# Reflections on the Validity of T21 and PCM, System Dynamics Integrated National Development Planning Simulation Models

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## *Abstract*

The impossibility to identify and represent events and emergent characteristics of the system analyzed with computer simulation models aimed at projecting future events has posed serious questions about their validity in the field of social science. While methodological issues, both concerning the foundations of the methodology and the formulation of models, are identified, the System Dynamics methodology seems to allow modelers to gain a deep understanding of the systems studied while answering the four dilemmas identified in this study. These models allow for the structural representation of the system through the identification of causal relations underlying its main functioning mechanisms, represent both dynamic and detailed complexity using wide social, economic and environmental boundaries. Dynamic simulation models are by no means perfect and will never be; nevertheless, modelers have the responsibility to use our best scientific understanding to develop reasonable and sustainable policies. T21 and PCM, integrated national development models, allow us to do so by enhancing the understanding of systems.

Keywords:

T21, System Dynamics, Model Validation, Computer Simulation Models

## *1. Introduction*

Computer simulation models are supposed to be useful "playgrounds" where different policy options can be virtually tested in a simplified micro world in which time runs faster to allow users to learn from their virtual experience and reduce risk and uncertainty when dealing with the real world. The use of management "flight simulators" or "microworlds" became common practice for many private companies dealing with high degrees of detailed complexity in the past 30 years,

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especially encouraged by the exceptional improvement in computing technology. Nowadays, in a rapidly changing environment, where issues are arising from apparently disconnected areas and time, the importance of dynamic complexity is rapidly emerging. As a consequence, a variety of simulation tools are more frequently used and governmental agencies are considering the adoption of such tools to complement the analysis presently carried out, mainly because our mental models and understanding of systems is evolving, while their models do not, due to the limitations of the methodology used.
A parallelism in the development of simulation tools and the need for a representation of complexity can be identified. Nevertheless, from the analysis of the two periods in which this has happened (i.e. early 80s and present) significantly different characteristics emerge. In the late eighties major corporations requested technology able to deal with detailed complexity, which mainframes were eventually able to provide. In recent times, conventional tools seem to be more and more inadequate to analyze a rapidly changing environment and new tools able to represent dynamic complexity are requested. In this case though, simulation models, which should provide a simplified representation of reality, are requested to be detailed and dynamic, in other words all-inclusive. Such a need is in contrast with the definition of models, which should propose a simplified representation of reality able to provide insights about the real world. As a consequence, modelers have the responsibility to use the various methodologies available with consciousness, making sure that tools are used to analyze the issues they have been designed for.

How can validity be defined in such a context? If it is to be considered as an abstract concept, as Dreyfus claims (Dreyfus, 2001), modelers would need to recreate reality, which is impossible, leading to the conclusions that no models are valid and insightful. If we instead define validity in relation to our objectives and what other models and techniques are already proposing, we take the conclusions of philosophers of social science as an ultimate challenge; in other words, as a statement of the goal that at last we intend to achieve.
As stated by Yaman Barlas, a well-known System Dynamicist, "*it is impossible to define an absolute notion of model validity divorced from its purpose*" (Barlas, 1996). Similarly, according to Forrester, validation can only be defined with respect to a particular situation (Forrester, 1968). These definitions imply that though nowadays we may not consider models of the early eighties as valid tools able to explain current problems, at that time they were providing the requested information, and therefore should be considered valid because they were consistent with their purpose. Nevertheless, as Barlas continues, "*Once validity is seen as "usefulness with respect to some purpose", then this naturally becomes part of a larger question, which involves the "usefulness of the purpose" itself. Thus, in reality, judging the validity of a model ultimately involves judging the validity of its purpose too, which is essentially non-technical, informal, qualitative process*" (Barlas, 1996; a very similar concept can be found in Shreckengost, 1996; Forrester, 1996; Rouse, 1985). On top of that, concerning policy-oriented models, Forrester and Senge (1980) state that "*the ultimate objective of validation in system dynamics is transferred confidence in a model's soundness and usefulness as a policy tool*" (Forrester and Senge, 1980).

For the purpose of this study, particular attention is given to System Dynamics during the analysis of the validity of models and methodologies. Barlas distinguishes between models that are "causal-descriptive", because they identify causal relations and describe the structure and functioning of a system, and those that are "correlational" (Barlas, 1996). The latter category is commonly based on optimization and econometrics, where historical data are used to define the structure of the model and its validity is defined based on the accuracy in which such models can replicate historical data, not on the validity of the structure itself (e.g. equations). This type of validation is challenged by parametric uncertainty, which, when analyzing complex problems, is not trivial and still very relevant (Kelly and Kolstad, 1998). In other words, it can be said that every model of this kind is as good as its assumptions.

Validation of causal-descriptive models, such as System Dynamics ones, goes beyond the analysis of inputs and outputs and includes an in depth scrutiny of the structure of the model. Since such tools aim at representing the functioning mechanisms of the system through the identification of causal relations, they define a theory of how the system works. This theory has to be validated, and this is why it is often said that "*a system dynamics model must generate the right output behavior for the right reasons*" (Barlas, 1996). In other words, this means that the validation of a System Dynamics model includes an analysis of the coherence of structure and purpose, as well as the verification of the technical soundness of the equations (Coyle and Exelby, 2000).

The following sections of the study aim at researching the extent to which System Dynamics computer simulation models relate to the main currents of thought on Artificial Intelligence and computer simulation in the philosophy of social science. This study focuses on Integrated Assessment Models, such as Threshold 21 (T21) (Millennium Institute, 2005) and the Primary Country Model (PCM) (Kopainsky et al., 2009), with integrated energy models -tools designed to support policy formulation and evaluation. T21 is largely based on System Dynamics, accounts both for detailed and dynamic complexity and generates future projections by accounting for cross sectoral interdependencies that are intended to identify the context in which issues arise.

## 2. Questions and Concerns on Computer Simulation Models

A computer simulation model is a computer program, or network of computers, that attempts to simulate an abstract model of a particular system (Strogatz, 2007). More in details, a model can be defined as a representation of a physical system that in some way simulates the behavior of the system, may consist of a computer program and may analyze a problem, increase understanding of the system, forecast future states of that system, or predict the outcomes of measures taken to change the system (Karas, 2004).
Models have become useful mathematical tools for the analysis of many natural systems, with the objective to gain insight into the operation of such systems, or to observe their behavior.
In the field of Social Science, a computer simulation model can be defined as "*... a powerful new metaphor for helping us to understand many aspects of the world*", with the interesting observation that "*... it enslaves the mind that has no other metaphors and few other resources to call on*" (Weizenbaum, 1976).
Building dynamic simulation models generally implies the execution of a series of steps that include the definition of the issues to be analyzed, a background study of such issues, data collection and analysis, formulation of dynamic hypotheses, creation of a simulation model and finally validation and analysis of the results (Sterman, 2000).
These steps require learning and understanding of the issues and the system in which they emerge, as well as a reduction of the complexity observed in real systems to actually create and customize a causal-descriptive simulation model.

When building dynamic simulation models aimed at producing coherent projections by understanding and representing history, two concerns emerge:

1) There is a difference between explaining and understanding the behavior of systems. While explanations can be derived from the analysis of past events, understanding presupposes a deeper investigation of the mechanisms on top of which decisions and events take place.
2) When aiming at generating and analyzing projections, there is an important limitation to be considered: models provide a prescriptive representation of the system, in which

immanence (i.e. events) cannot be based on (and reduced to) history. Descriptive models are needed, as they provide insights to the functioning mechanism of the system. Furthermore, the representation of detailed complexity is not a prerequisite for the identification of events, which in fact represents a paradox for prescriptive simulation models in a way that raptures and events cannot be forecasted. The representation of dynamic complexity is a necessary condition for the identification of events and the subsequent system adaptation.

Such concerns should be addressed considering the context in which modeling takes place, where learning about complex adaptive systems happens with the aim of reducing complexity to represent the real system analyzed, and its context, in a simpler form.

## 2.1 Methodological Issues: Foundation

### 2.1.1 Learning

According to Dreyfus, explaining and understanding can be found at different levels in the learning process (Dreyfus, 2001). Dreyfus identifies seven stages of learning. While the capability of properly explaining why certain events took place (ex-post), can be associated to Proficiency and Expertise, understanding the issues and the processes that generate them should be coupled with Mastery. In this analysis an event is to be considered as Badiou's "*immanent break with a given situation*", where a situation is a singular configuration, an "infinite multiple" which can be "politico-historical" or "strictly physical or material" for instance (Badiou, 2000). An event, as infinite multiple, can be coupled with chaos theory and the Lorenz Attractor, where a small set of interconnected equations, creating a high degree of dynamic complexity, can lead to unforeseeable behavior (Lorenz, 1963).

Proficiency, stage 4 in the learning process, according to Dreyfus identifies students who have made "situational discrimination" and are able to analyze the situation to identify problems that need to be solved. At this stage of the learning process the answer cannot be identified easily and the approach also requires some investigation. According to Dreyfus, being able to recognize and identify issues means also having the capability to clearly and coherently describe such problems and systems, which he identifies as "intuitive reaction" (Dreyfus, 2001).
Similarly, the first step of the modeling process with System Dynamics consists in identifying the key issues to be solved (Randers, 1980). Modelers therefore have to be able to analyze the system, identify issues and find their causes and impacts. The latter step requires further research for novice modelers, which have to study the "history" of the system, while it is a straightforward step for expert practitioners. Dreyfus describes such skills in the stage 5 of the learning process, Expertise.

Expert students and modelers can clearly identify what methods and approaches have to be used to find solutions to the issues being investigated. They can do so thanks to their vast experience in discriminating situations. Modelers, more specifically, when identifying dynamic hypotheses -the second step of the modeling process (i.e. defining dynamic hypotheses (Randers, 1980; Sterman, 2000)- are advised to draw causal maps of the systems analyzed. Such diagrams are very much based on personal experience and are usually created instantaneously based on already existing work. As Dreyfus states, this level of learning "*allows the immediate intuitive situational response that is characteristic of expertise*" (Dreyfus, 2001). Similarly, in System Dynamics two main feedback loops can be identified to define all types of behavior in real systems: reinforcing and balancing (Forrester, 1961).

The following stage of learning, stage 6, is called “mastery” by Dreyfus and can be considered as the threshold between the ability of explaining and understanding. In fact, mastery involves developing a personal style, which can be easily applied to modeling too, where a variety of models of different styles can be created and still lead to similar analyses and conclusions.
Such level of experience can be reached in different ways, through experience or through training with a number of different masters. The latter example is used by Dreyfus to define mastery: “*Working with several masters destabilizes and confuses the apprentice so that he can no longer simply copy any one master’s style and so is forced to begin to develop a style of his own. In so doing he achieves the highest level of skill. Let us call it mastery*” (Dreyfus, 2001).

Using Badiou’s definition of event and Dreyfus’ classification of learning, immanence results to be the ultimate challenge for modelers. As a matter of fact, if the modeling process is a learning journey in itself (Sterman, 2000), and if expert practitioners gather their knowledge from experience (Dreyfus, 2001), they will never be able to identify immanence, a singular and unique configuration (Badiou, 2000), before an event actually takes place, unless the models they build are dynamically representing the underlying causal structure of the system and allow for emergent behavior (through shifts in loop dominance). Modelers, therefore, attempt to represent something (e.g. events) that cannot be clearly identified before its manifestation (SD contributes to this effort, providing a descriptive framework). This constitutes a dilemma that modelers working with prescriptive tools have to face, represented by the impossibility to represent immanence through experience. As mentioned above, when dealing with descriptive models such dilemma can be solved by learning about and representing what the main forces driving the behavior of the system are.
A longer term focus then helps see the events that led the system to change and to the identification of those structural components that may generate new ones in the future (e.g. through a shift in trends and strength of selected feedback loops). The energy models proposed in this study, integrated into T21 and PCM, account for long time frames to test the results of the simulation against history and project into the future long enough for longer term trends to emerge.

### 2.1.2 Explaining and Understanding

Many similarities can be found with the processes modelers of different disciplines use to create their frameworks of analysis: when studying historical events, both proficient and expert practitioners would use their own knowledge and experience to define, ex-post, a framework that allowed events to take place or that would be able to reproduce them. Such representation is usually subjective for what concerns the identification of the main drivers of the system’s behavior, but it is still very much related to previous existing work.
At the Mastery level, in the System Dynamics field, it is commonly said that an infinite number of different models can be built to analyze the same issue and still lead to very similar results (Sterman, 2000; Shreckengost, 1996; Forrester, 1996; Rouse, 1985). This implies that the understanding of objective mechanisms is in place and those personal unique styles and techniques are being used. This is consistent with relativistic, holistic and pragmatist philosophies. In fact they say that “*No particular representation is superior to others in any absolute sense, although one could prove to be more effective. No model can claim absolute objectivity, for every model carries in it the modeler’s worldview. Models are not true or false, but lie on a continuum of usefulness*” (Barlas and Carpenter 1990).

A possible, though controversial, way of explaining (not understanding) why events took place, consists in a description of which happenings led to their creation (happenings are considered to be prerequisites for events to take place according to Davidson (Davidson, 1980)). This means abstracting and objectifying the object of analysis, typical of the first stages of learning, where a filter is applied based on personal judgment and experience. Such process of objectification increases the validity of a model according to the reductionist/logica1 positivist school. They state that a valid and valuable model is simply a correct objective representation of reality. In this philosophy, which provides a concept of validity closer to “correlational” models, the validity of a tool has to do with the accuracy of the results and not with the actual usefulness of the model itself (Barlas and Carpenter 1990).

Understanding why events emerged implies instead more than the accurate representation of reality. In fact, it requires the identification of the underlying structure of the system analyzed, which accounts for causal relations, non-linearity and feedback loops. Understanding, in fact, can be defined as “*a psychological process related to an abstract or physical object, such as, person, situation, or message whereby one is able to think about it and use concepts to deal adequately with that object.*” Understanding also implies the existence of a real world relation to those subjects or agents that allows decisions and thoughts to be correctly interpreted and dealt with (Skjervheim, 1996).
With such definition, understanding is highly connected to conceptualization, in a way that in order to understand a phenomena it is necessary to have it conceptualized, but also to have had a real personal, subjective, relation with the subject. Similarly, modeling consists in conceptualizing reality to a simplified form with the aim to identify what decision rules or options are made available to agents acting within the system. Computer simulation models with a prescriptive structure, which does not allow for emergence, will always be limited to the research of an objective set of decision rules or options (i.e. objective function), while descriptive models can reach higher levels of understanding through an investigation and a representation of the underlying causal structure of the real world. The limitation faced by prescriptive models represents a second dilemma for these tools, in the fact that conceptualization to reduce world’s complexity requires objectification with such methodology. It is therefore clear that, in order to represent emergent behavior, models should be able to incorporate structural components that are not based on objective rules only. This is consistent with the fact that it is impossible to define a formal or objective process of “theory confirmation” (Barlas, 1996). For this reason, it is not possible to expect that a validation process in the social sciences can be exclusively formal and objective (Barlas and Carpenter 1990).

When modeling, practitioners investigate what the underlying structure of a system is, being open to gather information and trying to identify what mechanisms drive the observed behavior independently from what they might be. Identifying these mechanisms means identifying a set of causal relations existing within the system, so that understanding can be reconducted to the explanation of what relations and interdependences generated the event being investigated, with limitations related to experience and objectification, and with a specific time frame (history).
This recalls the thoughts of Rostislav Persion: “*the process of introverted thinking (Ti) is thought to represent understanding through cause and effect relationships or correlations. One can construct a model of a system by observing correlations between all the relevant properties. This allows the person to generate truths about the system and then to apply the model to demonstrate his or her understanding*” (Persion, 2008). In the System Dynamics context, the identification of causal relations originates from the identification of correlations (through simulation) as an output of the model, which allows overcoming major challenges, such as objectification and oversimplification.
Conventional econometric and linear programming models, which base their analysis on correlation, are limited to explanation (not understanding) of phenomena especially when dealing with the creation of future projections (this does not exclude that modelers can understand the system thanks to their knowledge and dynamic mental models). With such methodologies

historical data are analyzed, relevant data series are selected and then used to obtain projections. With such a heavily dependence on historical data, this type of models loses confidence when new and unexpected events happen. This is due to the fact that they are unable to provide insights to the mechanisms driving un-experienced changes in the system and only use historical trends to extract projections.
In System Dynamics simulation models such as T21, understanding the processes that generate changes in the systems analyzed is the key objective of the modeling process. The structural foundation of the methodology lies in fact in the analysis of historical events that change the behavior of the systems to discern what the causes and effect of change were. SD models aim at representing the key causal relations underlying the system analyzed, leading to a deeper (though not full) understanding of the system itself and its mechanism.

### 2.1.3 Analyzing Issues Arising in Complex Adaptive Systems

Conceptualizing and defining understanding in the context of modeling is particularly relevant when considering that the object of investigation are complex adaptive systems, subject to continuous and often sudden change. Complex adaptive systems denote systems that have some or all of the following attributes (Johnson and Neil, 2007):
- The number of parts (and types of parts) in the system and the number of relations between the parts is non-trivial – however, there is no general rule to separate "trivial" from "non-trivial;"
- The system has memory or includes feedback;
- The system can adapt itself according to its history or feedback;
- The relations between the system and its environment are non-trivial or non-linear; and
- The system can be influenced by, or can adapt itself to, its environment.

A complex adaptive system, like any social system, is therefore characterized by feedback, delays and non-linearity, three crucial elements that define it dynamic behavior and complexity. Any complex adaptive system is also context dependent and is a learning environment where historic memory can influence the future development of the system itself (Holland, 1995).
When accepting such definition becomes more evident that the System Dynamics methodology accounts for the characteristics required for the analysis of complex adaptive systems. The representation of feedback (to account for embedded memory), delays (adaptation may occur in relation to history) and non-linearity (to represent non-trivial and at times counter intuitive relations within the system), contribute to the representation of the context, which can influence the future evolution of the system. Nevertheless, the system is in continuous evolution and both the identification of parts and relations is non-trivial.
When considering future projections and dealing with complex adaptive systems, in addition to the challenges in defining a structure for the system analyzed, the use of analogy (based on experience) can provide insights on future developments of similar issues in non-dissimilar contexts. On the other hand, the creation of an event would immediately produce new structures and modify the strengths of factors influencing the system or the agents forming it. This represents a challenge, if not a dilemma, for the creation of computer simulation models. Deep understanding is therefore required also to comprehend to what extent the system changes and evolves after events (natural or induced, emergent or expected) take place.

Examples of complex adaptive systems include any human social group-based endeavor in a cultural and social system such as political parties or communities.
John H. Holland defines a Complex Adaptive System (CAS) as follows: "*(CAS) is a dynamic network of many agents (which may represent cells, species, individuals, firms, nations) acting in parallel, constantly acting and reacting to what the other agents are doing. The control of a CAS*

*tends to be highly dispersed and decentralized. If there is to be any coherent behavior in the system, it has to arise from competition and cooperation among the agents themselves. The overall behavior of the system is the result of a huge number of decisions made every moment by many individual agents*" (Holland, 1992; Waldrop, 1992).

## 2.2 Methodological Issues: Application

### 2.2.1 Phenomenology

The ultimate objective of modelers is to understand systems. In order to do so they analyze such system and build a computer simulation model potentially able to provide insights on events and phenomena through the identification of the underlying structure that allows for their creation. This process presents many similarities with Edmund Husserl's definition of phenomenology: (Phenomenology is) "*the reflective study of the essence of consciousness as experienced from the first-person point of view*" (Smith, David Woodruff, 2007).
Phenomenology examines phenomena to understand and extract from it the main characteristics of related experiences. The System Dynamics modeling process does present similarities with this definition: its aim is to represent the underlying structure of systems, which is able to explain the mechanisms that allowed events to take place or that will do so in the future under specific and well defined conditions (Sterman, 2000).

When looking at the modeling process, and more specifically at the identification of structural drivers of behavior in a well defined system, phenomenology suggests that modelers can only identify causes after an event has taken place, while it is significantly more challenging to do so (if not impossible) in order to forecast happenings and events. This is particularly confirmed by the first and third dilemmas identified earlier, respectively the singular and unpredictable nature of immanence and the continue evolvement of systems.
Such dilemmas pose a major challenge to the validity of simulation models, indicating that a good part of the exercise of modeling would be in fact speculation based on an incomplete understanding of the system, a conclusion drawn based on the second dilemma. In other words a model could be used to simply simulate a variety of assumptions, as scenarios in fact, that would greatly influence its outputs and would actually represent no more than "educated guesses". To counter this problem, with Threshold 21, while recognizing the limitations of the methodology, the author selected a longer time frame to carry out an analysis of the past and most likely future causal relations affecting the system, to then proceed with the definition of the boundaries of the model, that is the identification of causal relations that determined a shift in the behavior of the system (or that might indicate one in the future). Though this process does not guarantee confidence in the results of the simulation, it indicates that an analysis of the major forces driving the system has been carried out with the aim to identify the main causes and effects that future exogenously simulated events (e.g. policy implementation) may generate in the system. This, in fact, represents an extension of the more simplistic (but not of easier execution) analysis of historical data to then select relevant data series and extract projections from longer-term historical trends.

### 2.2.2 Modeling Complexity

In order to gain insights on real complex adaptive systems, modelers aim at creating a reliable and valid model representing a simplified version of real systems. This way the complexity is reduced to the most important causal relations and feedback loops that already did (or might) influence the behavior of the systems being analyzed.

The definition of complexity is similar to the one of complex adaptive systems. Complexity is characterized by a number of factors (or elements) in a system, which are interconnected with each other (or depend on each other). From a different point of view, it could be said that complexity emerges from the interaction of various connected and apparently non connected factors (Waldrop, 1992).
Weaver defines the complexity of a particular system as "*the degree of difficulty in predicting the properties of the system if the properties of the system's parts are given*" (Weaver, 1948). In Weaver's view, complexity comes in two forms: disorganized complexity, and organized complexity (Weaver, 1948).
Interestingly, also in the field of System Dynamics two types of complexity are identified: detailed and dynamic (Sterman, 2000). While the detailed complexity is characterized by a large number of linear relations, the dynamic components imply the existence cross-sectoral connections characterized by non-linearity and delays. Weaver draws a very similar distinction between organized and disorganized complexity. Organized complexity emerges from well defined relationships within the system or across systems (e.g. the level of details embedded in the system, correspondent to detailed complexity). Disorganized complexity instead results from the size of the system, the large amount of parts that forms it and the connections existing among them. In this case, the interactions of the parts can be seen as largely random (correspondent to dynamic complexity in System Dynamics) and the behavior of the system can be explained by using probability and correlation. A fundamental characteristic of disorganized complexity is that the aggregated behavior of the system shows properties not resulting from the mere sum of its components.
An example of detailed and organized complexity is the representation of the steps of energy conversion processes from primary sources to end use fuels. Every single step can be identified, measured and defined even if the process accounts for thousand of steps. Dynamic and disorganized complexity can be identified in the definition of the price of such energy sources as well as in social systems, where the individual responses to price change do not necessarily provides insights on the aggregated behavior of the system.

As all frameworks, System Dynamics simulation models represent a simplification of a reality that is complex, dynamic and unpredictable. The complexity of the real world is limitless and reducing it to analyze specific issues is not always a straight forward exercise. This reflection stems from the fact that complexity always exists and reducing it to a limited number of factors may actually lead to erroneous analyses, especially in the case of dynamic and non organized complexity. One of the risks to be acknowledged is that, as Michael Behe states, irreducible complexity can be found in a "*single system which is composed of several interacting parts that contribute to the basic function, and where the removal of any one of the parts causes the system to effectively cease functioning*" (Behe, 1996). Although Behe's definition refers to the field of biology, creating a simplified representation of reality as a basis for the construction of a computer simulation model, by selecting the major factors influencing the behavior of such system, may not allow for a correct representation of the system itself because some relevant elements defining the system's functioning will be excluded from the analysis. On the other hand, it has to be noted that representing all factors would mean reproducing reality with all its complexity. This is a fundamentally important step in the definition of the structure of the model that should be taken into consideration when defining its boundaries, and when evaluating its validity.

## 3. Critics to Artificial Intelligence

Learning from and about real phenomena as well as attempting to identify optimal ways to reduce complexity, do not solve all the problems related to customization and use of computer simulation models. Dreyfus raises relevant concerns on the validity of such methodologies and how they are applied (Dreyfus, 1979), which can be used to summarized the challenges identified so far. Firstly, Dreyfus critiques what he calls a psychological and epistemological assumption of Artificial Intelligence (AI), which consists in the fact that the mind works by performing discrete computations (in the form of algorithmic rules) on discrete representations or symbols. This assumption reflects, in fact, how dynamic computer simulation models work. They do run on discrete computations on a closed algebraic system. Dreyfus arguments also that experts do not follow or create rules, they simply use examples to explain what their main skills or applied processes are (Dreyfus, Dreyfus, 1986). This indicates that computer simulation models, when working with rules and discrete algebraic equations, can never be very accurate in replicating or forecasting events because they do not take place based on formal rules. In other words, the emerging characteristics of systems cannot be captured or forecasted by models.

A second assumption criticized by Dreyfus, the ontological one, presupposes that reality consists entirely of a set of mutually independent, atomic (indivisible) facts. Accepting such assumption would mean that human behavior is, to a large extent, context free because all parts of the system can be isolated and analyzed separately according to specific laws, such as in physics. In epistemology, contextualism is the treatment of the word 'knows' as context-sensitive. Context-sensitive expressions are ones that "*express different propositions relative to different contexts of use*" (Stanley, Jason, 2005). Dreyfus strongly denies such assumption and argues that we cannot (and never will) understand our own behavior by considering ourselves as things whose behavior can be predicted via “objective”, context free scientific laws. According to Dreyfus, a context free psychology is a contradiction in terms (Dreyfus, Dreyfus, 1986).

System dynamics modelers recognize the importance of feedback and cross-sectoral relations and do create a simplified model of reality in which the causes of phenomena are broken down to better understand the origin of such events. While this process is in contrast with Dreyfus’ assertion that reality is indivisible, it does identify and represent some of the relations existing among various parts of the system. By doing so, System Dynamics models, such as T21, though using a closed descriptive structure, do take into account and represent the context that characterizes the system analyzed (this is mainly done by incorporating social, economic and environmental factors in a single comprehensive framework).

Acknowledging the limitations posed by computer simulation models, an analysis of the modeling process is carried out to identify eventual strengths that might help further developing the studies currently carried out to reduce the gap that Dreyfus identifies.

According to anthropology, more precisely ethnography, social phenomena take place thanks to a structure based on processes, which generate happenings (Davidson, 1980). These happenings at times turn into events, which are constructed by processes and determined by cultural factors or unique contexts (Davidson, 1980). Similarly, a dynamic simulation model is built upon a structure of differential equations, each of which can be seen as a process. Furthermore, the model generates simulated behavior, which corresponds to happenings. Events are represented by shifts in dominance that eventually help identifying tipping points. According to ethnography, in fact, emerging events strongly influence the structure of the system that generated them, which is evolving over time. In all computer simulation tools the structure of the model, hard wired into equations, cannot modify itself (i.e. new equations cannot be created by the software based on the results of the simulation), excluding from the analysis the study of raptures and elements of discontinuity. On the other hand, System Dynamics simulation models allow for changes in the strength of the structural causal relationships identified, creating a link between structure and behavior.

According to Dreyfus, a system can never close up in a defined structure because unpredicted emergent behavior would change its structure and further evolve. The representation of systems and their complexity with System Dynamics models proves the opposite.

In the case of Threshold 21 wide boundaries are utilized to represent what are considered to be the main factors that did influence the system in the past and that might influence it in the future. These include some relations that may not be relevant at present state but may become determinant in the future, or other that were responsible for changes at different past times. Though a closed-loop representation may seem to limit the detailed analysis of complex issues, it provides value added in improving the understanding of the system, both structure and behavior. System Dynamics models allow for a more holistic representation of the issues analyzed by adding their context (e.g. socio-economic and environmental dimensions) and crucial functioning mechanisms to the structure of the model.

## *4. Conclusions*

The impossibility to identify and represent events and emergent characteristics of the system analyzed has posed serious questions about the validity of computer simulation models aimed at projecting future events. A natural conclusion to this analysis would suggest that if factors that have profoundly changed our social, economic and environmental systems in the past, such as raptures and discontinuities, cannot be identified nor represented, the creation of forward looking scenarios may be considered a mere speculative exercise (i.e. educated guesses) providing little insights. Furthermore, prescriptive simulation tools are only based on past experience and incorporate potentially biased assumptions derived by the knowledge of the researchers who created them, especially if they have not reached the "mastery" stage of learning. Since society is in continuous evolution, the creation of prescriptive models couldn't contribute extensively to longer term policy analysis. Moreover, when simulation models do succeed in having a strong impact on society, they do create a new event that subsequently changes the course of things, creating the need for a further recalibration or modification of models.

The following four major dilemmas summarize the main challenges mentioned above:

1. Immanence cannot be identified only through experience, neither at the highest levels of learning (i.e. Mastery);
2. It is not possible to reach full understanding through conceptualization aimed at finding objective rules (e.g. modeling);
3. Social systems continuously change, therefore understating is a continuous, never ending process;
4. Reducing limitless complexity is not always viable and limits the validity of the analysis being carried out.

Given the above, a modeler's job resembles a journey searching for knowledge and a level of understanding that cannot ultimately be found with the tools he owns. As models are never perfect, modelers will never be fully satisfied with their work and will keep striving to improve it and make it more useful. The amount of information and understanding they will gather and accumulate through this journey will eventually allow them to reach the mastery level of learning, when they will properly interpret and conceptualize current and past events, still leaving the projection of future events largely unknown. A significant advantage gained in such process reside in the fact that the knowledge and understanding accumulated strengthen the capacity to analyze the causes and consequences that future events might have on the status of the system analyzed.

Considering strengths and weaknesses of descriptive System Dynamics simulation models, such as T21 and PCM, the challenges mentioned above seem achievable given that:

1) The identification of causal relations allows for investigation of the main functioning mechanisms of the system analyzed, providing insights on the conditions that would

allow future events to take place;

2) The full understanding of the system has to do with its complexity. System dynamics allows representing complexity through a descriptive, not prescriptive model;
3) Behavioral change is continuous, while structural change can be infrequently observed. System Dynamics focuses on the structural representation of systems, providing insights on the motivations for behavior to change;
4) Complexity has to be simplified to the extent reasonable to be able to understand why issues arise. Selecting boundaries is a crucial step of the modeling process, so as to take into consideration what the main factors influencing issues and behavior, in a specific time frame, may be.

The validation of a System Dynamics model therefore results to be a gradual, semiformal and conversational process (Barlas, 1996), where the soundness of the structure of the model is as important as the quality of the outputs of the simulation. Being "white-box" models, System Dynamics tools and T21 provide a transparent simplified representation of reality that can be validated against real systems. This poses challenges from both a technical and philosophical angle: the former would imply that we could state with a certain degree of confidence whether a model represents reality accurately enough, and the latter relates to the unresolved philosophical issue of verifying the truth of a (scientific) statement (Barlas, 1996). Barlas also adds that, as a consequence, "*our conception of model validity depends on our philosophy (implicit or explicit) of how knowledge is obtained and confirmed*" (Barlas, 1996).

When using System Dynamics and descriptive modeling tools the role of modelers aiming at providing insights on policy formulation and implementation should consists in (providing) "*... tools that exploit new ways to encode and use knowledge to solve problems, not to duplicate intelligent human behavior in all its aspects*" (Duda, Shortliffe, 1983).
System Dynamics models in fact can inform policy making by taking into consideration elements of the context in which issues arise and by providing insights on the functioning of the system studied (DeGeus, 1992; Morecroft, 1992). Dynamic simulation models should therefore be seen as learning tools on which to base a constructive dialogue to reach better decisions in an objective environment where various assumptions and the manifestation of events can be tested and where the audience can be abstracted from fully subjective positions.
Dynamic simulation models are by no means perfect and will never be; nevertheless, we have the responsibility to use our best scientific understanding to develop reasonable and sustainable policies. Integrated models allow us to do so by enhancing the understanding of systems and providing useful insights to be shared with stakeholders.

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