Issues to Consider While Developing a System Dynamics Model

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I. Introduction

Over the past forty years, system dynamicists have developed techniques to aid in the design, development and testing of system dynamics models. Several articles have proposed model development frameworks (for example, Randers (1980), Richardson and Pugh (1981), and Roberts et al. (1983)), while others have provided detailed advice on more narrow modeling issues. This note is designed as a reference tool for system dynamic modelers, tying the numerous specialized articles to the modeling framework outlined in Forrester (1994). The note first reviews the “system dynamics process” and modeling phases suggested by Forrester (1994). Within each modeling phase, the note provides a list of issues to consider; the modeler should then use discretion in selecting the issues that are appropriate for that model and modeling engagement. Alternatively, this note can serve as a guide for students to assist them in analyzing and critiquing system dynamic models.

II. A System Dynamic Model Development Framework

System dynamics modelers often pursue a similar development pattern. Several system dynamicists have proposed employing structured development procedures when creating system dynamics models. Some modelers have often relied on the “standard method” proposed by Randers (1980), Richardson and Pugh (1981), and Roberts et al. (1983) to ensure the quality and reliability of the model development process. Forrester (1994) Recently, Wolstenholme (1994) and Loebbke and Bui (1996) have drawn upon experiences in developing decision support systems (DSS) to provide guidance on model construction and analysis.

While Randers (1980) suggests four phases: conceptualization, model formulation, model testing and implementation/representation, current system dynamics practice seems to fall into five phases that vary somewhat from Randers. First, due to the numerous issues incorporated in the conceptualization phase and different objectives of those tasks, the proposed framework (Figure 2) decomposes Rander's initial phase into analysis and design. Richardson and Pugh (1981) refer to these two stages as problem identification and system conceptualization, respectively.

Second, and more importantly, Randers suggests model implementation as a final phase as would be found in a system development life cycle model. System dynamics consultants have questioned this view, describing their insights and contributions to organizations as "interventions," "modeling for learning," or "changing mental models" (Senge 1990, Graham 1994, Morecroft 1994). As Roberts (1972) suggests, "Indeed, to produce implementation of change the needed perspective is that implementation requires a continuous process of point-of-view that affects all stages of modeling."[1] Accordingly, the implementation phase is depicted as a parallel activity, overlapping the other four modeling stages.

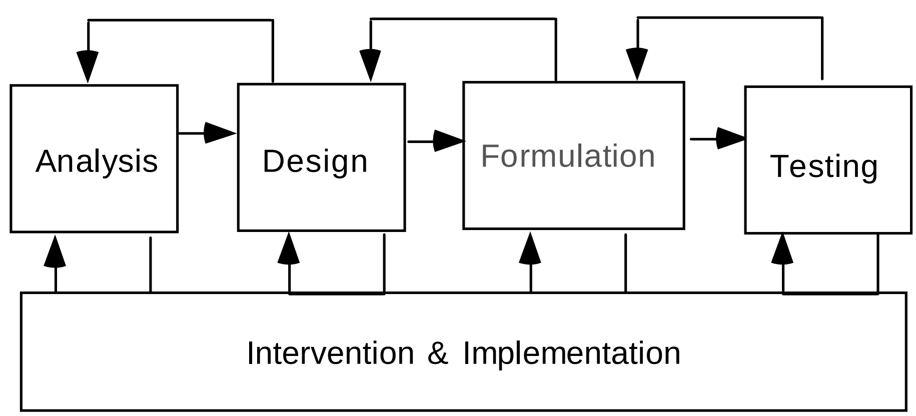

Figure 2. A System Dynamics Model Development Life Cycle

Over the past two decades, system dynamics modelers have identified a number of important questions to consider while modeling and have developed new modeling techniques that warrant inclusion in a comprehensive model development framework. In the following sections, issues that system dynamicists have identified as key modeling concerns are presented. These issues are posed as questions that the modeler should consider with key conceptual terms highlighted by underlining.[2] Accompanying each issue are references to system dynamics articles that examine the issue in depth and may offer specific tools and techniques that the modeler could use to address the concern.

Each issue is placed into a model development phase based upon the assignment in the "standard method" framework (Randers 1980, Richardson and Pugh 1981, and Roberts et al. 1983) and also the issue-specific references (for example. Forrester and Senge 1980 and Homer 1983).

III. The Phases in the System Dynamics Model Development

A. The Model Analysis Phase

During the model analysis phase, modelers become familiar with the problem area and work to clearly define the purpose of the model. At this point, it is important to assess what is the appropriate modeling technique to study the problem and what trade-offs are made in the selection of the modeling technique. The questions below cover problem definition and choice of modeling technique.

1. Problem Definition

"A model needs a clear purpose."[3]

- What is the purpose of the model? (Forrester 1961, Sterman 1988a).

  Richardson and Pugh (1981) explain,

  From the system dynamics perspective, a model is developed to address a specific set of questions. One models problems not systems. We emphasize the point because the purpose of a model helps guide its formulation. The problem to be addressed, the audience for the results of the study, the policies one wishes to experiment with, and the implementation desired all influence the content of the model.[4]

- What is the nature of the problem being studied? linear vs. nonlinear, static vs. dynamic.

In reference to econometrics and linear programming, Forrester (1976) suggests, "the techniques commonly used by social scientists to analyze statistical data can be inconclusive or misleading when applied to the kind of nonlinear dynamic systems found in real life."[5]

- What kinds of insights are being sought? Is it to study optimal or realistic behavior? Is it to better understand normative or positive behavior?

According to Senge (1987), "Statistical methods aim at accurate estimation of model parameters and formal hypothesis testing. Simulation methods aid in understanding how the structure of complex systems produces the observed behavior." Today, some simulation tools now allow the modeler to undertake both activities (Oliva 1996).

- What is the role of the model? Is it a descriptive, explanatory, predictive or teaching model?
- What are the hypotheses or theory underlying the model? Are these hypotheses dynamic?

2. Matching the Modeling Technique to the Performance Requirements

"In addition to the shared concepts general to all mathematical modeling, each

methodological school also employs its own special set of theories, mathematical techniques, languages, and accepted procedures for constructing and testing models. Each modeling discipline depends on unique underlying and often unstated assumptions; that is, each modeling method is itself based on a model of how modeling should be done."[6]

- What type of modeling technique is appropriate?

Forrester (1973) identifies 5 types of models: mental, descriptive, solvable mathematical, statistical, and system dynamics. The modeling technique should be consistent with the purpose as well as the nature of the problem being studied. Econometrics is often used to estimate parameters, study linear systems in equilibrium (Samuelson 1957). Linear programming is used to optimize an objective function in a resource-constrained environment. Discrete event simulation allows for spatially explicit and/or event-driven situations. System dynamics can be employed for non-linear and dynamically complex problems involving disequilibrium conditions, bottlenecks, delays, stock-flow relationships, and a realistic portrayal decision making (Sterman 1987).

- What are the assumptions associated with each modeling technique?

a) Discrete vs. Continuous Modeling

Social scientists often model discrete events and rely upon discrete modeling techniques. In addition, difference equations are imposing an assumption of discrete time (for justification, see Samuelson 1957, Mathematical Appendix B). In contrast, system dynamicists employ continuous modeling and differential equations (Forrester 1961).

b) Correlation vs. Causal

Most social scientists study correlation relationships, which are generally predicted by theory and may or may not be causal. In contrast, system dynamicists examine and model causal relationships which may or may not be supported in a correlation analysis. Richardson and Pugh (1980) explain, “The problem is that correlations made from total system behavior do not measure ceteris paribus causal relationships. Nature tends not to hold everything else constant while we collect data for the correlation.”[7]

d) Equilibrium

System dynamics permits disequilibrium modeling, while systems of simultaneous equations assume a stress-free equilibrium, in which desired and actual states are equal (Hines 1987). One econometrics text (Kennedy 1993) describes the shortcomings of time series modeling in analyzing dynamic problems as follows:

One reason for the relative success of ARIMA models is that traditional econometric structural models were too static -- their dynamic specifications were not flexible enough to allow them adequately to represent an economy which when observed is more frequently out of equilibrium (going through a transition stage) than it is in equilibrium. This lack of attention to the dynamics of models was a natural outcome of the fact that economic theory has some ability to identify long-run relationships between economic variables, as created by equilibrium forces, but is of little help regarding the specification of time lags and dynamic adjustments.[8]

d) Parameters

Econometrics imposes the assumption of equilibrium in which actual matches desired states (Hines 1987) in order to generate parametric estimates as the solution. System dynamics assume parameters and casual relationships between variables in order to better understand disequilibrium behaviors.

e) Feedback

System dynamicists view capturing feedback processes via stock and flow equations as critically important. In general, econometricans place less emphasis on feedback, although some relationships such as the multiplier-accelerator economic feedbacks are actively studied. When feedback is present, advanced econometric techniques, such as instrumental variables, are employed to remove the effects of feedback and allow unbiased estimation of parameters. In some cases, the feedback can be retained through lagged variables; in others, the feedback is removed through the use of proxy/instrumental variables in order to allow unbiased estimation.

f) Simultaneity and Time Delays

Econometricians and system dynamicists often disagree on the presence and relative importance of time delays. In general, econometricians view adjustment processes as being rapid, justifying the use of simultaniety as an assumption in their models. System dynamicists assume that a time delay is present in every feedback process and that one can only approximate simultaniety through the use of a low time step (dt).

g) Determination/Identification of the System

Both econometric and system dynamic models must be determined, i.e. as many independent, consistent equations as unknowns. The two modeling schools rely on different sources of information to determine their models. According to Forrester (1992), economists rely on numerical data and economic theory in model development, while system dynamicists utilize a wider range of data, including unobservable concepts and soft variables.

h) Linearity/Nonlinearity

A linear relationship is one in which a variable increases as a constant percentage of another, such as $y = mx + b$. Linear representations are used in system dynamic models when converting one unit of measure into another (years into months) or when the relationship between to variables is essentially constant in the operating range being studied. It is important, however, to assess whether the relationship breaks down at extreme values that may be experienced in the real system. Simulation techniques, such as system dynamics, can allow the modeler the flexibility to introduce important non-linearities into the model.

- Are there additional limitations of the modeling technique selected?

a) Robustness of Results

Senge observes, "Experiments with ordinary and generalized least-squares estimation (OLS and GLS) show that the parameter estimates derived from these methods are highly sensitive to errors in data measurement, especially when a model's feedback structure is not completely known."[9] Kalman and other forms of optimal filtering can be employed to address some of these concerns (Ventana

1994).

b) Units Consistency

Drawing upon its foundations in engineering control theory, system dynamicists are encouraged to ensure the consistency of units (Forrester 1973, Forrester and Senge 1980); economists do not emphasis this issue.

- Should multiple modeling techniques be employed, either for comparison purposes or to fulfill different needs?

Meadows (1980) suggests that econometrics and system dynamics are essentially complementary techniques that should be used to answer different questions. For example, comparative statics can be useful in understanding the relationship between model elements. Linear programming provides insight into resource allocation in a constrained environment.

B. The Model Design Phase

During the model design phase, much of the model conceptualization occurs. The topic areas and associated questions for this phase are largely draw from Randers (1980) and Richardson and Pugh (1981). Generally, the following topics are examined during the model design phase: The variables of interest and reference modes are described. The feedback loops are outlined often in verbal and causal-loop diagrams, then the model scope, including time horizon and system boundary are assessed. Finally, the appropriate level of model aggregation is examined.

1. Variables of Interest

- What are the variables of interest?
- Should the variable be endogenous or exogenous?
- Are pertinent variables included and the unnecessary ones excluded?

2. Reference Modes

Randers describes a reference mode as:

> ... a graphical or verbal description of the social process of interest. The reference mode of a model under developed can be stated by drawing a graph of the expected behavior of major variables...Often the reference mode encompasses different possible time paths for the model variables.[10]

- What are the behavior patterns that the variables display historically? Randers (1980)
- What are the expected and/or desired future behavior patterns?
- What level of confidence/certainty is associated with these values or patterns?
- What considerations have been given to appropriately "slicing the problem"? (Saeed 1992)

3. Dynamic Hypotheses

Randers describes dynamic hypotheses as the reference modes along with the "basic mechanisms" of a problem. Basic mechanisms are the key feedback interactions between the variables of interest and can be depicted in causal loop diagrams (Randers 1980).

- What are core dynamic hypotheses?
- How are they represented in causal-loop diagrams? Stock-flow diagrams?
- Are the dynamic hypotheses meaningful, tangible and specific? (Forrester 1961, Randers 1980)

4. Model Scope

"The art of model building is knowing what to leave out."[11]

- <u>Boundary Adequacy Test:</u> Is the boundary of the model appropriate given the purpose? Is the model too complex or too simple? Are the important concepts for addressing the problem endogenous to the model? (Graham 1974, Forrester and Senge 1990, Wittenberg 1992)

  Forrester states,

  > ...it follows that one starts not with the construction of a model of a system but rather one starts by identifying a problem, a set of symptoms, and a behavior mode which is the subject of the study. Without a purpose, there can be no answer to the question of what system components are important. Without a purpose, it is impossible to define the system boundary....In defining a system, we start at the broadest perspective with the concept of the closed boundary. The boundary encloses the system of interest. It states that the modes of behavior under study are created by the interaction of the system components within the boundary. The boundary implies that no influences from outside of the boundary are necessary for generating the particular behavior being investigated. So saying, it follows that the behavior of interest must be identified before the boundary can be determined.[12]

Richardson and Pugh (1981) define the system boundary as "includes all concepts and variables considered by the modeler to relate significantly to the dynamics of the problem being addressed."[13]

- <u>Time Horizon</u>: What is the appropriate time horizon of the model?

  First, the time horizon of the model should be related to the issue under study as well as the potential decisions being considered (Forrester, 1973). Second, the model should be used when the modeler has confidence in the validity of the model structure (Forrester 1973, Forrester and Senge 1980, Pindyck and Rubinfeld 1991). Therefore, the model should not be used to develop understanding or predict outside of a narrow time horizon if the structure of the problem is undergoing substantial change and if the model fails to account for those changes. In other words, the model should only be used as long as the model structure makes sense.

  Third, if the model is being used for prediction purposes, then a longer time horizon may be required during the historical period in order to improve the quality of parameter estimation (Pindyck and Rubinfeld 1991). Fourth, if possible, dynamic models should be simulated over a long enough time period so that transient behavior can be played out. Some control theorists suggest that this time period should be 5 times the longest time delay in the system (Franklin et al., 1986). System dynamists tend to measure the transient time as four times the sum of time constants around the dominant loop (Forrester 1961).

5. Aggregation

- Is the model consistent in its level of aggregation?
- Is a particular construct depicted at the appropriate level of aggregation?

As reported in Legasto and Maciariello (1980), Forrester suggests:

a) phenomena with similar dynamic behavior may be aggregated together

b) phenomena with different response times may not be mixed together in a model

c) phenomena with similar underlying dynamic structures may be aggregated together

d) model purpose determines the appropriate level of aggregation

Alfeld and Graham (1976) offer three conditions for aggregation:

a) The actions or processes influence the model variables in similar fashion.

b) The actions or processes respond to conditions represented by model variables in similar fashion.

c) The depiction of the individual actions or processes is not critical to the utility of the model.

Others suggest that the level of aggregation should be determined by what is necessary to address policy issues and -- when the underlying process can not be verified by real world data -- by the structure necessary to generate the reference mode.

- Is the model at the appropriate level of aggregation given the desired policy tests?

C. The Model Formulation Phase

The model formulation phase entails the construction of the model. Modelers employ different styles to complete this phase. Some system dynamicists proceed by writing out the proposed detail structure (with rates, levels and constants), building the model, testing it and revising it (Randers 1980). In contrast, Lyneis (1980) provides an example of constructing a core model based on a few feedback loops, conducting extensive model tests, particularly policy tests. He then modifies formulations and adds more feedback loops and tests the impact on model behavior.

1. Variable Formulation

- Do variables correspond with the real world? (Forrester 1961, Randers 1980).
- Should a variable be a stock or flow?
- Should the constants be constant? Should the variables be variable?
- Are units dimensionally consistent? (Forrester 1973, Forrester and Senge 1980)
- Are the names understandable and clearly convey the meaning? (Kampmann 1991)

2. Formulation of Table Functions

- Are the x-axis and y-axis normalized, i.e. dimensionless? (Richardson and Pugh 1981) In stress-free equilibrium, does the model use the normal operating point, which is often (1,1)?
- Does the table function generate unrealistic values? (Kampmann 1991)
- Is the shape of the function smooth (Alfeld and Graham 1976)?
- Is the shape of the table function consistent with reference lines that bound the potential values?
- Is there bias implicit in the formulation through an asymmetric table function?
- Does the table function depict a single effect or several dissimilar effects (implying it should be disaggregated) (Alfeld and Graham 1976)? Is the table function monotonically increasing or decreasing as disaggregated table functions should be?
- What sections of the table function are used? Does the model regularly

simulate off one end of the table function? If the model simulates off the end of a table function, what value is assumed by the software?

- If real world data are used to calibrate a table function, did the researcher take into account potential perception biases of information sources? (Ford and Sterman 1998)
- If the table is data-driven, is it still robust at the extremes?

3. Other Formulation Issues

- Extreme Conditions Test: Are the formulations robust under extreme conditions? (Forrester and Senge 1980, Kampmann 1991, Peterson and Eberlein 1994) For example, if division is present in an equation can the denominator become zero? Does first-order negative feedback control prevent stocks that are not negative in the real world from becoming negative in the model?
- System Dynamics Tradition: Are formulations consistent with the generic structures and "molecules of structure" used commonly in the system dynamics literature and their rationale? (Forrester 1961, Paich 1985, Richmond et al. 1987, Hines 1996, Lane and Smart 1996)
- Discrete vs. Continuous: Can a discrete formulation (e.g. IF THEN ELSE) be captured more effectively or realistically through the use of a continuous (table function) formulation? (Forrester 1961, Kampmann 1991, MacDonald 1996) Do discrete formulations correspond to the real world? Does the discrete formulation obscure bias?
- Rate Design: Is the classic "goal, current condition, discrepancy and action"

structure present? (Forrester 1961)

- Parameters: Are the values of constants and initial stocks reasonable? Are parameters relatively consistent with each other? Are parameters explicit?
- Initial Conditions: Are initial stock values set equal to algebraic expressions that are a function of other stocks and parameters in the system rather than numbers? If the model is initialized in a stress-free equilibrium, are the initial stocks functions of desired stock levels and normal conditions?
- Physical Structures: Are the "physics of the system" correctly depicted (structure verification test of Forrester 1973 and Forrester and Senge 1980)? Are materials conserved?
- Information Structures: Are the largest and more important information delays in the system present in the model? Are information structures consistent with the real world? (structure verification test of Forrester 1973 and Forrester and Senge 1980)
- Time Delays: Are time delays correctly depicted as material or informational delays? Is the length of the delay appropriate? Does the delay order chosen approximate well the delayed response of the system? (Hamilton 1980)
- Decision Rules: Are the decision rules realistic and boundedly/intendedly rational? Has bounded rationality been implemented effectively? (Morecroft 1983a, 1983b and 1985, Sterman 1985)

By bounded rationality, Simon (1976) means (1) incomplete knowledge, (2) values and outcomes can only imperfectly be anticipated, and (3) not all possible alternatives are known. Morecroft (1983) provides an expanded view of Simon's bounded rationality theory (1957). He believes that the key limitations that generate bounded rationality are: (1) decentralized/local decision making, (2) partial information, and (3) rules of thumb. As a benchmark, it can be useful to compare decision performance to optimal or near-optimal decisions (Sterman 1987).

4. Other Elements of Model Structure

- Time Step (dt): Is the dt selected appropriate? Is the model sensitive to changes in time step?

  Forrester (1961) recommends that the time step be 1/4 to 1/10 of the smallest time constant. Some software produces fewer numerical errors if dt is set to be $(1/2)^n$. If dt is too large, it may introduce an implicit delay in feedback (Kampmann 1991) or create integration error (Forrester 1961). Integration error can be detected by observing rapid changes in variable values that disappear once the dt is decreased.

- Integration Method: Is the integration method selected appropriate? Is the model sensitive to changes in integration method?

  Euler Integration is generally the fastest and simplest computational technique. Runge-Kutta is preferable for models with oscillations. Depending on the software, the choice of integration technique can influence the test inputs (e.g. step or pulse)

- Noise: Are noise variables introduced at appropriate locations in the model? What type of noise is introduced into the model?

  White noise assumes that the noise being introduced is uncorrelated with itself. Pink assumes that there is serial correlation. While modelers have historically used white noise, pink may more accurately depict the real world process. (Forrester

1961, Richardson and Pugh 1981, Glidden et al. 1995).

D. The Model Testing Phase

The model testing phase includes questioning individual formulations, sections of model structure, as well as the entire model. Unexpected model behavior can lead the modeler to conclude that the model is flawed, causing the modeler to revisit particular formulations and revise them. Alternatively, the modeler may conclude that the model is performing correctly and that it is one's understanding of the problem that was flawed. These insights may lead the modeler to reexamine the model analysis and design or provide a valuable lesson for how to address the problem area. The following questions are often addressed during the model testing phase.

1. Model Validity

- How do you determine if the model is valid? How do you develop confidence in the model? (Barlas and Carpenter 1990, Barlas 1996)

  Social scientists often differentiate between construct, internal and external validity (Judd et al. 1991). Construct validity examines whether the constructs of theoretical interest are well-operationalized. System dynamicists often ask whether the constructs correspond to the real-world. In a consulting environment, system dynamicists are often more concerned whether the client has developed confidence in the model (see Section E.1. Model Intervention below).

- What kinds of predictions or forecasts are the modelers making?

  Generally, econometricans seek to make "point predictions," while system dynamicists seek to predict qualitative changes in reference modes.

- In what operating range do the modelers feel comfortable making model predictions?

System dynamicists attribute many structural changes to a shift in loop dominance (Forrester 1987b, Richardson 1995) created by endogenous factors in the system, and hence they feel comfortable making forecasts about model behavior into the future and under varied assumptions. Economic modelers generally view structural change as arising from exogenous forces; additional model variables must be added to accommodate structural changes.

- Are the results of the model reproducible from publications or reports? (Sterman 1988a)
- How is the model documented, and will the documentation be publicly available? (Robinson 1980, Sterman 1988a)

2. Model Behavior Testing

"Testing is the intellectual highpoint of the modeling process."[14]

- Behavior Reproduction Test: How well does the model reproduce the historical reference mode? (Forrester 1973, Senge 1978, Forrester and Senge 1980)
- Pattern Behavior Test: Is the model capable of producing realistic future patterns of behavior in terms of periods, phase relationships and shape? (Forrester and Senge 1980)
- Is the model initialized as a stress-free equilibrium, in which inflows equal outflows and desired equals actual states?

Setting an existing model into a stress-free equilibrium can be a challenging and time-consuming activity. If the model is developed with the system always initialized in a stress-free equilibrium, then accurately assessing different policy tests becomes much easier.

- What forms of stressed equilibrium are possible?

  Stressed equilibrium exists when inflows equal outflows but not all actual states equal desired. For example, an inventory management system generates a constant level of inventory when production equals shipments; however, there are numerous potential levels for the inventory, many may be too low and many too high. The "unstressed equilibrium" exists when actual inventories equal the desired level.

- What is the origin of unusual or unexpected behavior? Is it generated by the use of discrete formulations or integration error (too large DT)? Is it actually an unexpected insight into the behavior of the system?
- <u>Dynamic Analysis</u>: How does the model respond to various inputs (pulse, step, ramp, sinwave)? Is the transient behavior as expected? What is the long term behavior, e.g. oscillation, limit cycle or steady state equilibrium? (The next two questions are closely related).
- Does the model display chaotic behavior?

  An extensive system dynamics literature has developed (see Andersen and Sturis 1988, and Sterman 1988b). Phase plots can often detect the presence of chaotic behavior (Andersen and Sturis 1988)

- <u>Parameter Sensitivity Test</u>: Have the "insensitive many" parameters been distinguished from the "critical few"? (Forrester 1971 and 1973, Forrester and Senge 1980) If the parameters are sensitive, were they estimated individually or in a multivariate fashion? (Richardson and Pugh 1981) Were the appropriate techniques used to develop parameter estimates? (Forrester 1973, Forrester and Senge 1980, Graham 1980, Peterson 1980, Oliva 1996)

- Behavior Mode Sensitivity: How does the behavior of the model change under different assumptions? What gives rise to the shifts in loop dominance? Has the model been systematically tested using dynamic analysis and analytical techniques to see if it can be pushed into different reference modes? (Mass 1991, Richardson 1995) What causes changes in the timing of behavior, amplification, or system stability?

  Mass and Senge (1980) ask:

  a) Does omission (inclusion) of the factor lead to a change in predicted numerical values of the system?

  b) Does omission (inclusion) of the factor lead to a change in the behavior mode of the system? For example, does it damp out or induce fluctuations in the system?

  c) Does omission (inclusion) of the factor lead to rejection of policies that were formerly found to have had a favorable impact or to reordering of preferences among alternative policies?

  Homer (1983) recommends that to answer these questions one should undertake partial model testing. It allows the modeler to test a sub-system of the model and understand its behavior before adding it to a more complex model.

- Are the behavioral responses realistic? boundedly rational? Could "smarter" agents or better decision rules change outcomes or policy conclusions?

- Does the model reflect forms of policy resistance present in the real world?

  Richardson and Pugh (1981) observe "compensating feedback is a property of real systems, as well as system dynamics models, and is the reason real systems tend to be resistant to policies designed to improve behavior....parameter change may weaken or strengthen a feedback loop, but the multi-loop nature of a system dynamics model naturally strengthens or weakens other loops to compensate. The result is often little or no overall change in model behavior."

- Event Prediction Test: Can the model predict events based on particular changes in circumstances? (Forrester and Senge 1980)
- Family Member Test: To what degree is the model generalizable to a family of similar situations, i.e. externally valid? Are the model structures generic?
- How well is the model calibrated to real-world data?

Statistical tests are frequently conducted to assess the validity of models, particular econometric models. In the 1970s and 1980s, system dynamicists had been hesitant to employ statistical tests. Mass and Senge (1980) note the limitations of statistical tests, "such tests actually measure the degree to which available data permit accurate estimation of model parameters and thus, should be viewed more as test of data usefulness than as tests of model specification."[15] More recently, system dynamicists used statistical tests such as Theil statistics (Theil 1966) and other tests (Sterman 1984, Barlas 1989 and 1990, Oliva 1996) are recommend by system dynamicists to assess how well simulated variable values conform to real world data.

- How is the modeling outcome influenced by the selection of modeling technique? How might the answer change if a different technique were employed? (Andersen 1980)
- Are the modeling insights surprising or not?

3. Policy Implications and Testing

- What structures must be added to accommodate policy testing? Do the structures represent policies that could be instituted in the real world?
- Are the policies effectively implemented in the model from a formulation viewpoint?
- <u>System Improvement Test</u>: What behaviors in the system are desirable to improve? What policies/controllers can improve them? (Forrester and Senge 1980)
- <u>Policy Sensitivity Test</u>: Is the model sensitive to the policy introduced? Is the policy a leverage point?

> According to Sterman (1997) **"**Policy sensitivity exists when a change in assumptions reverses the desirability or impacts of a proposed policy. If reducing the federal deficit benefited the economy under one set of assumptions but ruined it under another, the model would exhibit policy sensitivity. Obviously, such sensitivity is far more important than numerical sensitivity. Policy sensitivity tends to arise when one considers changes in assumptions about model boundary and time horizon."

- Is the effectiveness of the policy dependent on the state of the system? In other words, is the influence of the policy the same if it is implemented in stress-free equilibrium, stressed equilibrium, near equilibrium and well out-of-equilibrium?

E. The Model Intervention and Implementation Phase

Systems thinking concentrates its focus on gaining systems insights during the model analysis and design phases, by identifying feedback processes and leverage points that can serve as policy levers (Senge 1990). System dynamicists have also highlighted counterintuitive or "surprise" behavior in systems that occur during the model formulation and testing phases as another important source of insights (Forrester 1987a, Forrester and Senge 1980, Mass 1991).

While the system dynamics literature describes methods for gaining insights, less focus has been placed on the implementation phase. Traditionally, system dynamic modelers generated reports highlighting the studies' findings and left the implementation to their clients. Today, more emphasis is placed upon converting the modeling insights into effective interventions within organizations. The questions below are drawn largely from recent articles that have focused on converting model insights into organizational change.

1. Client Interaction

- What are the key deliverables to the client? Are the insights learned during the modeling process the key deliverable or is it a functioning model or simulator?
- What is the most desirable interaction with a client (managers) and observers (academics)? If so, in what fashion?

The system dynamics community has become increasingly aware of the limitations of the expert mode of consulting and have increasingly emphasized “learner-centered” learning and “modeling as learning” (Graham 1994, Lane 1994) and developing educational environments in which managers can learn effectively (Isaacs and Senge 1994).

- What process will be followed to help build the client’s confidence in the
- model and modeling process?

a) Knowledge Elicitation

The process of building the client’s confidence should occur throughout the modeling process. Brainstorming, hexagon, or other group process techniques can be employed to elicit information from clients (Vennix et Gubbels 1994, Hodgson 1994).

b) Group Model Building

An entire issue of the System Dynamics Review (Vol. 13, No. 2, Summer 1997) is devoted to articles on group model building and working with clients to build confidence in models.

- Do the users understand the role of the system, its appropriate uses as well as limitations?

As Meadows (1980) reminds us:

A model is simply an ordered set of assumptions about a complex system. It is an attempt to understand some aspect of the infinitely varied world by selecting from perceptions and past experience a set of general observations applicable to the problem at hand....The model we have constructed is, like every other model, imperfect, oversimplified, and unfinished.[16]

2. Evaluation of the Modeling Process

- Was scientific method followed?

  Scientific method is employed to try to falsify the underlying theory (Popper 1959). Scientific methods call for first developing the theoretical basis along with hypotheses and subsequently testing the hypotheses and searching for disconfirming evidence.

- What is the world view held by the modelers employing the technique selected? How may that bias the model, results and interpretation of results?

  It is important to discern the world view and mental models held by the modelers. Arrow observes, "There is really an identified model in the minds of the investigators, which, however, has not been expressed formally because of the limitations of mathematics or of language in general."[17] Meadows (1980) suggests that system dynamicists believe that the real world is non-linear, multi-variable, time delayed and disaggregated, while economists believes that world is linear, open loop and conforms to economic theory. The world view influences one's confidence in various techniques. For example, Richardson and Pugh note that it is disturbing for those with experience in statistical models to hear that statistical estimation of model parameters are not important.

  Econometricans are often accused of "tape spinning," i.e. searching for significant relationships rather than developing adequate theory or real world understanding. System dynamicists have been accused of "falling in love with their models," inadequately testing their model against data and fully taking advantage of testing opportunities.

- What kind of impact did the model and the modeling process have on the world?

  Some system dynamicists hold the view: “Modeling is not functional unless it leads to an improvement of operational conclusions ***on the client’s side***.”[18] Others seek to have an impact on the academic community rather than upon the actors in the real system, viewing that the knowledge will then be disseminated to a broader audience and become common rather than proprietary knowledge.

IV. What Next?

By following a rigorous model development methodology, the system dynamics community may benefit from more reliable models that better meet the users’ needs, are faster to produce, and are more economical to develop. The System Dynamics Model Development Life Cycle framework provides a methodology to be followed when developing a model. As the model moves through the different development phases, the modeler can employ the associated list of issues as a procedures checklist to support the model development process.

The current paper is designed to provide an organized list of issues to consider; the modeler should then use discretion in selecting the issues that are appropriate for that model and modeling engagement. This paper can serve as a guide for students to assist them in analyzing and critiquing existing system dynamic models. In addition, system dynamics software is increasingly including controls (e.g. not simulating if equations are not defined) and tools (e.g. graphical depictions of variable types, unit checking, causal tracing) to assist the modeler in following a more rigorous and disciplined model development process.

Just as systems developers have adapted the traditional systems development life-cycle to be more compatible with new development techniques, system dynamic modelers may find it desirable to expand and modify this framework to be more consistent with their model development approach. For example, some system dynamicists are gravitating to a more object-oriented approach, using software layers (Peterson 1994, iThink/Stella software) and software components (such as the molecules of structure described in Hines 1996). These modelers could modify the model development life-cycle framework to include procedures to test standardized components prior to inclusion in models. Over time, the framework and associated procedures will also need to be expanded and modified to reflect new modeling insights.

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Notes

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[1] Roberts (1972), pg. 78.

[2] By setting this electronic document to outline form, the reader can print out the phases and associated questions, eliminating the background description.

[3] Sterman (1988), pg. 137.

[3] Robinson (1980), pg. 267.

[4] Richardson and Pugh (1981), pg. 38.

[5] Forrester (1976) as cited by Legasto and Maciariello (1980) pg. 34.

[6] Meadows (1980), pg. 23.

[7] Richardson and Pugh (1980), pg. 239.

[8] Kennedy (1993) pg. 250.

[9] Senge (1987), pg. 177.

[10] Randers (1980), pg. 122.

[11] Sterman (1988), pg. 137.

[12] Forrester (1968), pg. 84.

[13] Richardson and Pugh (1981), pg. 42.

[14] Robinson (1980), pg. 262.

[15] Mass and Senge (1980), pp. 206-7.

[16] Meadows et al. (1972), pg. 20.

[17] Arrow (1951), pg. 154.

[18] Robinson (1980), pg. 267.