Learning in and about Simple Dynamic Systems

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Abstract

System dynamics-based interactive learning environments (ILEs) have been developed to address shortcomings in policy design and decision making with regard to complex systems. A primary purpose of these ILEs is to identify effective learning strategies for these domains. Typically, these ILEs are themselves complex, but little is understood about how we come to understand complex, dynamic domains. It is, therefore, difficult to identify causes for improved learning. We begin with the design of learning support for simpler dynamic system and present an instructional design strategy based on principles of graduated complexity and problem-based learning. Our methodology addresses the need for simple, understandable representations of complex realities. To establish that this design methodology is effective, it is necessary to conduct learning studies across a number of dimensions of complexity with variations in the design of the associated learning environments. We demonstrate examples of the design methodology and present preliminary results.

Introduction

The system dynamics community is firmly committed to and believes in the value of using system dynamics in order to improve understanding of complex, dynamic systems. Much has been written about the uses of systems dynamics to support learning in and about complex systems (see, for example, Sterman, 1994). Unfortunately, there is insufficient evidence to establish that or how system dynamics has contributed in significant ways to improved understanding. Moreover, what has been shown to be effective with system dynamics students and practitioners has not been established to be generally effective outside the system dynamics community. What is lacking is an instructional design methodology to support the design of system dynamics-based learning environments.

In order to make progress in this regard, we believe that the appropriate place to begin is with the design of learning support (i.e., instruction) for simpler dynamic systems. The focus of this paper, therefore, is on an instructional design methodology to facilitate learning in and about simple systems. The paper is primarily conceptual in nature, drawing on lessons learned from the system dynamics literature as well as from the cognitive psychology and instructional science literature. We have applied the principles illustrated here in a number of learning environments and will also present preliminary findings.

In order to develop an appropriate instructional design methodology for system dynamics-based learning, it is necessary to identify a number of relevant assumptions and then to elaborate a perspective on learning appropriate for supporting understanding in and about dynamic systems. We share with most system dynamicists the general belief that system dynamics has much to contribute to understanding complexity. Specifically, we shall assume that a learning environment that integrates system dynamics models and simulations can facilitate learning. We are especially interested in supporting those who are not system dynamicists in coming to understand dynamic systems. As a consequence, our first two assumptions are as follows:

1. System dynamics can be used to facilitate understanding dynamic systems.
2. One need not become a system dynamicist or skilled system dynamics modeler in order to understand a particular complex system.

The learning perspective which informs our thinking is based on principles derived from cognitive psychology, learning theory, and instructional design. The learning perspective we find most appropriate is based on notions derived from situated and problem-based learning (Barrows 1985, Lave 1988, Lave & Wenger 1990), especially as informed by cognitive flexibility theory (Spiro et al. 1987, 1988). Instructional design methods and principles consistent this learning perspective can be derived from elaboration theory (Reigeluth & Stein 1983) and cognitive apprenticeship (Collins et al. 1989).

In the course of elaborating these principles for the design of system dynamics-based ILEs, we shall indicate why such principles are relevant and how they can inform a design rationale. We shall pay special attention to the concepts of a unit of instruction (which has a single and identifiable learning objective) and a learning module (a collection of related units of instruction). We shall call our instructional design approach model-facilitated learning (MFL). Our fundamental argument is that MFL is an appropriate methodology to support the design of system-dynamics based learning environments for complex domains. We shall illustrate MFL for a simple dynamic system, because we believe that will make the methodology most clear and is in fact consistent with one of our primary design perspective, graduated complexity (Spector & Davidsen 1998).

A third assumption we share with many persons designing system dynamics-based learning environments is that a deep understanding of dynamic systems is based on an understanding of the relationships between structure and behavior. To put it differently, understanding how a complex system behaves involves being able to provide causal and structural explanations for observed system behavior, and, further, being able to anticipate and explain changes in those underlying causes and structures that may occur as the system evolves over time. This kind of understanding is not acquired easily nor is it likely to be acquired from observations of either real or simulated behavior (Dörner 1996). Additional support is required. This paper elaborates one way to conceptualize and design such support.

Broadly stated, we adhere to a principle we have called graduated complexity (Spector & Davidsen 1998), according to which learners are confronted with increasingly complex aspects of a problem. This principle is necessary due to the need to begin with simple, cognitive representations of complex realities. In the development of ILEs, implementation of this principle leads to graduated transparency and support for learner-directed evaluation. Yet another assumption, consistent with the principle of graduated complexity, is that learning is most effective when interactions are cognitively engaging. The design of cognitively engaging interactions and activities around system dynamics in order to support learning is, therefore, the primary focus of this paper. First, however, we wish to briefly review the relevant learning and instructional design theories.

Theoretical Background

As already indicated, we derive our model facilitated learning (MFL) perspective from learning and instructional theories. That these theories are reasonably well established and articulated but have not been embraced by the system dynamics learning community is somewhat disturbing. Situated learning (Lave 1988) is a general theory of knowledge acquisition which is based on the notion that learning (stable, persisting changes in knowledge, skills and behavior) occurs in the context of activities that typically involve a problem or task, other persons, and an environment or culture. This perspective is based on observations indicating that learners gradually move from newcomer or novice status (operating on the periphery of a community of practitioners) to advanced or expert status (operating at the center of the community of practitioners). As learners become more advanced in a domain, they typically become more engaged with the central and challenging problems that occupy a particular group of practitioners.

Situated learning has been most directly and successfully applied in the domain of medical training. The medical community has embraced the notion of problem-based learning, which is a particular application of situated learning theory (Barrows 1985). In the last twenty years, the medical community has gradually recognized that physicians gain diagnostic skills and understanding as a consequence of treating patients, not as a consequence of traditional medical training. In order to promote the acquisition of diagnostic skills and understanding, many medical training curricula now integrate clinical problems and experience into the education of physicians. Typically, small groups of learners encounter actual clinical problems and they work individually and together to develop a diagnosis and recommended treatment plan. The learning typically proceeds in five stages: problem presentation, problem analysis, problem synthesis, problem abstraction, and problem reflection (Barrows 1985). These stages are derived from clinical practice and integrate collaborative interactions that naturally occur among specialists in such settings. These stages are consistent with our notion of graduated complexity and fit nicely into the general instructional design guidelines provided by cognitive apprenticeship and elaboration theory. The particular stages that are emphasized in terms of our units of instruction described later in this paper are analysis, synthesis and abstraction.

Learning in complex and ill-structured domains places significant cognitive demands on learners, as appropriately recognized by the medical community. Ill-structured domains include those which do not remain constant over time, those which involve variables and constraints which are not well-defined, and those which are influenced in not easily predictable ways by a number of internal and external factors. According to cognitive flexibility theory (Spiro et al. 1987, 1988), understanding in such domains requires the following: the ability to construct multiple representations (mental models) of a problem; the ability to relate apparently disconnected parts of a system; and, the ability to integrate information on a holistic level (to view problem and system features as interconnected rather than as compartmentalized). As a consequence, learning to support the acquisition of such understanding should be designed so as to promote multiple representations, to promote appreciation of the underlying complexity of the system, and to promote the ability to interrelate various components of the system. Moreover, learning should be supported with a variety of problems and cases. Cognitive flexibility theory shares with situated and probem-based learning the view that learning is context dependent, with the associated need to provide multiple representations and varied examples so as to promote generalization and abstraction processes. Additionally, cognitive flexibility places particular emphasis on the importance of learner-constructed representations. In MFL, this would mean that learners are provided the opportunity and challenge to become model builders and experiment with those models. We agree that this is an appropriate activity for advanced learners, but model building and construction is not always required in order to understand dynamic systems. Moreover, we believe that the units of instruction to be illustrated are appropriate pre-cursors to model building activities.

Elaboration theory (Reigeluth & Stein 1983) is an instructional design theory, consistent with many cognitive learning principles, which argues that units of instruction should be designed in accordance with clear and consistent elaboration sequences (e.g., simple to complex, depth first, breadth first, etc.). The basic presupposition is that sequencing of units of instruction is a fundamental instructional design task that should not be taken lightly. The first item in an elaboration sequence should be an epitomizing example. An epitomizing example need not and should not demonstrate all of the complexity of the final targeted learning outcome, but it should be rich enough to provide learners with an appreciation for the scope and complexity of the problems associated with a particular learning module (collection of units of instruction). The goal behind a well-articulated elaboration sequence is to help the learner develop stable cognitive structures that can accommodate increasingly rich and complex subject matter. The particular elaboration sequence which we believe generally appropriate for complex domains is one that progresses from the relatively simple to the more complex, and we have already referred to that as graduated complexity. It should be noted that there some educational researchers draw on these same theories and argue that learners should not be provided simplified versions of real systems, and that some other elaboration sequence should be supported, or even that learners should be left to develop their own elaboration sequences. We find insufficient evidence to adopt such an extreme position. In other words, we do believe that there is a need to support and facilitate learning (i.e., to design instruction).

According to cognitive apprenticeship (Collins et al. 1989), one elaboration sequence which should be supported follows the path of the learner from novice to more experienced practitioner. Specifically, those new to a challenging domain require more initial support and guidance than more experienced persons. Consequently, there should be a variety of support structures to scaffold learning processes and assist new learners in developing appropriate representations of problem domains. As we shall illustrate, causal loop diagrams and stock and flow diagrams can provide relevant scaffolding. As learners become more sophisticated, the burden is shifted to the learner to provide explanations for observed problematic behavior. Consistent with cognitive flexibility theory, learners may even construct and test their own system dynamics models as part of the learning process. In this paper, however, we do not illustrate such units of instruction, although as already stated, we do believe that they can facilitate learning, especially for more advanced learners. We briefly address this issue in the next section and then turn to an elaboration of our units of instruction for a system dynamics-based ILE.

To summarize our overall learning and instructional perspective, we adopt the basic notion from situated and problem-based learning that concepts are best learned in a context of used – a problem setting in which it is then necessary for the learner to apply and use the relevant concepts. Such learning should improve retention by providing a clear and relevant context and it promotes transfer of learning to work-task situations by providing relevant aspects of a learning situation which can be realistically compared with real world settings.

Piaget (1929) argued that children pass through four identifiable stages of mental development: sensorimotor, pre-operational, concrete operational, and formal operational. There is a clear progression in these stages from physical action towards abstract reasoning. We believe it reasonable to extend the last two stages to adult learners. For a particular topic, learners may begin with concrete operations, physically manipulating objects in order to solve specific problems. As these operations are mastered, they can then progress to more abstract representations and solve increasingly complex problems. This is consistent with the notion of graduated complexity already presented. One such elaboration sequence for a set of MFL learning modules for an entire curriculum might be as follows:

1. Start with concrete operations. Introduce a specific problem in the context of manipulating physical things. The board game version of the Beer Game is typically used for such purposes. This physical manipulation of orders and shipments and inventories provides a setting in which the concepts of delays and feedback mechanisms are then introduced. This fits well with the classical notion of problem-based learning -- introduce concepts in a problem setting, especially one involving concrete objects which can be manipulated. In this context, the problem to be solved is how to place and fill orders in order to avoid excess, inadequate or badly oscillating inventory.
2. The next stage towards formal operational understanding is to introduce the first level of abstraction, still within the context of solving specific kinds of problems. This can be accomplished by asked students to engage in some kind of hypothetical reasoning. The problem to be solved then becomes something like this: What would happen if X does this, and Y does that, and Z remains constant, all within the context of the Beer Game. This shifts the problem-solving context into something more appropriately supported with a dynamic or interactive simulation so that alternative scenarios and hypotheses can be tried out. This kind of learning is more abstract and can be characterized as inquiry-based learning to indicate that it is a different form of

problem-based learning than that associated with the first and more concrete stage. A management flight simulator such as Beefeater or Peoples Express supports this stage of learning as has been demonstrated by a number of researchers (see, for example, Sterman 1994). At this stage, it is important to begin to form a holistic view of a system, and causal loop diagrams can help facilitate this process.

3. A higher level of understanding occurs when a learner is able to explain why things happen the way they do in a complex system. The focus of this kind of learning is not only to be able to predict what would happen under different circumstances but to be able to explain exactly why they will happen that way. In stage two, one formulates what one believes to be a reasonable hypothesis in response to an inquiry about a complex system and then checks to see if the hypothesis fits observed behavior (either in a simulation or in a real setting). In this more formal operational stage, learners are asked still more challenging questions about causes for and reasons underlyling observed and hypothesized behavior. This might be called policy-based learning to distinguish it from the second stage. At this stage it is important to introduce some representation of a system's structure so as to make clear exactly what kinds of feedbacks and delays exist within the system.

It is at the third stage that transparency becomes important for system dynamics-based ILEs, and it for this stage that we provide elaborated units of instruction consistent with the MFL perspective. By transparency we refer to the notion that learners need to be able to see through an interface to a high level representation (e.g., a causal loop diagram) through to deeper structures and causal mechanisms (e.g., stock and flow diagrams). Just as there has been a progression from simple and concrete to more complex and abstract when going from stage 1 to stage 3, within stage 3 we can image a similar progression from simpler representations to more complex representations, consistent with our principle of graduated complexity. The emphasis in the remainder of this paper is on the first level of elaboration within stage 3 of a system dynamics-based learning environment.

Learning by Modeling and Learning with Models

There is a general consensus among system dynamicists that learning that results from modeling a reality is more effective that learning that results from the use of a model that is made to represent reality (synthetic reality). There are a number of interesting questions to be addressed when making such a comparison, and it is not our intention to argue one way or the other on that issue. Probably, there is insufficient empirical data to support a definitive argument either way. One main point is, however, that modeling in the face of reality is quite a different exercise than experimenting with an existing model as if it represented such a reality. Our main questions are in which learning contexts and in which ways might synthetic realities be used to support and facilitate learning.

One way to compare these two learning approaches (by modeling versus with models) is by to challenge the learner to understand the synthetic reality in just the same way the modeler is challenged to understand reality. In that case, a synthetic environment should help us emulate the situation that a learner might later face as a modeler (consistent with the learning perspective already presented). In principle, one can come a long way, synthetically, towards providing such a realistic context for modeling. In that case, the synthetic reality is represented in the form of a model that is valid in the sense that the assumptions included serve as the basis for learning just as well as the facts of reality would have. This ensures that the learning gained from such a model is relevant and applicable to the reality it represents. In short, we accept the notion from situated learning that the learning context should be realistic and authentic. Furthermore, we accept the notion from the system dynamics community that identifying and understanding causal structures are critical for learning about dynamic systems.

In many ways, existing ILEs do not provide an appropriately rich environment to facilitate this kind of learning. Too often, ILEs do not provide a view of or access to an underlying causal model. Thus, learners cannot benefit from an explicit model centered approach to learning. We do believe that people, when confronted with an ILE, either consciously or sub-consciously, seek to capture or reconstruct that synthetic reality in some kind of mental representation, a representation that is internal, hidden (even from the learner), individual and intermittent. In the design of ILEs, little has been done to elicit an explicit representation of such mental models, although according to cognitive flexibility theory (Spiro et al. 1987, 1988) developing multiple mental representations is critical to understanding complex systems. In existing ILEs few tools and techniques have been made available to the learning for that purpose. In principle, however, there is nothing preventing us from furnishing the learner with such modeling tools and techniques. Moreover, model-based ILEs provide the learner with a synthetic reality that, in ways that are well known, offer a number of advantages to experimenting with and learning from reality (e.g., cost and time efficiencies). Moreover, providing learners with explicit models should facilitate their ability to construct their own models and internal representations. This premise is fundamental to our model facilitated learning (MFL) perspective.

As indicated, we are not arguing that emulating a formal modeling process is the only way by which we can learn about a complex, dynamic domain. There are other strategies for learning that could, conceivably, be successful. We do assume, however, that they all involve some kind of representation or modeling activity, at the very least the construction of a mental model. For that purpose, according to MFL, learning should be situated in a real or synthetic, complex, dynamic environment.

In the following discussion, we will focus on learning based on a synthetic reality (i.e., model-facilitated learning). This implies that we can assume that the designer of a model-based ILE fully understands (see below) that synthetic reality, and, based on that insight, can provide ILE support according to the principles of MFL to facilitate learning at different stages in a learner's development. In reality-based learning, the instructional designer is forced to rely on other methods.

Considerations behind the design of an Interactive Learning Environment

The point of departure for a system dynamics based activity is a problem, a conflict that exists between what is desired and what exists. The embodiment of such a conflict may range from a pure curiosity to be satisfied to the state trajectory of a system that does not follow an expected or a predetermined path. The real reference attributes with which the conflict is associated, are represented by the reference variables in a system dynamics model. The model is intended to represent the problem at hand. It is an expression of our understanding of that problem. To be more specific, the model embedded in a learning environment is intended to represent the system underlying that problem, and should generate the problem (reference) behavior. The reference variables are expected to reproduce the reference behavior, exhibited by the reference attributes, under the influence of the underlying model. If it does so for the right reasons (Barlas, 1996), the model can be said to embody a theory for why the problem exists. In system dynamics, such a problem identification is considered a prerequisite for problem solving. You need to understand the problem before you can set out solving it.

Understand is a key concept here as in other sciences. What we need to understand is the relationship between structure and behavior, - how the behavior characteristics arise from the structure and how the structure that essentially dominates the behavior, varies in response to the behavior exhibited over time. The ultimate target for learning in system dynamics is such an understanding acquired for the purpose of management. Such management might take the form of strategy development, policy design or, simply, decision making and implementation. Consequently, learning includes the application of systems understanding to the identification of a strategy, a policy or a decision that modifies the reference behavior of the system to a goal behavior.

By "complexity" in system dynamics we usually mean structural complexity. This implies that complexity is associated with the characteristics of the relationships that constitute the system structure. Implicit is the fact that we find it difficult to analyze dynamic systems that are characterized by a complex structure; i.e. to infer behavior from knowledge about the system structure. For the same reason, we find it difficult to synthesize dynamic systems for a particular purpose. When challenged to define the concept "complexity", we typically list feedback, delay, non-linearity and, possibly, uncertainty and vagueness, -- and we do so in a random order. We believe that this characterization leaves out the most significant feature of dynamic systems that contributes to complexity, the integration process. Consequently, our interactive learning environments are designed with particular emphasis on the integration processes that take place.

We also believe that a process that leads up to an understanding of complex, dynamic systems must rely on an alternation between analysis and synthesis. This implies that we must repeatedly synthesize models of component structures and subsequently analyze them in terms of their behavior. The process of synthesizing a model must be designed so as to ensure that the model never develops beyond the point of our ability to understand. For most purposes, the model is useless beyond that point. Consequently, it is of outmost importance to identify procedures to ensure that this constraint is being satisfied. We assume that it is not possible to understand a model as a whole unless we understand each of its components. The implication is that we always need to understand the model components we use before we synthesize them. It is a necessary, yet not sufficient condition to ensure that we understand the result of the synthesis. Such a packet of structure and associated behavior can be considered a unit of analysis or a unit of synthesis, depending on which mode of investigation we are in, related to the specific problem at hand.

A model results from a synthesis and, associated with that, there is, ideally, an understanding of that model, i.e. an understanding of the relationship between the model and the characteristic set of behavior patterns that potentially can be generated by the model. (Note that a complete systems understanding may not necessarily result from a modeling exercise). If we abstract from the specifics of that model and behavior, we obtain a generic model and the associated behavior, a general unit of investigation that potentially can be transferred and reapplied in a variety of contexts.

Each learning environment that we design should enable the learner to uncover a problem in accordance with the principle of graduated complexity. For that purpose we develop a number of Units of Instruction (UoI). They generate a behavior relevant to the problem at hand and do so for the right reasons, - i.e. based on a structure that has been proven valid. This implies that they reflect the current systems understanding. Each step of the way, the learner is expected to acquire and retain an understanding of the relationship between the structure and the behavior presented in the current UoI. For us to assess the level of competence, the learner is challenged to develop a policy so as to govern the system covered by a single unit of instruction.

So, what do these units of learning look like in a complex, dynamic environment and how do we identify them? And how do we utilize them for learning purposes? We have been struggling with these issues for a number of years and this is a brief report on some of our findings and suggestions. Since our results are preliminary, rather than presenting the them in the form of a theory, we would like to illustrate our line of thinking through the utilization of a generic manpower management model, - one that is being utilized in our system dynamics program. As such, our suggestions can be considered a contribution to the ongoing discussion regarding how to learn from using system dynamics and how to utilize system dynamics for teaching purposes. Note that many of our suggestions are far from original and must be considered an endorsement of current system dynamics practice. We do, however, annotate the procedure suggested with our own rationale.

In association with ILEs, we suggest some investigative principles be developed as part of a method for model facilitated learning (MFL). Such principles cannot determine the outcome of the investigation. There are two reasons for that: (1) Several of the principles will typically be conditioned upon the investigator's findings. (2) Even when these conditions are determined, the principles may still be open-ended and must be applied with discretion. In particular, there will be a large number of opportunities for branching out in such an investigation and, presumably, it is not always obvious which branch to follow. In fact, at each stage of the investigation of a problem, we can engage in a number of activities, one of which we need to select at any point in time. Yet, we do expect that principles of this kind will provide guidelines that improve the likelihood of a successful investigation. The examples provided are snapshots along the way to the learner's understanding of a system.

1. Challenge the learner to identify and characterize the reference mode of behavior, in short called the reference behavior

As we uncover a system, that system will be represented in a model. The system attributes will be represented by variables, and their properties by values. The reference mode of behavior is assumed to identify a problem. By implication, there is a preference associated with each of these system attributes, called **target attributes**, that defines the reference mode of behavior. In a model, they are represented by **target variables**. Target attributes are interrelated by the structure of an underlying system. To uncover the problem, we need to identify that system, called the **target system**. A model of the system, a **target model**, is a record of our findings. The model structure is assumed to inter-relate the target variables the same way the system structure inter-relates the target attributes. In the subsequent discussion, we will simplify our terminology and refer to variables, whether we discuss the system attributes or the model variables. Since this is common in system dynamics literature, we expect no confusion.

As our example, the learner is presented with a case in which the production rate in a manufacturing company is increasing. Yet the growth is considered insufficient to meet demand, reflected by an order rate. Consequently, the production rate is defined as a target variable and its trajectory a component in the reference behavior that can be compared to the behavior of the order rate as illustrated in figure 1.

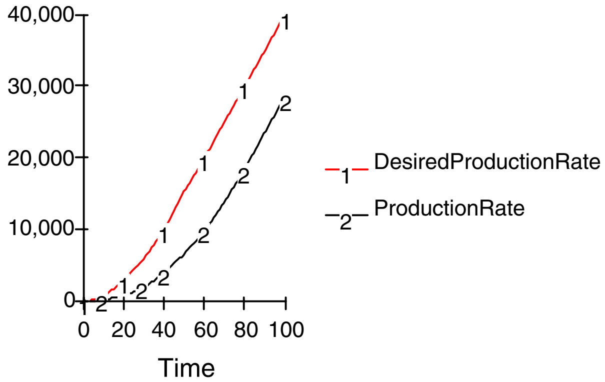

Figure 1: Reference behavior as compared to goal behavior.

2. Challenge the learner to identify the preference variables, each associated with a target variable and uncover the underlying preference structure.

Since a problem is assumed to exist, there is a preference associated with some target variable. Consequently, we ask the learner to define a **preference variable** associated with each target variable. In system dynamics, the preference variables are often identified by the prefix **desired**, e.g. *DesiredProductionRate*. A preference variable can be a constant. Typically, however, its value varies relative to other variables in the system. A structure that relates a preference variable to other variables is called a preference structure. In our example, the learner is expected to define the desired production rate, *DesiredProductionRate*, as a key preference variable associated with the key variable *ProductionRate*.

A *preference structure* is a preferred relationship between a (sub)set of preference variable and, possibly, other variables (i.e. between the values they take). A preference variable may be related to variables in the environment exogenous to the target model uncovered so far. The implication is that the system is preferred to adjust to that environment. In our example, we prefer the production rate to follow our expectations regarding an exogenously generated order rate, *OrderRate*. If we disregard expectation biases, the implication is that the *DesiredProductionRate* should be equal to the *OrderRate*.

As we shall see, preference variables can be related to other preference variables and to parameters and variables in the target system so as to adjust to that system as well. Note that the fact that the order rate is considered exogenous does not imply that it will remain so forever. In fact, the gradual uncovering of a system, implies that we establish temporary boundaries to support our investigation. Consequently, variables that are initially defined as parameters (constants) or exogenous variables (generating time-dependent trajectories exclusively), may later be incorporated in the model to serve as endogenous variables.

The educational purpose of identifying the preference variable is to explicitly establish a **goal behavior** that can be compared to the reference behavior as early as possible in the learning process. The discrepancy between the two is what will trigger and drive the learner through an investigation into the underlying system.

3. Challenge the learner to identify the structure underlying each the target variable and the associated preference structure

In the form of a precedence analysis, the learner is expected to trace the causes underlying the behavior of the target variable. This may uncover variables that are themselves preference variables or that influence such variables.

In our example, the target variable, *ProductionRate*, is influenced by the size of the workforce, *Workforce*, and the productivity, *Productivity*, of that workforce, -- one multiplied by the other. As illustrated in figure 2, neither workforce nor productivity is currently mirrored by preference variables.

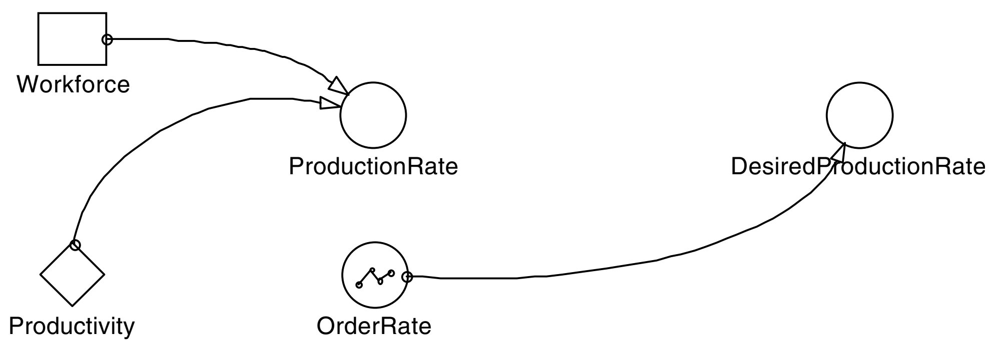

Figure 2: Desired and actual production rate.

The learner is now challenged to infer a secondary preference from the key preference. This way, he can create a mirror system of preferences to the target system. The educational value of that is that it allows him to identify the systemic implication of the original key preference in the form of secondary preferences and compare this implication, i.e. the desired state of affairs in the target system, to the actual one. Thus it is possible to identify the origin of discrepancies between the preferred and the actual values of the original preference variables. This refers to the diagnostic approach of problem based learning.

The implication of preferring a certain production rate, given a certain productivity, is to prefer a certain workforce, *DesiredWorkforce*. Alternatively, the implication of preferring a certain production rate, given a certain workforce, is to prefer a certain productivity, *DesiredProductivity*. The first one of these alternatives is illustrated in figure 3.

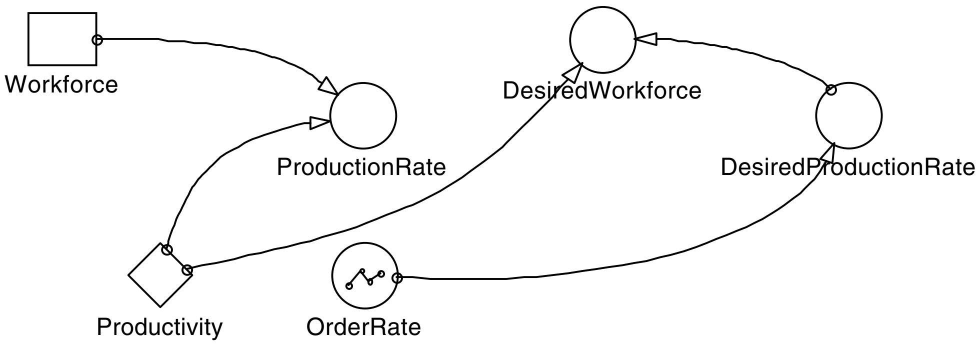

Figure 3: Desired and actual workforce.

When we set the potential preference variable, *DesiredProductivity* equal to *Productivity*, we imply that *Productivity* is determined by the target system itself in such a way that there is no explicit preference currently associated with that variable. Consequently there is no intent to change its value. Moreover, this implies that the desired workforce will be determined based on the actual productivity.

In our case, we will based the subsequent discussion of the alternative illustrated in figure 3. Note, however, that, depending on its purpose, an ILE could allow the learner to pursuit an investigation into the productivity of the workforce, whether the workforce is considered constant or varying. For the moment, however, we encourage the learner to take that alternative path.

The learners choice leads us to a situation where a preference variable is not only related to exogenous factors characterizing the environment, but also may be related to parameters or variables in the target model. By anchoring a preference variable, such as *DesiredWorkforce*, to a parameter, such as *Productivity*, the preferred state of affair comes to rely on the static characteristics of the target system. By anchoring in a variable, our preferences will become dynamically dependent on the behavior of the target system. This will be the case if we let the productivity of the workforce vary, say, in response to the workforce utilization. So, the value preferred adjusts in response to the dynamics of the system. This implies that the preference system is, in part, influenced by the target system. Since the preference system must be expected to influence the target system, there is a mutual interdependence between the two.

One of the important reasons for introducing the preferred magnitudes explicitly as preference variables in the model of a learning environment is to be able to investigate the consistency of the model, representing the target system and the associated system of preferences. If all the variables in the model take their preferred values, the equations that describe the structure of the system should all be satisfied simultaneously. When the workforce matches the desired workforce, for example, the production rate should match the desired production rate. If not, the preferences associated with the model cannot be satisfied simultaneously due to the constraints of the target system structure. From an educational point of view, it is important to understand at the outset whether the model is consistent or not. That information sets the expectations regarding whether the preferences can be satisfied simultaneously or not, i.e. whether a solution can be found or not. The learner is challenged every step of the way to check consistency.

4. Challenge the learner to halt at each stock encountered, to investigate its dynamic characteristics, to infer the associated preference and to develop a management policy

From the key variable, we trace back along the causal links until we identify a stock. Such a stock is the first clue to the dynamics of the system. A stock is a state variable and its level constitutes an element in the state of the system. The stocks are accumulators. They change their state over time as a consequence of the influence to which they are being exposed. Moreover, they retain their state from one such modification to the next. The stock equation is the only kind of equations in system dynamics models that span over a time period. Stocks thus constitute the memory of the system.

So far, the model developed is static. All relationships are instantaneous. Having identified the first stock in the target system, *Workforce*, the learner moves on to investigate the structure that governs its dynamics. Thus he needs to identify the associated flows and the rates that govern these flows. Since we originally needed to increase the workforce, we start with an inflow of persons and governed by the *HiringRate*.

The accumulation process is the core of the dynamic system and, at the same time, the most difficult process to understand. Consequently, at this stage the investigation includes a thorough analysis of the behavior of the stock.. Therefore we furnish the learner with a simple Unit of Instruction and an associated ILE, illustrated in figure 4 that enables him to investigate how the workforce responds to a variety of hiring and layoff patterns. The goal of such a unit of instruction is for the learner to develop a dynamic intuition based on familiarity with integration processes. Since the designer of the learning environment is familiar with the behavior pattern potentially exhibited by the model upon completion, such patterns of behavior can be used to test the learner's dynamic intuition and prepare him for the subsequent investigation. The *Workforce*, for example, responds with a phase shift to a cyclical hiring and layoff patterns, considered common in our case. Therefore, such a pattern should be available among the behavior patterns that potentially may characterize the *HiringRate*. In figure 6 we illustrate a very simple control on those rates for that very purpose. As seen in the last button, the learner is also allowed to experiment freely with both rates.

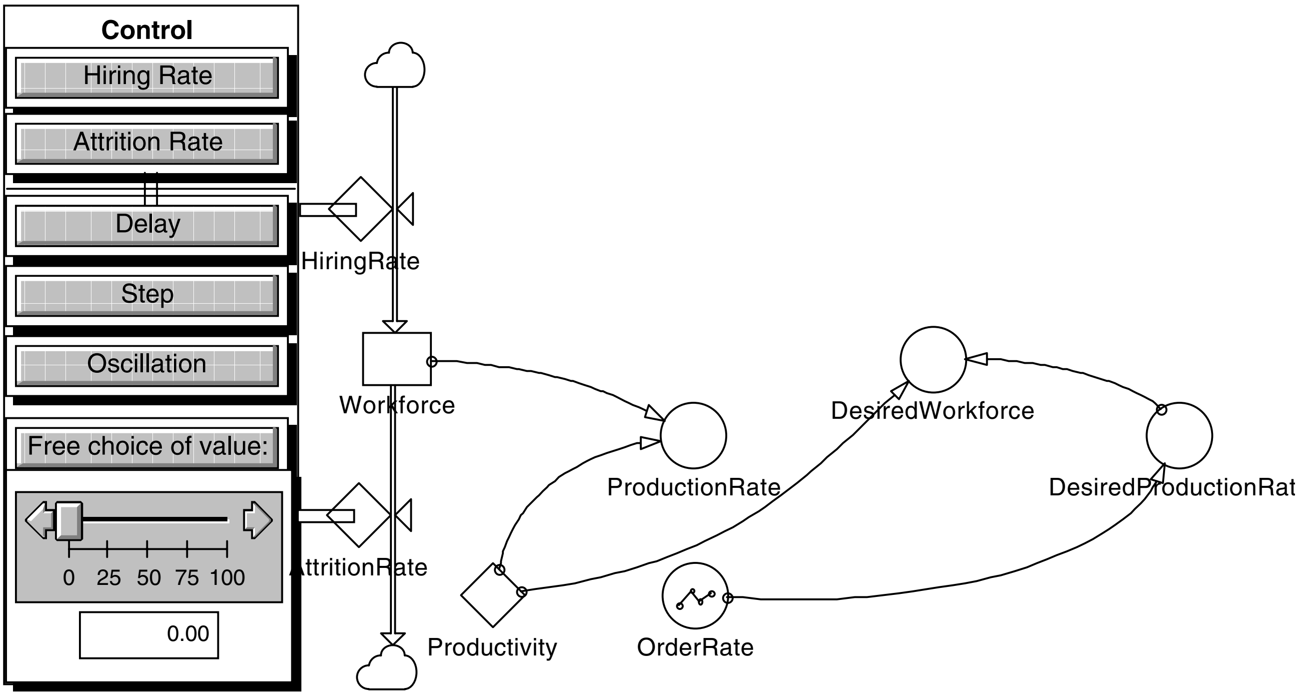

Figure 4: Investigating the dynamic characteristics of stock and flows.

In this first unit of instruction, the learner is challenged to meet the demand for workforce in view of the current order rate. A control can also be assigned to the order rate so as to select between the current problem behavior and a variety of synthetic conditions, such as steps, oscillations etc. Moreover, a variety of delays can be introduced in the hiring and layoff process so as to challenge the learner. The purpose of which is to enable the learner to develop a robust hiring policy for a variety of order rate patterns so as to firm up his understanding of integration processes.

The learner is, thereafter challenged with a second unit of instruction, where an attrition mechanism is in place causing the workforce to leave after an average duration of employment (*ADE*). Moreover, we introduce the current hiring policy that is based on the desired workforce. As illustrated in figure 5, this policy determines the preferred hiring rate, *DesiredHiringRate*. The equation governing the policy is of course;

$$\mathit{DesiredHiringRate} = \mathrm{MAX}(0, \mathit{LayoffRate} + (\mathit{DesiredWorkforce} - \mathit{Workforce}) / \mathit{TimeToHireAndTrain})$$

DesiredHiringRate is a preference variable that relates the preferred to the actual workforce in the target system, taking into account the average time it takes to hire and train a new member of the workforce, *TimeToHireAndTrain*, and compensating for the attrition. Consequently, it is a policy that adjusts to the current state of affairs in the target system.

The policy constitutes a negative feedback loop. Based on the understanding of the integration process gained from the first unit of instruction, the learner is expected to understand the logic behind this policy and is granted the task to change the *TimeToHireAndTrain* within a pair of reasonable boundaries. Thus the learner takes part in calibrating a policy already specified.

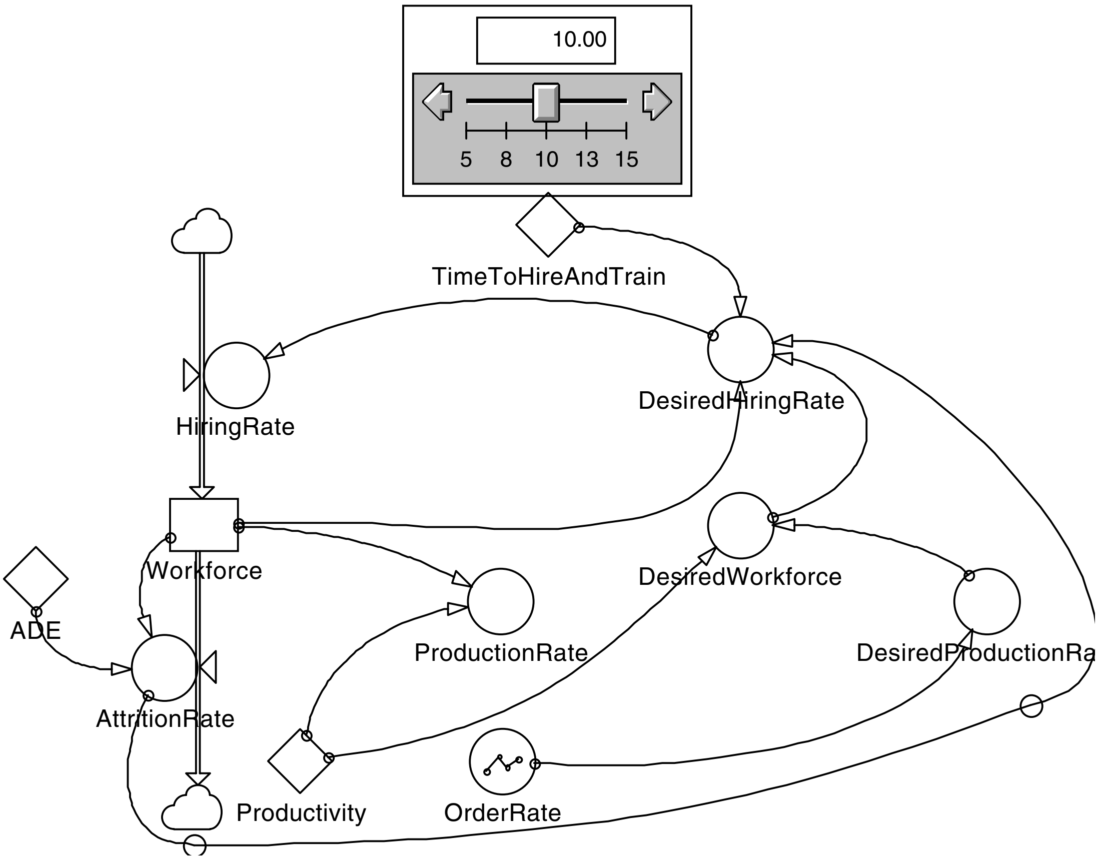

Figure 5: The investigation of a negative feedback loop governing the hiring rate.

5. Challenge the learner to encapsulate the unit of instruction and incorporate it into his body of knowledge

Having understood the relationship between the structure and behavior in this, second UoI, the learner is assumed to recognize the response of this system to any typical input patterns of behavior. This implies that he can encapsulate the insight gained in a learning packet. In a sense that packet becomes incorporated by the learner as a unit of analysis. In the analysis of the model behavior, it is no longer necessary for him to investigate this structure in great detail. He understands the first order response of this system to a change in the order rate, to a change in productivity, and to a change in the time to hire and train the workforce.

6. Challenge the learner to diversify and generalize

The next unit of instruction challenges the learner with the following problem: The workforce is inhomogeneous and can be split into an experienced and an inexperienced workforce, - characterized by very different productivities. The implication is that the learner is challenged to make an abstraction from the model developed and to question to what extent the structure governing the two different workforce segments resembles the structure already developed for the workforce as a whole. The implication is that the learner considers the workforce to be a generic workforce, that the hiring of workforce is recruitment in general and that attrition applies to both. Figure 6 is an illustration of the resulting model.

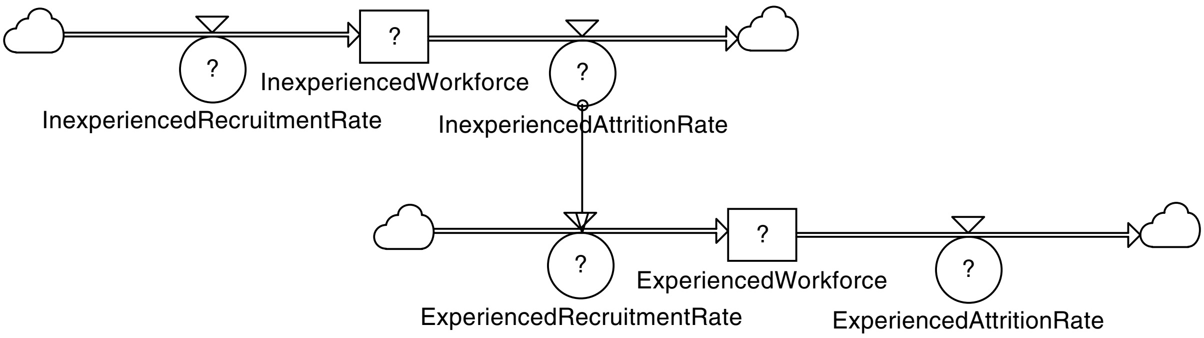

Figure 6: Diversification and generalization.

The learner typically recognizes that attrition is equivalent to the recruitment from one segment of the workforce to the next so that the two components of the model in figure 6 can be integrated as illustrated in figure 7.

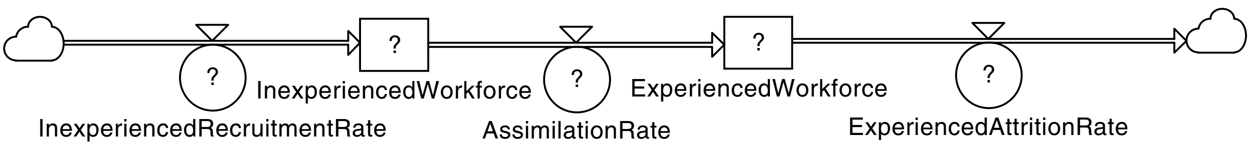

Figure 7: Integration.

The learner is challenged to investigate whether the remaining structure generalizes and, in that case, how each component integrates into a model of the workforce as a whole. Indeed there are similarities: The learner is expected to recognize that the assimilation of the inexperienced workforce into the experienced one is similar to attrition in general. The average duration of employment transfers to the average duration of assimilation, i.e. how long it takes for inexperienced workers to reach the productivity of an experienced worker.

But this implies that the recruitment of the experienced workforce is no longer governed by the desired rate of recruitment of the experienced workforce. Therefore, the learner typically halts at this stage. He is being told that recruitment of workers in general can only take place through the recruitment of inexperienced workers.

The learner is then directed to the preferences that apply to the system. The original preference attribute, *DesiredWorkforce*, must be diversified into secondary *DesiredInexperiencedWorkforce* and *DesiredExperiencedWorkforce*, respectively. This is no trivial matter and, is in a sense dependent upon the definition of desired workforce. The learner is led to apply the productivity of one of the kinds of workforce, say that of the experienced workforce. Thus *DesiredWorkforce* is measured in experienced equivalents, i.e. the number of experienced workers that is required.

As in the case of the DesiredProduction leading to a *DesiredWorkforce* and/or a *DesiredProductivity*, we now face the following situation: The learner could arbitrarily prefer a certain amount of experienced workers and let the remaining workload be carried by the inexperience workforce. In this case, however, restrictions apply. In an interactive learning environment associated with a third unit of instruction, the learner is challenged to identify other conditions in the target model that limit the degrees of freedom that a workforce manager would be facing in this context.

By operating in that learning environment, the learner comes to the realization that, in equilibrium, the ratio between the experienced and the inexperienced workforce remains the same. The learning environment also allows the learner to identify the parameters that determine this ratio. Thus, based on the assumption that the system is in equilibrium, the learner is able to find a closed form expression for the ratio existing between the two. As such, the learning environment helps the learner not only to identify the equilibrium condition, but also to understand the significance of that condition. Moreover, this discovery can be utilized to identify the need for recruitment in view of a certain preferred production, *DesiredProduction*.

Considerations behind the design of an Interactive Learning Environment

In this paper, we have presented some of the considerations we typically face while designing interactive learning environments for simple domains. We expect the same considerations to apply to the design of environments for complex domains. These considerations are rooted in learning theory and lead to the definition and application of units of instruction. We are still far from a formal definition of such a unit. Yet we do define such a unit to have a clear and simple learning goal, to be based on other units of instruction, to facilitate the understanding of the relationship between structure and behavior in a system, and to enable the integration of such an understanding into the body of reusable systems knowledge held by the learner.

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