments, it is stressed that the model is not a black box, and the approach is often called "transparent-box", when the underlying simulation model ban be directly accessed and explored. However, there are reasons to believe that users do not take advantage of this possibility: many rush to action, either because they are just playing or because they prefer acting over reflecting.

Discovery learning	System dynamics
• define problem; • state hypothesis; • design experiment; • observe, collect and interpret data; • apply results; • make predictions.	• define problem and purpose of the modeling; • develop a dynamic hypothesis; • quantify and validate a simulation model; • exploit the model (designing and conducting change experiments and analyzing the results) to derive a conclusion; • implement the conclusion and evaluate.

Table 1. Comparison between discovery learning and system dynamics modeling.

In terms of the concepts and theoretic aspects implied by system dynamics models, users will lack relevant long term memory structures (Merriënboer and Liesbeth, 2005; Meyer, 2005, Sweller, 2005) and be subject to the well-known restriction of 5 +-2 items (Miller, 1956). So they need some external help that makes up for the lack of long term internal structure. Only such "guidance" will allow them to take advantage of the possibilities given by the "transparent-box" approach. The same holds for the cases where learners are supposed to make use of specific representation languages and methods.

Many times, even if they looked at the model structure, they would not understand the dynamic implications; the cognitive shortcomings in stock-and-flow thinking are well documented (Booth-Sweeny and Sterman, 2000, 2007, Sterman and Booth-Sweeny, 2002, Cronin and Gonzalez, 2007, to mention only the most prominent ones; refer to these articles for more references). A user who does not intuitively know how a stock variable relates to the incoming and outgoing flows may simply not grasp what will be going on when the model runs.

Several ways to help are proposed (de Jong and van Joolingen, 1998):

- previous access to relevant domain knowledge;
- help for hypothesis generation;
- support for experiment design;
- support for regulation (planning and monitoring).

According to these above, it is both necessary and possible to provide external help or guidance to inexperienced individuals who wish to understand a phenomenon and could benefit from the use of a simulation model. This guidance should take the form of mediating prompts that lead to asking the right questions to generate hypothesis, doing convenient simulation experiments, correctly interpreting the resulting data.

3.2. Learning as development of mental models

Judgment and decision stem from mental models of a dynamic system: "a mental model of a dynamic system is 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 that system" (Doyle and Ford 1998, 1999). The learning challenge is to develop a sufficiently detailed, accurate, coherent and conscious mental model. The following figure illustrates the case for ILEs.

If there is a situation S and an "appropriate simulation model" $SM(S)$ of it, the ones who built it will understand S because they understand SM – they have elaborated the modelers' mental model MM_m of S by building $MM_m(SM(S))$. If SM becomes the heart of a simulation game of the "black-box" type (for instance for purposes of experimentation), then users cannot directly perceive it and many activities that are relevant for learning become impossible to perform. If one builds a "transparent-box" ILE, users will be able to perceive SM, but they did not elaborate their mental model MM_u yet. This will happen by the formulation of questions and hypothesis with the appropriate help mentioned above.

For those who develop system dynamics simulation models, the figure 5 represents the typical sequence.

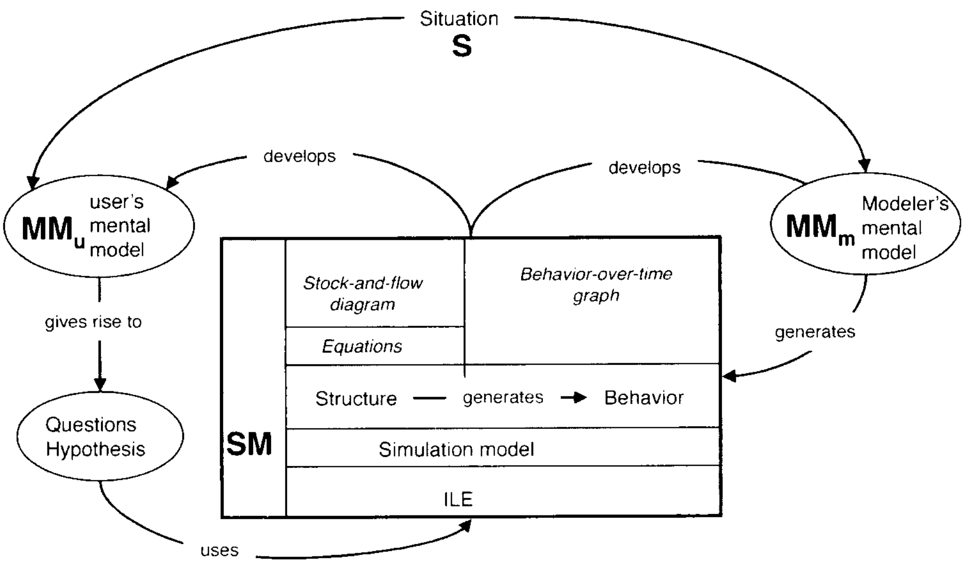


Figure 4. Learning with an ILE.

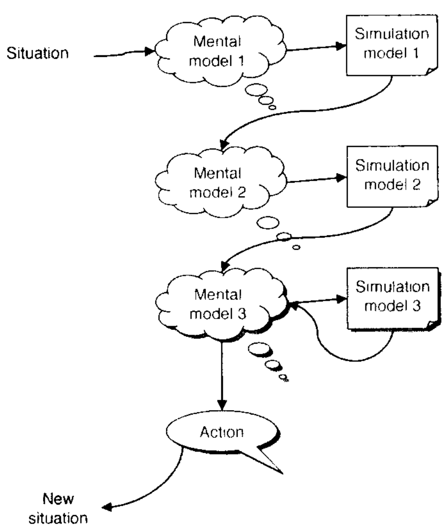


Figure 5. Interaction between mental and simulation model for modelers

The problematic or challenging *situation* is represented by an initial *mental model 1*. Now an iterative process of formulating the simulation model begins. Interaction with *simulation model 1* leads to *mental model 2*, which in turn leads to reformulating the *simulation model* into a second version. In the figure, the process comes to a provisory stop with the respective third versions of the *mental* and *simulation model*; some *action* is derived on base of the now ruling *mental model 3*, and this helps transforming the initial *situation* into a new *situation*. This in turn may trigger a new round of modeling, but we halt at this point.

The sheer fact of creating the stock-and-flow diagram with tentative equations as "external knowledge representations" has learning effects, mainly "clarification or elaboration of a learner's own conceptual understanding of a problem space" (Stoyanov, 1997, cited in Lee *et al.*, 2005, p. 118). However, in system dynamics, the model is more than a static diagram.

It is common to divide the process of modeling into the conceptualization and then quantification of the model, followed by the validation or testing (Sterman, 2000, p. 86). Surely the limit between the "formulation" and the "testing" phases is rather diffuse in practice: the model developer needs simulation to see if his expectations are adequate; usually, there will be "surprise model behavior" and it is not clear if it stems from errors in the mental model or in the simulation model. Modelers use specific tactics in order to find out, and relevant insights arise during these explorations (Mass, 1991). During this work, many questions arise and the modeler has to manipulate the simulation model to answer them. By asking questions and answering them, he arrives at insights. Not all the questions may turn out to produce insights, but this can only be known afterwards, and the modeler does know this after having arrived at an "adequate" simulation model. So the reason why one can stand up and talk about the situation without running into contradictions is that he has already run into all thinkable contradictions before – which is doubtlessly why the process takes so much time and why personal experience is so valuable.

4. ACTIVITIES IN VARIOUS LEARNING ENVIRONMENTS

For those who do not conceptualize and formulate the simulation model but get into touch with an artifact based upon this simulation model (a book, an ILE), the activities are different. With this in mind, we will now visit various "learning environments" and compare them to the fullest possible system dynamics learning environment, which is the modeling and simulation software itself. In doing so, we will only use "transparent-box" cases, that allow users at least to look at the underlying model (recalling the limitations mentioned in the section on discovery learning). For each example, we will ask how they relate to the activities of the full modeling process.

4.1. A classical case of system dynamics ILE

Davidson (1994) describes a sequence for working with ILEs consisting of the following steps: make assumptions about the environment (which gives users an initial context for getting started), formulate a strategy, submit it to the computer, let the computer compute the behavioral consequences, evaluate the consequences of the strategy, repeat the previous steps. During the investigation process of finding out what went wrong and formulating strategies, the model itself can be viewed in its behavior, its causal loop representation and as a stock-and-flow model, where equations can be seen and modified, and variables needed for policy formulation can be added.

The figure 6 represents the sequence, ready to be compared with the reference sequence of figure 5.

For the ILE users, the initial *simulation model* replaces the initial *situation*. In principle, users can do whatever they need with the simulation model in order to understand the causes of its behavior. They may experience "surprises", which presumably stem from errors in their mental models. By the time they have been able to formulate a strategy without surprising consequences, and are able to explain why this is the case, they can claim to have sufficient judgment and decision capability.

To the extent that the users of such an ILE do not bring with them the technical skills of the system dynamicist, they may not be able to see the possibility of diagnosing their surprises. This may be overcome by adding a facilitator into the environment.

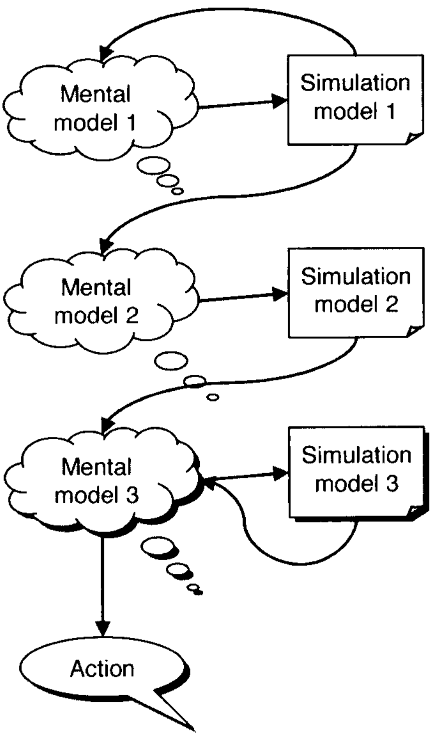


Figure 6. Davidson's 1995 ILE case.

4.2. The World dynamics book and model

The "World dynamics" book (Forrester, 1972) was the book written "around" the first world dynamics simulation model. The book presents the stock-and-flow diagram, each of the variables is introduced in word and equation (or graphic function), and each of the important feedback loops is presented and explained. Then the base-run and further scenarios are discussed. The interested individual can re-build the simulation model or download it from the Internet, and engage in an active exploration of it.

Of course, the model has some more feedback loops than those explained in the initial chapters, and the naive explorer might spend much time trying to figure out just what matters in this model. But then, the book's author has already done the exploration and understood what matters; the "why" of the model formulation can be read in each variable's justification. Each important loop is already identified and can be put to run in isolated manner, to explore its workings. For the base run and scenarios, the key variables are explained in the book and the explorer can trace back from them through the loops of the model. In other words, the modeler's understanding guides the reader/explorer and saves him a lot of time. Still the explorer can have some "surprises" and ask himself some questions. By elaborating the answers, he will develop a mental model that will allow him to stand up and talk about the subject.

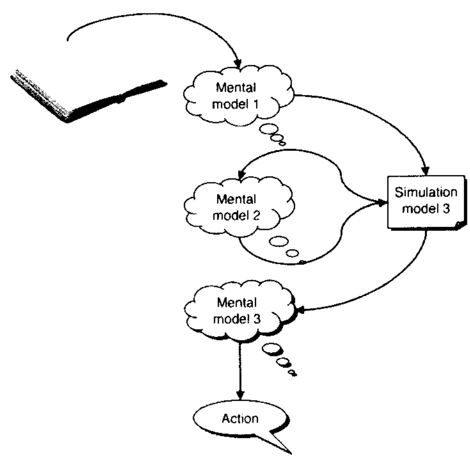


Figure 7. The world dynamics case.

Comparing figures 6 and 7, the initial *situation* has been replaced by a *book*. Also, since the *simulation model* has been tested and all devices for scenario runs are already built into it, it will probably not change during the process. However, the explorer's *mental model* will go through changes on this way.

Can we consider this to be an ILE? As mentioned above, each modeling/simulation software package is a most complete ILE: these environments allow their users to see and modify a model and ask it just any question they consider important. However, they come without the model. This book adds the model. As far as readers bring with them the dynamicist skills for interacting with this re-built model, the process has all the chances to work.

The possibility of using books like World dynamics as ILE depend on the readers' model exploration skills: those who do not know how to manipulate the model and the software in order to experiment and trace through would need some additional guidance.

4.3. MacroLab

Some ILEs do not intend to involve their users into system dynamics modeling for some relevant reason. One example is the MacroLab environment (Wheat, 2007). This package is used for teaching macroeconomics to students who are not intended to learn system dynamics. It contains a simulation model of the US economy and the "rest of the world", as well as a set of interaction devices. Students taking this course have to develop understanding of employment and part of their tasks is predicting and problem solving. They can explore the underlying model using STELLA's "storytelling" mode and for each task, causal-loop diagrams are displayed.

MacroLab offers a rich set of interactions, and purposefully engages its users in the development of causal loop diagrams. For the reasons mentioned above, the possibilities to interact with the model are limited. MacroLab may thus be used as an example of the state of the art in system dynamics ILEs.

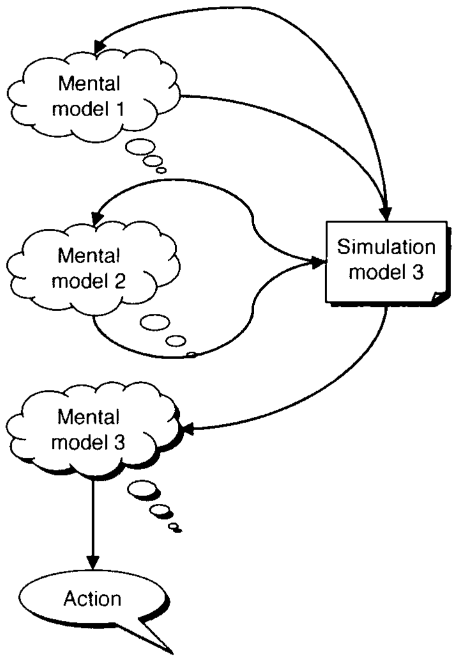


Figure 8. The MacroLab case.

The users get into touch with the *situation* in form of the ILE which contains various modes of non-SD presentation. They are challenged by tasks that require the use of causal loop diagrams, representing important parts of the underlying *simulation model.* The users cannot modify the *model's* structure by inserting variables or changing equations; however, they can change the operation of the model by deactivating/activating loops and sectors and they can switch between historic and experimental mode.

All this interaction with the underlying model helps them to build *mental models* that enable them to outperform peer students that have studied the matter in a traditional manner (Wheat, 2007).

4.4. Discussion of the examples

Each of these examples allows us to see an important aspect of learning with models. Davidson's case shows that it is not necessary to conceptualize and formulate the simulation model in order to engage in diagnosing activities. It also indicates that this, by itself, is not enough to help individuals without model and software manipulation skills to do the explorations.

The World dynamics example shows that the modeler can give a lot of guidance to the users of his model, and that it may not me necessary to build a sophisticated interface between the simulation model and the user. Like the first example, we saw that unprepared readers would need model manipulation guidance. The example also shows that it is useful to walk the user through the three different levels of description of a system dynamics model

The MacroLab example shows that alternative means of representation can constitute a progress over traditional learning environments (in this case, the economics textbook with its typical graphics), but it is plausible to assume that those who dig into the simulation model would go further.

If we can provide an environment that guides a user through asking questions, obtaining answers and interpreting them, along with an itinerary that takes users across the different levels of the model and is able to combine different representational means, we can indeed help them re-discover relevant insights that the original modeler has made before (during the model quantification and validation process). For the inexperienced individual, elaborating mental models $MM_{II}(SM(S))$ without having to build $SM(S)$ in the first place is a process of discovery. However, since it is not an original discovery, it is suggested here to consider this a re-discovery. That which is discovered is a causal understanding of why the model behaves in a particular way and why a certain intervention has this or that effect.

It might also be that at some points, more fundamental insights concerning the relationship between the model's structure and its behavior are reached; for instance, the individual may come to grasp the principle of stock-and-flow thinking (Booth-Sweeny and Sterman, 2000; 2007) and from then on have a more accurate understanding of stock-and-flow components in general. In these cases, we would be reminded to Bateson's "learning 2", where a subject learns regularities concerning a context (Bateson, 2000). This is, though, a hypothetical possibility which is currently not backed up by empirical observations.

A prototypical procedure for guided rediscovery will now be presented together with the architecture of the learning environments in the following section; we call this kind of environment "systemic exploratory".

5. GUIDED REDISCOVERY AND SYSTEMIC EXPLORATORIES

5.1. Goals and requirements for systemic exploratories

Systemic exploratories should enable users to develop a successful decision policy in some meaningful, dynamically complex problematic situation, as opposed to receiving training for one particular decision. Users should be able to justify their policy based on a causal-loop diagram of their own elaboration, which will be considered as the expression of their mental model: sheer performance would not allow us to know if *understanding* has changed. In these two points, a systemic exploratory is different from usual ILEs. This subsection presents the special functional features of these tools.

To truly understand a model means to truly understand each of its variables individually, as well as each loop and the whole model. Such understanding is the fundament for decision policies (in our case). Designing the user's itinerary from his initial state of ignorance towards understanding is not trivial. To understand the model, each feedback loop has to be understood; however, each loop depends on what is going on in the rest of the model. At the level of the individual feedback loop, one has to understand each of its variables, and again each variable depends on the rest of the loop. The user's mental focus cannot be put on several levels at the same time, so there has to be a sequential path.

Since the first thing to appear – even before modeling begins – is the entire situation, it may appear reasonable to start at the level of the whole system and to move from the general to the particular, and then go back from the bottom upwards. This is the way taken by *World dynamics* (Forrester, 1972) and Morecroft's textbook (2007). Many educators (like Montessori) believed this to be important if learning is to be meaningful and enduring.

The first contact users have with the case is with the whole model, and then they are taken to the level of the individual variables. From there on, they proceed to the individual loops and eventually, they return to the whole model. This combines the need for context with the need for bottom-up understanding. Thus it is a functional requirement that the learning environment guides the learners through this itinerary: whole-model context → individual variables → individual loops → whole model.

The modeler comes to insights because he has to find answers to the surprises the model generates; he then knows what the important surprises were and where/how to search for answers in the model. If he can pass on these questions to an explorer (model user) in such a way that they replicate the searches of the modeler, then the model user can gain the same understanding as the modeler. Accordingly, another functional requirement is that the user has to be prompted to think on his own, because we want him or her to develop their own mental model. Asking questions is one involving way to prompt thinking[1]. So the exploratory is like a workbook where the users are asked questions that will trigger the elaboration of a response for each item we want them to understand. Together with this, it is important that each response be corrected before proceeding to the next question: this is to make sure that we do not continue on a faulty base, and also because rapid responses augment user satisfaction.

One especially important issue is the need to understand the relationship between structure and behavior at each of the levels and with each of its entities. Our users will not be experienced dynamicists, so they will generally not have an intuitive understanding of this relationship. We believe that such understanding can be trained by repeatedly passing through a sequence of questions:

- what is the formula? what will it do (predict numerically or the shape of the graph) in this or that case?
- simulate; what did it do?
- why did it do this?

1. The exercixe books by Diane Fischer (2001; 2004) are a good example.

A "systemic exploratory" is an ILE that incorporates these functionalities and guides users towards rediscovery. The discovering itself can only be done by each individual.

5.2. The process of guided rediscovery

The following procedure indicates a sequence of activities that guides through the different levels of the simulation model in the appropriate way. A systemic exploratory should therefore be structured according to the same procedure.

1. Go through the introduction to the case which includes references to the problematic behavior of key indicators.
2. Inquire at the level of individual variables, based on their introduction in the text. Describe each variable and its links from the viewpoint of its structure (equation or table function), its behavior and its relationship to the linked variables (causal diagram).
3. At the global level:
   a) Develop a causal diagram indicating the respective equations or table functions of each variable.
   b) Identify the loops and their respective polarities.
4. Identify a key variable and draw its desired or expected behavior over time.
5. Simulate the model. Describe the key variable's behavior and separate it into episodes of distinct behavior (linear, exponential, logarithmic, oscillations). Describe each episode in words.
6. Compare the expected and the simulated behavior, for each episode. Ask "why did the variable behave this way?" and "why is it different from my desire or expectation?"
7. For each of the individual feedback loops (contained in distinct models), do the following:
   a) Identify an important variable (the key variable or some other variable that calls your attention) and explain your choice.
   b) Simulate the model with different values for the variables on the border (that have been cut off the other loops). Describe the behavioral episodes.
   c) For each episode, ask "how did the variable come to behave this way?" and then:
      i. Develop a causal loop diagram including the behavior graph of each variable and answer the question (in words).
      ii. Write the answer into the loop on the main causal loop diagram.
8. Answer the two questions from point 6 using the main causal loop diagram, in text format.
9. Develop an action plan for having the model generate the desired behavior in the key variable. Justify the plan with reference to the causal loop diagram. Use the gaming version of the model to corroborate the plan.
10. Explain the outcomes of the simulation and how it compares to the desired outcome using the causal loop diagram.

This procedure is the first attempt to build a bridge between the domains of modeling – *chasse gardée* of trained specialists –

and model use. In all the examples, books or a human facilitator are used, and users are not required to systematically explore and understand the model beyond reading the book or replicating indicated simulation experiments or simulation games.

5.3. First experiences

An initial version of this method guided the development of a first prototype that took the form of a printed workbook built around a simple fishery model published in the first chapter of Morecroft's textbook (2007). Besides a slight modification of the steps, two inconvenient features of the paper version were detected: there is no possibility of autonomous error correction and it takes too much time to go through the whole process in one session. As long as the workbook is a printed artifact, errors can only be detected and corrected by a human facilitator, which limits the learners' autonomy; still it is important to check each choice of the user before allowing him making the next one. The length of the workbook (40 pages for a model consisting of 3 accumulations, 5 flows and 5 auxiliary variables, making up 3 feedback loops) lowers learners' motivation for sticking to it until the end. Currently, we are developing a second version of the exploratory with Authorware, a authoring software. We plan to develop a second exploratory based upon the "boom and bust" pattern.

6. PRELIMINARY CONCLUSIONS

6.1. On guided rediscovery

This article has elaborated a conceptual framework and a process that suggest the possibility of obtaining conceptual change from model exploration and avoid the need for model development without sacrificing the depth of learning.

By looking at those modeling activities that are particularly important for learning, it was found that the key to learning is to find the right questions to ask, know how to obtain responses from the simulation model and know how to interpret them. If an individual is guided through a system dynamic model to ask, experiment and interpret at its different description levels – variable, single loops, loop set – then it is theoretically sound to expect "insights" to be produced. The proposed "guided rediscovery" procedure and the described functional characteristics allow us to develop "systemic exploratories": interactive learning environments that support these activities, without losing the possibility to ground the environment in one existing simulation model.

At the conceptual level, "guided rediscovery" has the possibility to reconcile strongly antagonistic positions held in the controversy between "model development" and "model use".

6.2. Does guided rediscovery yield better learning?

The contribution of this paper is conceptual. Even though it is logically coherent with available experience in the system dynamics field and with what is known about "discovery learning", empirical research is now called for as the next step. Such investigations are currently under way, in order to find out to which degree users of an exploratory perform better than users of a traditional ILE and if they are able to give better causal explanations. Our hypotheses are:

Hypothesis 1: users of the exploratory perform at least as well as individuals that have to resolve the same task without previous guided rediscovery.

Hypothesis 2: users of the exploratory articulate a more accurate mental model in their explanations.

These hypotheses are consistent with current thinking about "discovery learning" (Penner, 2000; Mayer, 2006b). We define "accurate" as being similar in variables and feedback loops to the underlying simulation model. Experimentation takes place with two groups of students – exploratory and ILE. Both groups receive the same introduction into causal loop diagrams in the introductory part of their respective supporting material and have to do the same task interacting with the same model through the same interface. Their performance will be directly comparable. The analysis of the articulated mental models of a system dynamics model will require some previous methodological development, since the usual methods have some differences and do not take into account the feedback loop concept [2] (refer to Schaffernicht and Grösser, 2009).

6.3. A look into the future

In his outlook over the next 50 years, Forrester (2007) reminds us that K-12 education (in system dynamics) is still introductory, that there are no schools of education where teachers receive proper training, and that universities are not designing or running 4-6 year long programs in system dynamics.

We dare to imagine that exploratories which implement guided rediscovery may become a step into the following direction:

> "Such a management education will evolve over time, but we might start with the following image. Suppose that we had some 20 generic structures that would cover more than 90 percent of the situations that a manager ever encounters. One example would be a production/distribution system such as dates back to the earliest days of system dynamics. Each such generic structure would require a separate textbook [...]" (Forrester, 2007: 368)

We believe that the type of workbook+ILE that we are developing, can be inserted into existing business school programs without previous curriculum reorganization. In the domain of managers and decision makers, the insights which can be reached through exploratories can improve dynamic understanding of business situations and improve intuitive stock-and-flow thinking.

The repeated use of such exploratories should have a second-level learning effect: repeating the typical sequence of how exploring a model shapes a context (Bateson, 2000) or paradigm (Kuhn, 1996). The dynamic vocabulary which thus becomes part of the current language, may well improve communication with modeling specialists and expand the use of more complete modeling in business situations.

2. For details concerning metal models, refer to Schaffernicht (2006; 2008) or Schaffernicht and Grösser (2009).

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Achevé d'imprimer le 19 février 2010 sur les presses de

52200 Langres - Saints-Geosmes
Dépôt légal : février 2010 - N° d'imprimeur : 8372