System Dynamics as a Technology of Learning for New Liberal Education

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Abstract

Technology provides a framework for problem solving which the educational endeavors for learning about technology must also incorporate. Most problems in current day world are, however, unforeseen and not amenable to being addressed through an inventory of situational solutions. Technology also having many facets, the education of technology requires a multi-disciplinary approach that should unify knowledge and offer a common vehicle for recognizing and analyzing complex problems. The proposed paper examines the experimental process of system dynamics as a possible learning vehicle for multi-disciplinary education on technology. The heuristical procedure of system dynamics is compared with Kolb's model of learning. The various tasks needed to be performed in the implementation of the learning process and the competencies required to be inculcated for performing those tasks are discussed.

Key Words: Learning, System Dynamics, Methodology, Pedagogy

Introduction

The concept of multi-disciplinary education is not new. All education was multi-disciplinary when the size of organizations we dealt with was relatively small. The appearance of specializations was most likely a part of the process of growth and differentiation in the size of these organizations and their complexity. However, with growth in size and complexity, the need to integrate inevitably appeared, which again made multi-disciplinary education necessary. Thus, while medieval scientists invariably acquired multi-disciplinary skills, modern sciences have tended to be compartmentalized. The notion of multi-disciplinarity appeared in the modern science in 1930's when Norbert Wiener introduced the concept of cybernetics dealing with the systems formed in man-machine interaction. The scope of this interaction expanded considerably when the need to deal with the complex problems arising from the interaction of the economic and societal decisions with the built and natural environment reactions came to fore in the working of large-scale systems.

It should, however, be observed that early efforts to introduce multi-disciplinary analyses were shunned by the established specializations in science. Cybernetics was applied to industrial problem solving much after Norbert Wiener died. And Jay Forrester's efforts to integrate economic, demographic and environmental agenda into formal models of problems met with intense resistance from the neo-classical economics in the 1970s when technological optimists believed that both backstop resources and the technological potential to tap them were unlimited, although this belief could not be supported by the physical laws. It is perhaps a human fallibility that, irrespective of the logic of facts, a distant problem cannot be foreseen unless its symptoms appear. Now that the ecological capacity of the world has already been exceeded, the problem of limits is not distant any more and the need to deal with the abstract systems formed through the interaction of society, built environment and natural environment through multi-disciplinary analysis has become critically important [Saeed, 1994].

This paper carefully examines the classical system dynamics practice in the context of human learning process and attempts to explicitly state an implementation procedure that should enhance the use of modeling as a thinking companion at a wide scale. A generic model of learning is used to delineate the principles of conduct of system dynamics modeling. Further, the various activities called for are grouped into a set of four core competencies, which are based on four key human abilities. The organizing principles that must be superimposed on the learning abilities to deliver the core competencies are also discussed. A clear statement of the principles of the learning process in system dynamics practice should transform system dynamics modeling from an art learnt mostly through apprenticeship of experts to a wisely used technology of learning for new liberal education that must combine engineering and liberal arts in a multidisciplinary framework.

System dynamics as a technology for learning and problem solving

Since its introduction almost forty years ago by Jay Forrester, system dynamics method has been applied to a variety of pursuits, ranging from advanced research in universities and research organizations, to brainstorming in boardrooms, to classroom learning in pre-college education, to systems thinking for everyday use. Since the quest for learning is a common denominator in all applications of system dynamics, the versatility with which it appears to have been applied should offer a great promise for creating a learning continuum for mankind extending from cradle to grave. Evidently, this promise is yet to be realized. System dynamics, however, remains a mysterious art, which must be learnt through painstaking apprenticeship of the people who have themselves learnt this art through similar apprenticeship. Acquired through personal self-learning initiatives from the books and articles currently in print, system dynamics often yields writing computer codes for causal and association-based relationships and using the models so created for forecasting. Needless to add that few people can muster the dedication and the perseverance needed to learn and teach system dynamics through apprenticeship, hence it remains a limited art instead of having become a widely practiced craft in spite of its promise for supporting a wide spectrum of learning activities.

When learnt from written word without the benefit of apprenticeship, system dynamics appears to subsume a large variety of heterogeneous practices, with an equal variety of expectations from its use. These expectations vary from providing point forecasts of events, to creating microworlds of concrete systems, to making mental maps, to getting magical insights into problems, to finding shortcuts to an ocean of wisdom. This variety of system dynamics practices has rather created an abundance of models without meeting the expectations pinned to those models. Evidently, a common set of precepts guiding the modeling process is yet to be delineated in terms of a clear statement of the organization of the learning process in system dynamics practice and the core competencies needed to be developed for carrying it out [Doyle 1997].

Drawing on a generic model of experiential learning developed by Kolb (1979, 1984), I have attempted in this paper to outline the principles of conduct of system dynamics modeling whose exercise should enhance its learning component. The tasks entailed in this conduct can be grouped into four basic competencies, which extend from four common learning faculties we all possess – watching, feeling, doing and thinking – but making a productive use of these faculties into creating good system dynamics work requires superimposing on them certain organizing principles, which I have also attempted to define drawing on my own personal experience of extended system dynamics practice. These principles are implicit in the protocol of the classical system dynamics method many of us seem to have learnt and internalized through apprenticeship of Jay Forrester and his adherents, but they have not been succinctly stated in the literature. An explicit statement of these principles will, hopefully, facilitate the learning of good system dynamics practice at a wide scale without the need for apprenticeship. This should help the task of transforming system dynamics from a limited art to a widely practiced craft.

The classical system dynamics practice

The term *system* is used extensively both in the context of science and mathematics. In the context of science it implies natural and societal organisms which exist independently of how we view them. In mathematics, however, a system necessarily implies an abstraction visualized through perceptual and methodological filters. Although, it is impossible to see the natural and societal systems in their true natural form, the various methodologies following the principles of science attempt to define criteria to create a consensus on how natural systems should be viewed, albeit only in terms of transcendental models.

The transcendental models of systems are also divided into two classes. The first often termed concrete systems concentrates on the common characteristics of natural and societal organisms, viewing them as living systems. The second focuses on specific functions or problems and are often referred to as abstract systems [Rappoport 1980]. The open system defined by Ludwig von Bertalanffy belongs to the former category [Bertalanffy 1968], whereas the closed system referred to by Jay W. Forrester belongs to the later [Forrester 1968]. Thus, a system dynamics model is an abstract system, conceptualized around a pattern of behavior and it may not represent any concrete system *per se*.

The classical system dynamics practice is aimed at arriving at a clear understanding of how information relationships in an abstract system create a problem behavior, so policies for system improvement may be conceived. The procedure followed in the classical system dynamics practice creates a cyclical learning process which calls for the development of a number of rather abstract concepts in a sequence requiring use of both cognitive and physical skills, which are not clearly defined. A widely recognized view of this process is illustrated in Figure 1.

Empirical evidence is the driving force both for delineating micro-structure of the model and verifying its macro-behavior, although the information concerning the macro-behavior may reside in the historical data and that concerning the micro-structure in the experience of the people. Thus, the modeling process draws on both historical and experiential data.

The first requirement of the method is to organize historical information into what is known in the jargon as "reference mode." The reference mode leads to formulation of a "dynamic hypothesis" expressed in terms of the important feedback loops existing between the decision elements in the system that create the particular time variant patterns contained in the reference mode. The dynamic hypothesis must incorporate causal relations based on information about the decision rules used by the actors of the system, and not on correlation between variables observed in the historical data.

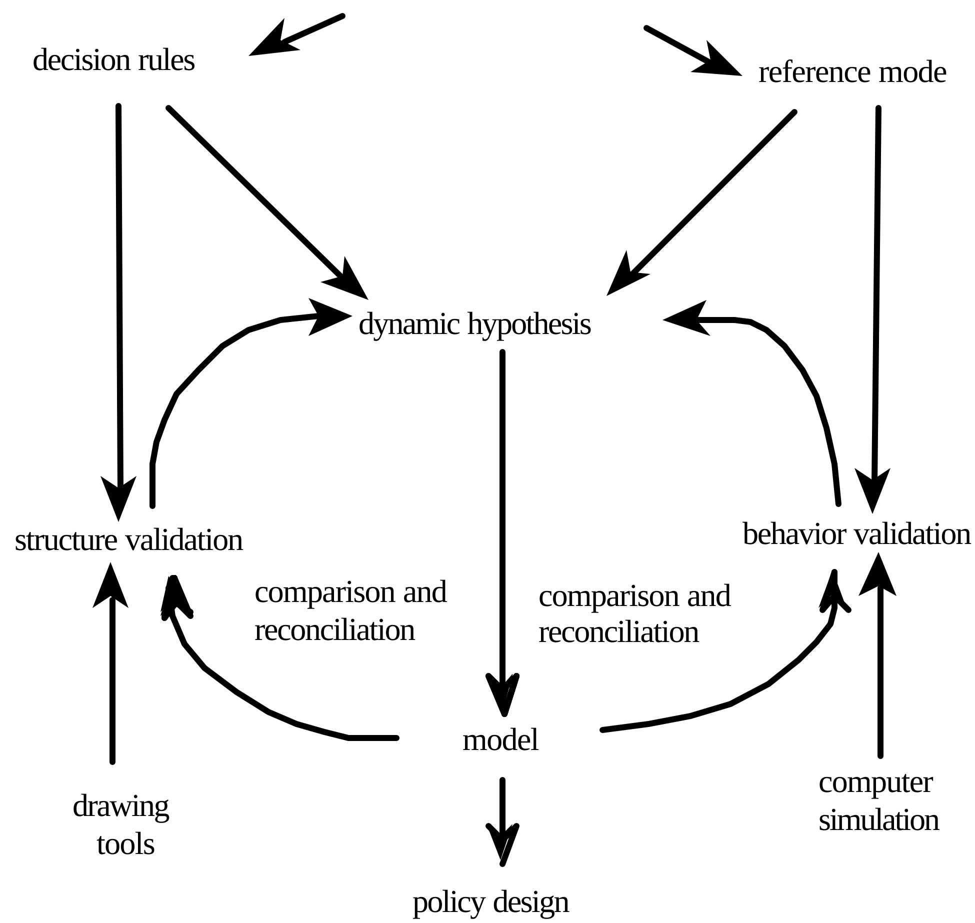

Figure 1 **A widely recognized view of classical system dynamics practice**

A formal model is then constructed using the given rules of information structure and incorporating the dynamic hypothesis along with the other essential detail of the system relating to the problem being addressed. The model structure must be "robust" to extreme conditions and be "identifiable" in the "real world" for it to have credibility, where real world consists both of theoretical expositions and experiential information. A model might undergo several iterations in a cyclical process to arrive at an acceptable structure, and this process creates a basic "understanding" of the information relationships in the system underlying the problem being addressed through an iterative learning mode it embodies.

Once a satisfactory correspondence between the model and the real world structure has been reached, the model is subjected to behavior tests. Computer simulation is used to deduce time paths of the variables of the model, which are reconciled with the reference mode. If a discrepancy is observed between the model behavior and the reference mode, the model structure is re-examined and modified if necessary, and this leads into to another cycle of behavior tests. This iterative process creates additional learning that further enhances "understanding" of the information relationships in the system and how they yield the problem behavior. In rare cases, such testing might also unearth missing detail concerning the reference mode, leading to a restatement of the reference mode, although for most cases, the reference mode delineated at the start of the modeling exercise must be held sacred.

When a close correspondence is simultaneously reached between the structure of the model and the theoretical and experiential information about the system, and also between the behavior of the model and the empirical evidence about the behavior of the system, the model is accepted as a valid representation of the system [Bell & Senge 1980, Forrester & Senge 1980, Richardson & Pugh 1981, Saeed 1992].

Since there exists large variability in the outcomes of the modeling procedure described in Figure 1, in terms of the learning and new knowledge it creates, its accuracy in representing the actual process carried out by an experienced modeler is in question. It is instructive to look at a generic model of learning proposed by Kolb (1979, 1984) to identify the missing links in the prescribed procedure for system dynamics practice so it becomes possible to represent it more accurately.

A generic model of experiential learning

While there exist many views of the experiential learning process, a model developed by David Kolb appears most relevant to the system dynamics modeling practice [Kolb 1984, Hunsacker and Alessandra 1980, Kolb, et. al. 1979, Kolb 1974]. Kolb perceives experiential learning in his model as a four-stage cycle illustrated in Figure 2.

Four basic faculties - watching, thinking, doing and feeling drive Kolb's learning cycle. For the learning process to be effective, watching must result in careful observation of facts, leading to discerning organized patterns. These patterns then must drive thinking, which should create a concrete experience of reality. The implications of the concrete experience must be tested through experimentation conducted mentally or with physical and mathematical apparatuses. Finally, this experimentation must be translated into abstract concepts and generalizations through a cognitive process driven at the outset by feeling, which would, in turn, create further organization for careful observation thus invoking another learning cycle.

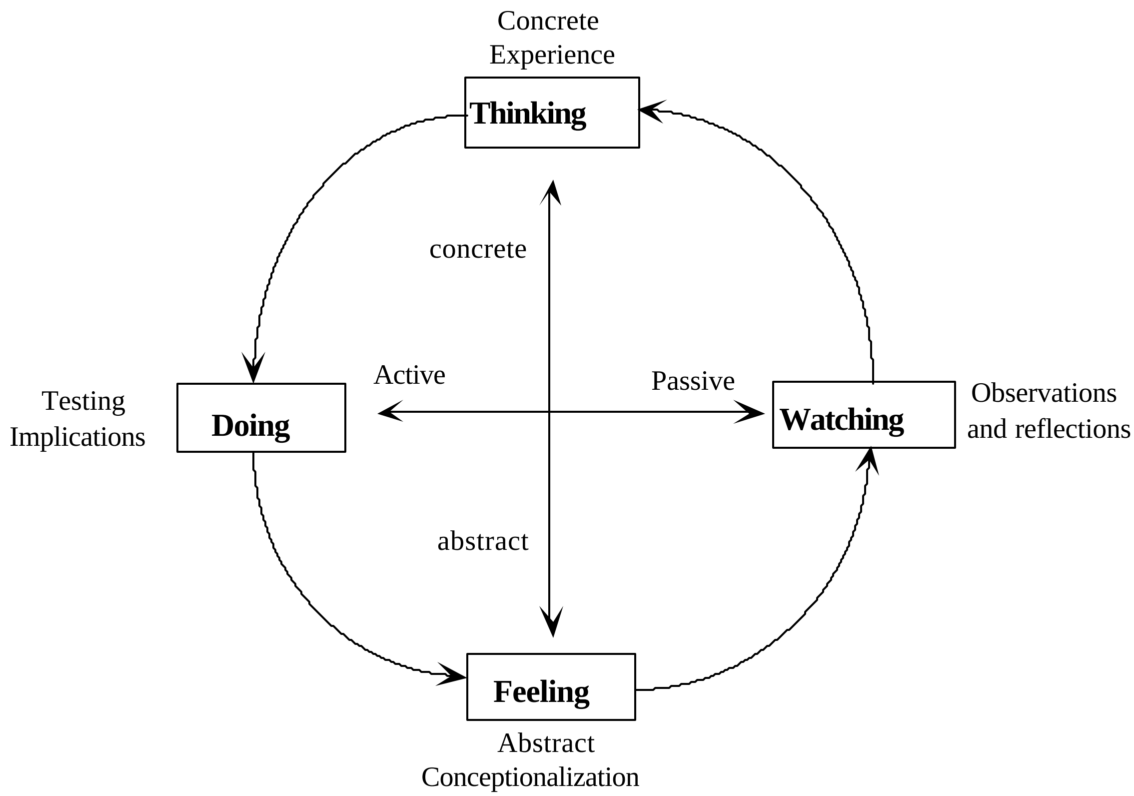

Figure 2 **Kolb's model of experiential learning**

The learning faculties, according to Kolb's model, reside in two basic human functions, physical and cognitive; each integrated along two primary dimensions, which are also illustrated in Figure 2. The first dimension, concerning the physical functions is passive – active. The second, concerning the cognitive functions is concrete – abstract. Thus, the faculty of watching is a passive physical function, thinking a concrete cognitive function, doing an active physical function and feeling an abstract cognitive function. Since the mental construction of reality and its interpretation must filter unwanted information, each faculty must be guided by certain organizing principles to effect learning. Additionally, the learner is required to shift constantly between dissimilar abilities to create opportunities for refuting the anomalies that would appear among the constructs of each ability.

Even though the practice of system dynamics on the simplistic lines illustrated in Figure 1 may not appear to conform to Kolb's model of the learning cycle, it is known to have created learning and new knowledge, in cases when it has been carried out "skillfully," by an "experienced modeler." Clearly, Figure 1 does not fully describe the process actually implemented when learning is created through skillful system dynamics practice. Evidently, the experienced modeler implicitly goes through the steps of a learning process that is not explicitly known. I have attempted to draw on Kolb's model of experiential learning to help me describe those implicit steps.

Creating learning cycles in system dynamics practice

The oldest formal reference to the learning context of system dynamics I could find comes from Professor Jay Forrester, who underscored this context as far back as 1971 when he wrote a brief note to his Urban Dynamics modeling staff emphasizing the importance of the modeling process rather than the model it creates. This note concluded:

“In fact, for any particular real life implementation we can expect that there will be a series of models simultaneously existing and simultaneously in evolution. Different models will address themselves to different issues. The various issues will become evolved and clearer. New issues will arise which require new models, or combinations of models that previously had existed separately. 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 1985]

On the surface, two learning cycles appear in the modeling process described in Figure 1, after a reference mode that in itself is an abstract concept, has been delineated. The first cycle corresponds to the structure validating processes and the second to the behavior validating Processes. The first cycle walks the modeler through the construction of a dynamic hypothesis - model formulation - and validation of model structure through comparison and reconciliation with the evidence. The product of this cycle is a preliminary model, which is further tested through simulation experiments. The second cycle requires going through the tasks of deduction of the model behavior - and further comparison and reconciliation to achieve its behavioral validity. The conduct of the two cycles in theory must create enough learning about the abstract system represented in the model to issue a logical basis for a policy design for system improvement. In reality, this basis can be created only by a handful of artful modelers, who seem to possess a mysterious feel for the process. In my observation, the mysterious feel comes from carrying out implicitly a number of steps, which conform closely to Kolb's model of learning, but which are not reported in Figure 1.

First of all, the components of the so-called learning cycles in Figure 1 appear to lie mostly in the cognitive domain and literally moving from one to another, without an intervening physical process, is bound to create artifactual models removed from reality. Second, moving only within the cognitive domain without the opportunity to touch basis with the physical domain will eliminate the opportunity to encounter anomalies that create learning opportunities. Since there exits evidence of system dynamics practice having created a respectable amount of learning and new knowledge, some of us modelers evidently do not move directly from one abstract conceptualization to another without carrying out other steps implicitly, although we are unable to report accurately how we make this move.

Carefully re-examining the system dynamics modeling practice in the backdrop of Kolb's model of experiential learning, I have attempted to represent in Figure 3 the physical and cognitive tasks an experienced modeler actually performs in the pursuit of learning through system dynamics practice. These steps have seemingly gone unreported since they are learnt subconsciously through painstaking apprenticeship.

As stated earlier, all components of the cyclical process described in Figure 1 indeed fall in the category of conceptualizations lying in the abstract cognitive domain and moving directly from one to another will be unproductive from the standpoint of learning. To create any learning, moving from one abstract conceptualization to another must involve a learning cycle calling on all learning abilities as described in Kolb's model.

Thus, reference mode must be viewed as an abstract concept created by first drawing upon the observation ability in the passive physical domain to examine historical evidence, which at the outset becomes a basis for delineating system boundary when processed through drawing on the thinking ability in the concrete cognitive domain. An effort is made then to graph patterns to represent the reference mode, which is an experimental process in the active physical domain asking a number of what if questions aimed at understanding the behavioral implications of the system relationships represented in the model. Finally, reference mode is conceptualized as a mental picture of a fabric representing a multi-dimensional pattern in the abstract cognitive domain. The graphed time profiles drawn in two dimension space rather poorly describe the multidimensional mental image constituting reference mode - like the straight lines representing all two-dimensional objects in Abbot's flatland, whose real shape can only be imagined [Abbot 1987]. The graphs we create are nonetheless important for constructing a mental image of the multidimensional fabric the reference mode actually is.

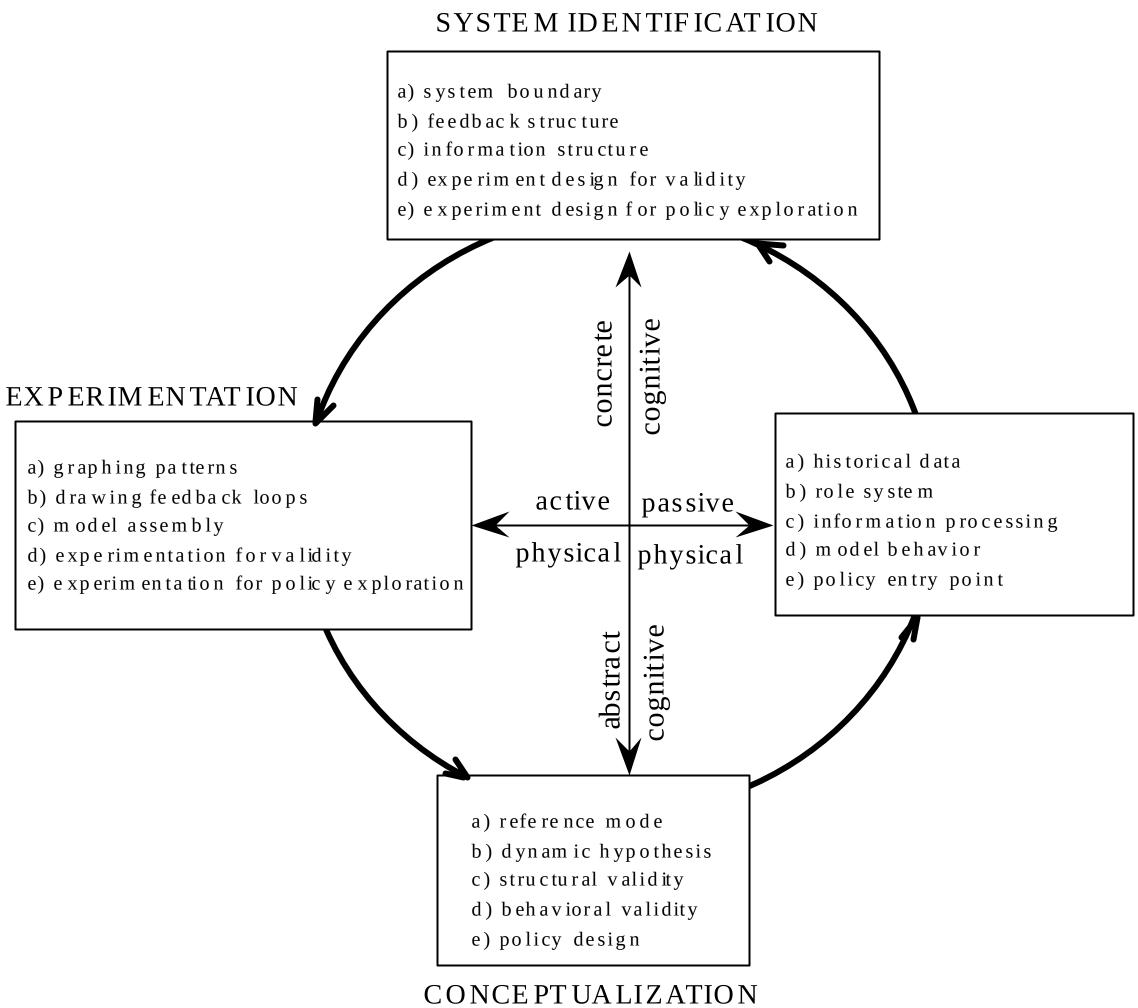

Figure 3 **Learning cycles implicit in good system dynamics practice**

The dynamic hypothesis represents an aggregate intuitive appreciation of the system lying also clearly in the abstract cognitive domain. Its formulation originates, however, in the passive physical domain where role systems are carefully observed. This observation is followed by the delineation of the feedback structure in the concrete cognitive domain, which creates the basis for drawing the feedback loops in the active physical domain. A conceptual image of how those feedback loops translate into an archetypal explanation of the reference mode constitutes the dynamic hypothesis.

The structural validity of the model formulated is, likewise, an abstract concept creating the confidence that the model structure indeed represents equivalent information processing norms in the real world. Its appreciation originates in the passive physical domain through recognition of the information processing patterns discerned through experience, and literature descriptions. The information processing patterns recognized lead to the formulation of the mental image of the information structure in the concrete cognitive domain. This image is translated through an experimental assembly process into an explicit model, which is carried out in the active physical domain and this provides the basis for the abstract concept of structural validity.

The behavioral validity of the model is also an abstract concept bridging the gulf between the system decision relationships and its behavior through use of deductive logic. It originates in the passive physical domain through recognition of patterns in the model behavior. This leads to the creation of the experiment designs in the concrete cognitive domain to test the sensitivity of the model behavior to various assumptions and to refute anomalies observed. The results of this experimentation deliver an intuitive appreciation of the behavioral validity of the model, which resides in the abstract cognitive domain.

Finally, the conceptualization of system improvement is an abstract cognitive process, which likewise the processes described earlier, originates in the passive physical domain through the observation of possible entry points into the system. Experimentation to investigate these entry points is conceived in the concrete cognitive domain. Experimental exploration occurs in the active physical domain and the results of this exploration are translated into system improvement concepts in the abstract cognitive domain.

The modeling practice represented in Figure 3 involves five successive learning cycles described above. The shift from one cycle to the next occurs after the preceding cycle has yielded learning in its own context. The shift actually takes place when moving from the abstract cognitive domain to the passive physical domain. The five cycles, thus, lie on a spiral converging into system improvement.

In performing above tasks over the conduct of the five learning cycles, the modelers draws upon both physical and cognitive functions as in the case of Kolb's generic model of learning. Also, the physical and cognitive tasks carried out in these cycles seem to appear alternately while they also lie at the opposite extremes of the continuums representing the physical and cognitive functions similar to Kolb's model of experiential learning. It should be expected that system dynamics practice conducted in this way creates learning. Learning gets inhibited when above process is severely truncated from literally following the simplistic procedure for system dynamics modeling reported in the literature which seems to require moving between abstract concepts within the cognitive abstract domain of human functions.

Core competencies for system dynamics practice and their organizing principles

The five tasks performed in each of the four domains of the learning system represented in Figure 3 seem to display common characteristics translated into the labels placed on the boxes representing the various domains. The tasks performed in the passive physical domain have a common element of pattern recognition; all those in the concrete cognitive domain seek system identification. The tasks in the active physical domain fall into the category of experimentation. Finally, all tasks in the abstract cognitive domain are conceptual and are labeled conceptualization. The core competencies for practicing system dynamics are therefore defined as, *pattern recognition, system identification, experimentation* and *conceptualization.*

The core competencies discussed above seemingly emanate from the learning faculties of *watching, thinking, doing* and *feeling* in Kolb's model. The acquisition of these competencies has also been difficult without the apprenticeship of a master modeler since what they entail is not clearly known. I recall a question from an undergraduate student while I worked as a teaching assistant in an introductory course on system dynamics at MIT. He asked me what makes a good model. I also recall my somewhat artless but perhaps not inaccurate reply that making a good model was like learning to swim or bike. The art of balance in those activities is acquired from carefully observing a biker or a swimmer and internalizing the process through practice. The same was needed in learning to build a good system dynamics model. The problem with this mode of learning, however, is that it is limited, whereas, the art learnt might also be highly stylized depending on the personal fixations transmitted through apprenticeship. It is not surprising that there has appeared a large variety in the practice of system dynamics while its growth is also greatly constrained by the apprenticeship opportunities available.

While the core competencies and how they should be called upon for the conduct of system dynamics practice has been illustrated in Figure 3, the organizing principles that must be superimposed on the common learning faculties to yield system dynamics core competencies still remain largely unclear. The learning of these principles has to-date also remained implicit in the process of pursuing system dynamics through apprenticeship.

I have attempted to reflect carefully on my own experience as a professional modeler to state explicitly the organizing principles guiding the four key competencies involved in system dynamics modeling – pattern recognition, system identification, experimentation and conceptualization. Each core competency is created by superimposing the indicated set of organizing principles on a related learning faculty. These principles, their relationship with the learning faculties commissioned, and the respective products delivered are listed in Table 1.

CORE COMPETENCE	LEARNING FACULTY	KEY ORGANIZING PRINCIPLE	OUTCOME
pattern recognition	watching	a) time horizon b) decision space c) bounded rationality d) time horizon e) parameter interpretation	a) time patterns b) decision patterns c) information flow patterns d) model behavior patterns e) policy sensitivity patterns
system identification	thinking	a) purpose b) causation c) stocks/flows d) validity criteria e) policy space	a) system boundary b) feedback structure c) information structure d) experiment design for validity e) experiment design for policy
experimentation	doing	a) multiple modes b) diagramming tools c) software structure d) simulation e) simulation	a) graphs of time patterns b) causal diagrams c) model assembly d) sensitivity scenarios e) policy scenarios
conceptualization	feeling	a) fabric b) archetypes c) reality checks d) deductive logic e) feedback	a) reference mode b) dynamic hypothesis c) structural validity d) behavioral validity e) system improvement

Table 1 System Dynamics Core Competencies, Relevant Learning Faculties and their Organizing Principles

The skill of pattern recognition stems from the fundamental learning ability of observation. It delivers organized perceptions of what is observed. The key organizing principle for delivering time patterns is the designation of an appropriate time horizon. Different patterns will often dominate different time horizons. Depending on what is the time horizon of interest, irrelevant patterns must be filtered out and relevant patterns highlighted.

The key organizing principle for delivering decision patterns is the perception of the decision space in which the actors can be seen to play their roles. Structure outside of this space must be perceived as environment represented by a parameter set. Likewise time horizon, the appreciation of decision space should help to filter out irrelevant decision processes and include the relevant ones in the system boundary. The organizing principle for delivering information flow patterns resides in the recognition of the bounded information sets in which we operate. All information in the system is not available at all decision points. Patterns of bounded information flow must be carefully discerned to accurately represent the information flow process. As in the case of discerning time patterns in the real world, the recognition of an appropriate time horizon is the key organizing principle also for discerning patterns in the model behavior. Finally, the ability to interpret parameters as policy levers will guide the observation of the policy sensitivity patterns in the system under study.

The skill of system identification is a manifestation of thinking in a concrete framework. It delivers the boundary of an abstract system, which does not have any concrete existence, through the organization of a purpose for the modeling exercise. An appreciation of the cause and effect relationships helps to conceive feedback structure. The organization of stocks, flows and generic processes helps to conceive information structure. Validity criteria delivers a design for validity experimentation and a recognition of the policy space from the point of view of the model user leads to the creation of a productive design for policy experimentation.

Experimentation is a function of the faculty of doing, which resides in the active physical domain. An appreciation of multiple modes helps to separate different modes of behavior while graphing patterns. The organization of the diagramming tools delivers causal diagrams. The software icons and specification rules create a model assembly, while knowledge of the simulation process helps to create accurate and error-free behavioral deductions from the model structure.

Finally, abstract conceptualization stems from the faculty of feeling. A focus on a multi-dimensional fabric rather than isolated graphs helps to conceive reference mode; the recognition of archetypal structures delivers dynamic hypothesis; reality checks deliver structural validity; deductive logic delivers behavioral validity; and the perception of feedback helps to conceive designs for system improvement.

While most experienced modelers would recognize the organizing principles stated in Table 2 as an integral part of what they practice, most would be unable to explain how they learnt them. The task ahead is to develop further text and exercises that should facilitate the learning of the above principles and putting them to practice.

Conclusion

System dynamics is a promising technology for the new liberal education that has become increasingly inter-disciplinary, since it allows the creation of experimental apparatuses representing systems whose boundary extends across disciplines. There has, however, appeared considerable heterogeneity in the practice of system dynamics, whose extent is coterminous with the variety of its applications. It appears that the variety of system dynamics practices are devoid of a common set of precepts, and lack fundamental organizing principles or a statement of core competencies that should harmonize them.

System dynamics model building has often been likened to an art, learnt through apprenticeship rather than from books and this has created considerable heterogeneity in system dynamics practice as well as a large variety in the expectations from its use. The core set of skills needed for the practice of system dynamics is not clearly defined, hence acquiring them is difficult. Using a widely recognized model of experiential learning, I have attempted in this paper to outline the correct way to practice system dynamics that should create learning. Also outlined are the core competencies needed for system dynamics practice and the organizing principles of each of these competencies, which should facilitate learning them. Further work is needed to device teaching materials and exercises that should help to learn these principles without having to go through the apprenticeship of an expert. Implemented as a learning system and taught as a set of core competencies, system dynamics can be applied quite widely as an educational process.

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