To support the transport problem project
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# System Dynamics Modeling with the System Improvement Process

## 1. Executive summary

This user guide focuses on the details of how to use system dynamics (SD) modeling when applying the System Improvement Process (SIP). The purpose is to support the Transport Problem Project, as well as to serve as a guide for anyone who wants to learn how to do this. Readers should be familiar with SIP and the basics of SD modeling.

The perspective is *how to do SD modeling using SIP*, rather than the normal approach of the Thwink.org material, which revolves around how to apply SIP. This should be useful for the transport project, where from the start emphasis is being placed on models as the main project output (?), rather than the SIP analysis results matrix.

## 2. Limitations of standard SD modeling compared to SIP

SD defines a **reference mode** as the behavior over time of the problem to solve. “Reference” means you will refer to this again and again. **Reference mode data** is time series data that graphically plots the history of key problem behavior, especially problem symptoms. A **reference mode model** is one that can reproduce the reference mode data to the desired level of accuracy.

**The Standard SD Process Steps**: The standard SD modeling/problem-solving process uses the steps listed below in a very iterative manner. The steps are simplified to allow a high-level strategic view of the process. The steps are at such a high level they are about the same as the process we use to solve everyday problems that require a mental rather than a physical model.

1. **Learn about the problem itself:** its history, past solution attempts, predicted trends, various hypotheses for problem behavior, and so on.
2. **Collect reference mode data.** For example, if it’s a sales problem then this might be a sales graph for companies A, B, and C, plus data for marketing expenditures.
3. **Build a reference mode model.** This model can produce graphs with curves that come close to actual data.
4. **Validate the model** using a checklist of best practices. The strategy is that the model behaves the way it does “for the right reasons.” This is determined mainly by model inspection by the model builders, getting problem experts to agree that the structure and behavior of the model reflects their knowledge of the problem, testing the model for all plausible ranges of constants, and examination of the model boundary. Does it include what’s needed and exclude everything else?

5. **Find solution strategies** by examining the model's structure and dynamic behavior. If the model is reasonably valid and its behavior is endogenous (generated from within), it will automatically contain areas that can offer solution insights.

6. **Refine the model as necessary** to explore and test the most promising solutions.

7. **Recommend the solutions** that the model shows to be the most promising for further work, such as elaboration, real world testing, and implementation.

These steps were extracted from the SD literature, mainly the field's standard text book for SD modeling (Sterman 2000, p. 86) and Jack Homer's outstanding collection of articles from the System Dynamics Review (Homer 2012), especially *Why We Iterate*.

The SD process has succeeded for decades. The business world has achieved routine success using SD on a wide variety of business and engineering problems.

However, when SD has been applied to difficult large-scale social problems it has largely failed. The only significant success, to my knowledge, has been Jay Forrester's classic study of the US urban decay problem (Forrester 1969). Yet even this modest success did not solve the urban decay problem. Slums with high crime, low average income, and poor-quality housing still exist in countless US cities and around the world. But the US urban riots of the 1960s have stopped.

SD has also been applied to the global environmental sustainability problem. This began with *The Limits to Growth's* World3 model (Meadows et al. 1972) and continued with many integrated world models (Costanza et al. 2007). As we now know all too well, this line of research failed to solve the problem.

Why has the standard SD modeling approach failed on difficult large-scale problems like environmental sustainability? *Because this class of problems differs radically from typical business and engineering problems.* Compared to business/engineering problems, difficult large-scale social problems have these three defining characteristics:

1. **Ultra-high complexity**: They are at least ten orders of magnitude more complex since they involve entire nations, political systems, and in some cases the biosphere. This defines large-scale. Because political units are involved, these are social problems.

2. **Repeated solution failure**: These problems have a long history of solution failure at the government level for over a generation (25 years) or more. This defines a difficult problem.

3. **Mode lock-in**: Because these problems are systemic, they are mode change problems rather than optimization, scientific discovery, or information search problems, etc. Solving them requires systemic mode change.

The standard SD process steps contain nothing that directly addresses these characteristics. The standard process is a "one size fits all" process. It arose from study of business and engineering problems. When Jay Forrester (the inventor of SD) and others applied it to social problems, beginning with urban decay and World3, *no changes were made to the process*. This imposed a severe limitation that has prevented SD from solving difficult large-scale social problems. The standard SD process simply cannot scale up to this class of problems, creating three enormous gaps.

# 3. The revised SD modeling process using SIP

How SIP works is summarized in the two figures below:

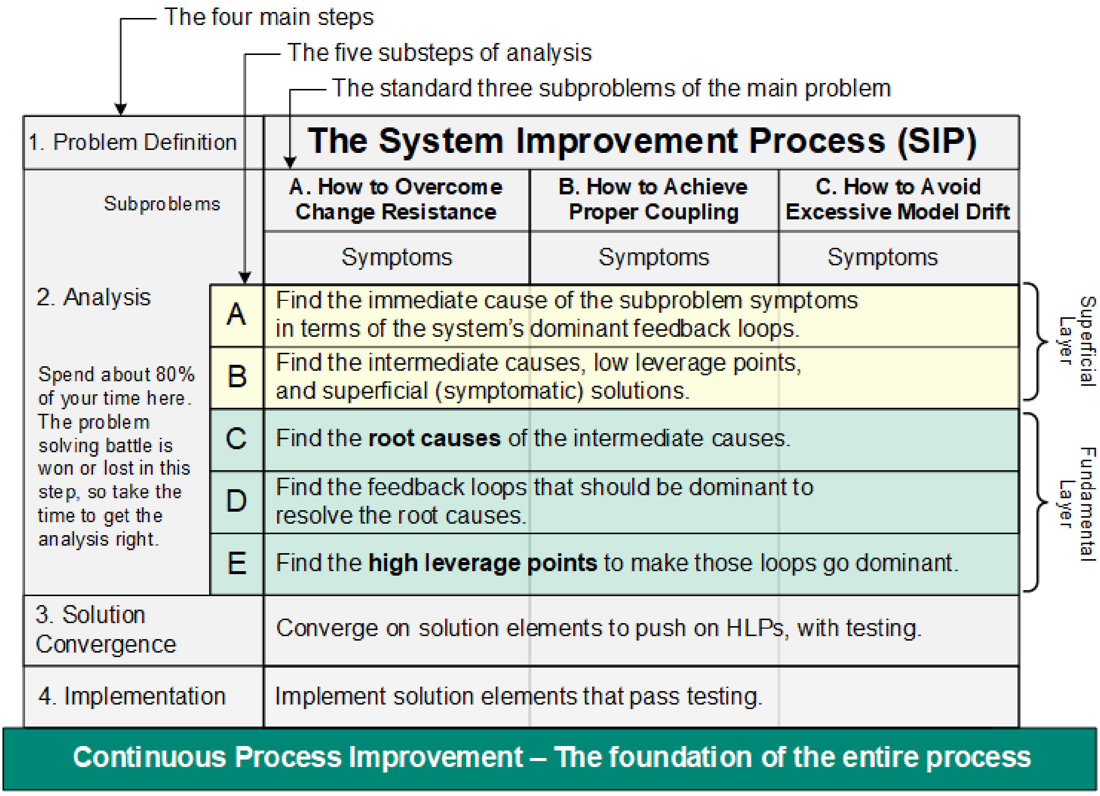



Figure 1. The SIP matrix. Each subproblem employs a social force diagram and necessary models. Each cell in the matrix is a research question. As the process proceeds, the cells are filled in with a summary of results.

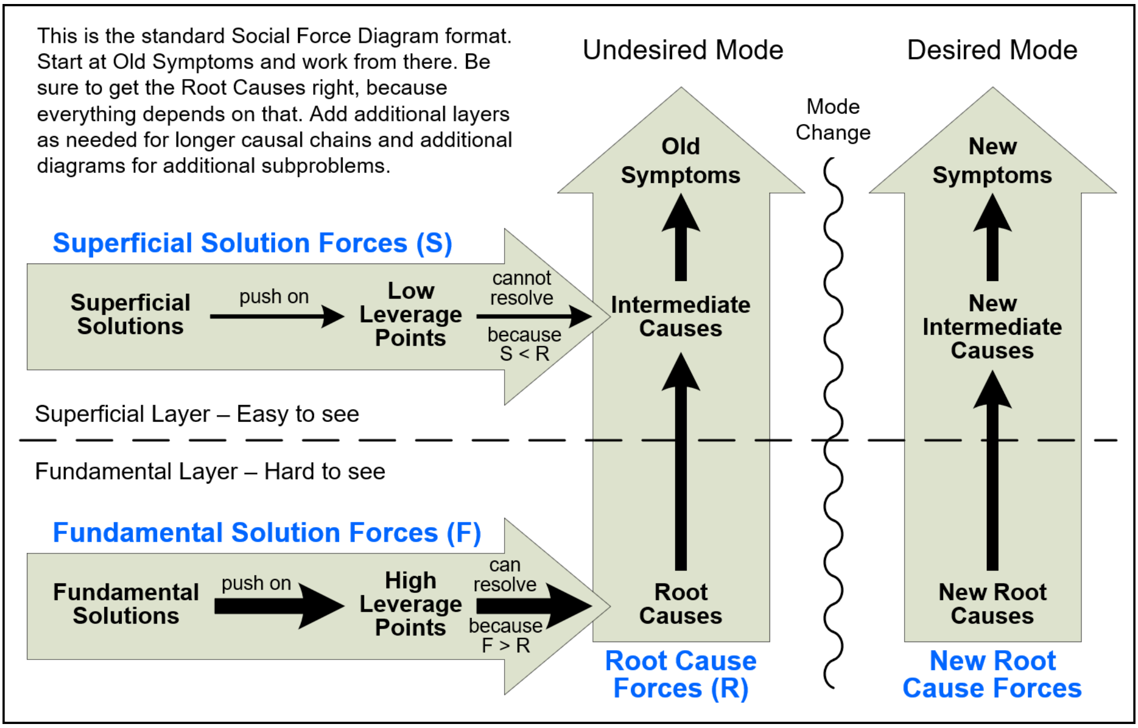



Figure 2. The standard social force diagram. This provides a standard vocabulary of terms, illustrates the two layers, and shows the all-important mode change. SIP treats an unsolved problem as a system locked into the wrong mode due to well-hidden root cause forces.

The previous section explained how the standard SD process cannot reliably solve difficult large-scale problems due to its inability to correctly analyze problems with ultra-high complexity, repeated solution failure, and mode lock-in. SIP fills these three gaps with these specific procedures:

1. SIP addresses **ultra-high complexity** with process driven problem solving, problem decomposition, and root cause analysis, in a cohesive manner using the SIP matrix.
2. SIP addresses **repeated solution failure** by organizing analysis into superficial and fundamental layers. First why past solutions failed is understood. Then, building on that knowledge, how future solutions can succeed by resolving root causes is understood.
3. Finally, SIP addresses **mode lock-in** by first determining why the present root cause forces cause lock-in to the present mode. In difficult large-scale social problems, some portion of the human system is locked into an undesirable mode and is unable to easily change to the desired mode. Lock-in occurs due to the unrelenting strength of a system's dominant feedback loops. For each subproblem, the desired mode change requires reengineering the system's structure such that when force F is applied, a new force R is created, and the system's current dominant feedback loops are replaced by new ones, causing the desired mode change to occur. Once all subproblems have achieved mode change the overall problem is solved because the system now "wants" to stay in the new mode.

**Model-based analysis** means model construction drives application of the analysis framework (SIP) and that the model contains the logical and empirical justification of the most important analysis results. *To use SD for model-based analysis with SIP*, the standard SD problem-solving process must be revised to work as follows. The key steps are underlined.

**The Revised SD Process Steps:**

### *3.1. SIP Step 1. Problem definition:*

1. **Learn about the problem itself:** its history, past solution attempts, predicted trends, various hypotheses for problem behavior, and so on.
2. **Define the original problem** using the standard SIP format: Move system A under constraints B from present state C to goal state D by deadline E with confidence level F.
3. **Collect reference mode data** for the original problem.

### *3.2. SIP Step 2. Analysis*

1. **<u>Decompose the original problem into subproblems</u>** using the standard three subproblems found in all difficult large-scale social problems, plus more as needed. This requires beginning analysis and iterating until the right subproblems are found.

Then perform the five sub-steps of analysis for each subproblem. From the perspective of SD, this involves:

2. **Collect reference mode data**, with emphasis on solution failure data.
3. **<u>Build a superficial-solutions-forces reference mode model.</u>** Simultaneously, construct the upper left quadrant of the social force diagram for this subproblem. This contains the causal chain leading from *superficial solutions* to *low leverage points* to *intermediate causes* to *old symptoms*. The model should explain why the system is locked into the present undesired mode. The model cannot yet explain why the superficial solutions failed, since the root causes are not yet known.
4. **Validate the model** using a list of SD requirements for validity, plus those specific to SIP. In addition, inspect the model for understandability, using a list of SD requirements. These lists are presented later in the sections on understandability and validation requirements.
5. **<u>Extend the model to include the fundamental-solution-forces.</u>** The *high leverage points* and *root causes* are added. The model now shows the superficial solutions failed because S < R. The *superficial solutions* are not added here, but later in SIP step 3.
6. **<u>Extend the model to include the mode change</u>**. This adds the desired mode casual chain of *new root causes* to *new intermediate causes* to *new symptoms*. The model can now explain how the desired mode change can be achieved, by pushing on the high leverage points such that F > R. A **high leverage point** is a solution strategy and is a specific node in the model that one or more solution elements will "push on" to solve that subproblem.
7. **Validate the model** as described before.

## *3.3. SIP Step 3. Solution Convergence*

If no iteration to previous steps is needed, this step contains no further SD modeling. This step is included so that the full context of SD modeling with SIP is described. What usually happens is some further modeling is necessary, due to discovery of new ideas and new system behavior while converging on solutions.

1. **List all solution elements that could possibly work**, using knowledge of the high leverage points and model structure. This can be done with deep thinking, brainstorming, client involvement, popular and academic literature review, etc.
2. **Reduce this list to the few solution element candidates that are highly plausible.** This involves expert judgement, client involvement, review of similar solutions and their outcome, etc. Note there is no need to test the candidates on the model. That's already been done for the higher-level abstraction of high leverage points.
3. **Test, refine, and reduce the solution element candidates to the one or very few that have a proven high probability of success.** The two main forms of testing are laboratory studies on test subjects and real word studies such as pilot

programs. This step ends when there is a high probability the selected solutions will work to initiate the desired mode change scenario.

4. **Recommend the solution elements that have passed testing**. This involves writeup and presentation of the research leading to the recommendation, with emphasis on how *the SD model has been proven to be valid* and how testing shows the recommended solution elements *to behave as predicted by the model*.

### *3.4. SIP Step 4. Implementation*

This step is unchanged. However, it's important to remember that *implementers are seen as part of the SIP team*. They should be fully aware of the crucial findings of the previous steps. Ideally some will participate in prior steps for a smooth handoff.

This knowledge and involvement will help implementers do the further fine tuning of intervention policies that is inevitably required to optimize solution quality, which is a mixture of effectiveness, cost, and speed. If implementers discover that the system does not respond as predicted by the analysis, then the analysis must be updated to reflect this new knowledge and process results must be reviewed starting at that point. This way solution managers always know the full context of *why* a solution is working well. If it's not and the reason cannot be found in solution management and implementation issues, then they know where to go to begin to find the structural reason for *why not*.

### *3.5. Discussion of the revised process*

The revised process differs substantially from the standard SD process in order to close the three gaps. The largest difference occurs in step 2.1, analysis, where the one big problem is decomposed into smaller and much easier to analyze subproblems. This instantly transforms a difficult problem from insolvable to solvable because you are no longer trying to understand multiple problems (each of which has its own social force diagram) at once without realizing it. We found it impossible to analyze the environmental sustainability problem without this decomposition.

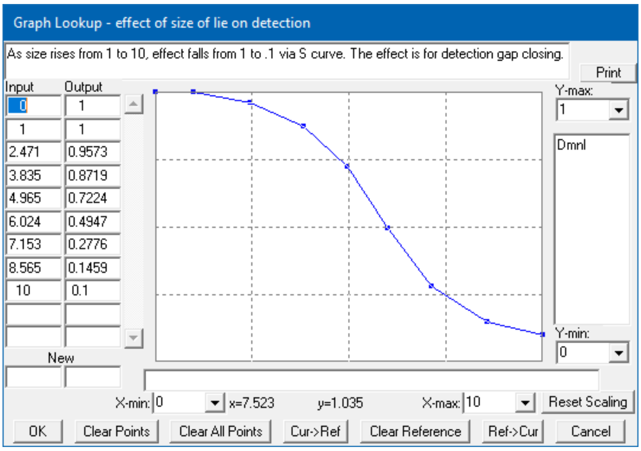
The second largest difference occurs in steps 2.3, 2.5, and 2.6. These three steps first build a superficial layer model, then the fundamental layer model, and finally the full mode-change model using rigorous root cause analysis. This tightly organized process makes it possible to analyze previously impossible-to-solve difficult large-scale social problems in an engineering-like manner. These three steps replace the single step of the standard SD process of "Build the reference mode model." That model might later be changed slightly in the step "Refine the model as necessary to explore and test the most promising solutions," but this would usually have minor effects on model structure.

The standard SD process can be summarized as data → model → solution. The revised process can be summarized as data → decomposition → superficial layer RCA → fundamental layer RCA → mode change design → model → solution. The critical synthesis of data → model has 2 steps in the standard SD process. The revised process replaces this with 6 steps.

*Steps 2.1, 2.3, 2.5, and 2.6 thus hold the key to successful use of SD modeling with SIP*. To support steps 2.3, 2.5, and 2.6, the model creation steps, the next two sections provide lists of requirements. These are a first version, so they are certain to evolve.

## *3.6. The myth that an endogenous model must contain the root causes*

In SD models, **endogenous** behavior is model behavior that arises from the structure of the model and not its constants or lookup tables. **Exogenous** behavior is behavior external to the model that is included in the model by use of constants and lookup tables. A **constant** is a fixed numeric value, like water freezes at zero degrees Celsius. **Lookup tables** are graphs showing the causal effect of one variable on another. An example from the Dueling Loops model is shown.




An **endogenous model** is one that uses no lookup tables. In practice, most serious SD models contain some lookup tables, so that a subsystem doesn't have to be built to endogenously create the dynamic behavior, and are routinely called endogenous models since the critically important behavior is generated endogenously by the feedback loop structure.

The SD modeling community passionately believes that since an endogenous model contains all the causes for the model's behavior, then it must contain a problem's root causes. I say this because this was the response when, in the period from 2010 to 2013, I tried to show this myth wasn't true (without using the word "myth" to be diplomatic) in an email list discussion group of SD community members. Their response was how can you say that, when we know that ALL of an endogenous model's behavior comes from within?

There was no indication that root cause analysis had ever been used to construct an SD model. Thus, this community had no idea what root causes really are and how they are found. This means they were living in a different paradigm from me. Our viewpoints were, in the words of Thomas Kuhn, incommensurate paradigms. Small wonder we had disagreement that could never be resolved.

Let's consider an example. Suppose you had an SD model of a person's body. The problem symptom is a fever. The cause is infection, as modeled by antigens (such as a virus) invading the body and the body's immune system. To the SD community, the root cause of the fever is infection. The infection can be treated with an antibiotic to strengthen the person's immune system and thereby kill the invading microorganisms. This analysis is correct given all the information presented. The causal chain is infection → fever. Conceptually, the causal chain is cause → problem symptoms.

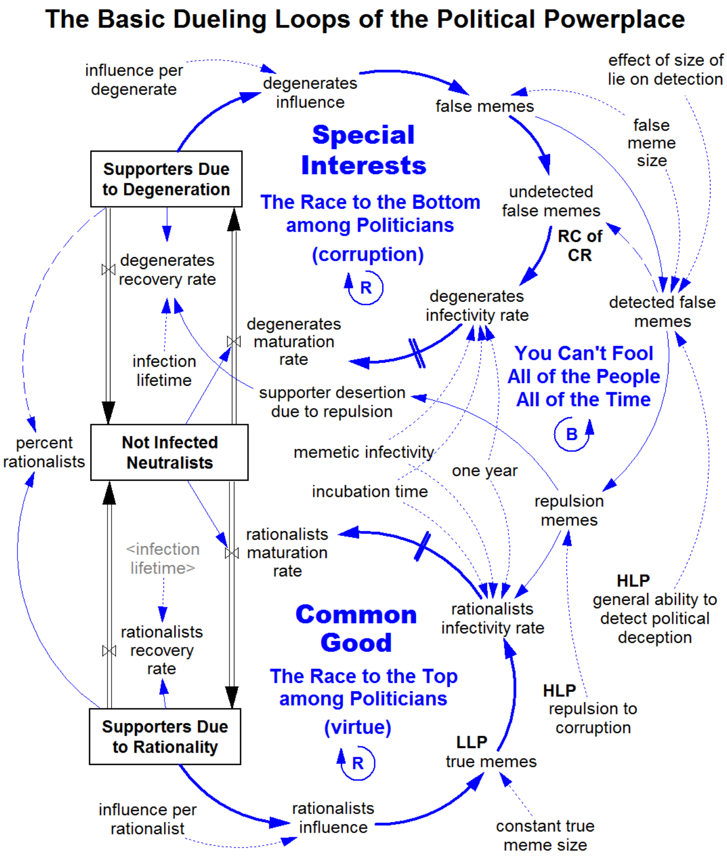
Now suppose there was a deeper reason for the infection. The patient had a secondary immunodeficiency disorder, in this case caused by radiation therapy. The radiation weakened the person's immune system, such that it was unable to fend off the infection. Now the causal chain is weakened immune system → infection → fever. Conceptually, the causal chain is root cause → intermediate cause → problem symptoms.

If the model lacked the concept of a weakened immune system and its effect on infection, it would NOT contain the root cause. Prescribing an antibiotic would treat (in vain) the intermediate cause: infection. Either the patient's reaction to the antibiotic would be less than expected, or the infection would return later once the antibiotic wore off. People relying on the model to find the root cause of the patient's fever would never find it.

*Falling into the trap of this myth can be avoided by applying root cause analysis.* First, one must remember that *all model constants are exogenous constants*, except for universal laws of behavior like gravity. This is easy to forget. In the above model, there would be a constant(s) or lookup table(s) that governed the body's response to infection. Let's assume it was a constant. *By applying root cause analysis*, model builders would trace the causal chain from the symptom of fever, to the intermediate cause of infection, to the constant. This would happen due to the question "Why is the body not responding properly to the infection? What is the deeper cause?" Then they would say something like "It could be that the response constant is wrong. It's not a constant, since it's subject to being weakened by things like radiation treatment." By then modifying the model to include the effect of secondary immunodeficiency disorder, including one caused by radiation, the model would now contain the missing root cause.

This example is analogous to the integrated world models of the environmental sustainability problem. *They lack the problem's root causes.* No amount of model inspection and scenario testing will find the missing root causes. Instead, such effort will only lead to the conviction that the (superficial) solutions that have been tried and failed were somehow not ingenious enough, were poorly managed or funded or promoted, were never tried due to change resistance, and so on.

# 4. Model understandability requirements




Here the goal is to build a model that is easily understood by other SD modelers and the model builders, and is somewhat easily understood by non-modelers with high interest in the model. An example of an SIP model that follows the conventions listed below is shown.

*The importance of model understandability cannot be understated.* SD models are inherently complex and abstract. As SD models evolve, they tend to become more and more complex, and thus less and less understandable. Eventually, unless precautions are taken, they become incomprehensible to anyone except the model builders. A little after that, even the model builders begin to have trouble clearly conceptualizing the model as they work with it, especially after some time away from the model. These tendencies can decay and even paralyze a project, and also make describing the model to others in publications difficult. The purpose of these requirements is to minimize these problems.

The requirements are:

1. **A well-named model.** This should be like the title of a book: clear, descriptive, and memorable.

2. **Clear concise unambiguous variable names.** For names, use *influence per degenerate* rather than *influence*. Use *degenerate infectivity rate* rather than *infectivity*. Don't be afraid to use long descriptive variable names when necessary, like *general ability to detect deception*. Use special care when naming stocks. By convention, stock names are capitalized and other variables are lowercase.

3. **Well-organized well-named important feedback loops.** The conceptual backbone of SD models is their important feedback loops. Take the time to arrange the nodes so that at a glance, the main feedback loop structure of the model is obvious. Take special care to name the important loops so they instantly tell a dynamic story. A good loop name is like the title of a news article: short, clear, incisive, and interesting. Optionally, the most important loops can have thicker arrows.

4. **Well-chosen and well-organized stocks.** Stocks anchor the main feedback loops and play an important role in model structure, so much so that some SD modelers

feel stocks are the backbone of an SD model, not its main feedback loops. Take the time to get the structure of your main feedback loops *and stocks* as clear and productive as possible.

5. **Clearly identified node types.** Stocks are boxes. Constants and lookup tables have dotted arrows. **Shadow variables** refer to the original variable somewhere else in the model. These have gray text and brackets (a Vensim convention).

6. **Clearly identified node relationship and loop types.** Arrows indicate node relationships. Direct relationships should be solid arrows. Inverse relationships should be dashed arrows. Important loops should have R or B below the loop name to indicate a reinforcing or balancing loop. Delays in relationships should have double slashes. Arrange all arrows so they are easy to follow. Minimize arrow crossings.

7. **Explanatory notes as needed.** For example, the Basic Dueling Loops model identifies the root cause of change resistance (RC of CR), the low leverage point (LLP), and two high leverage points (HLP). These are the most important nodes on the model.

8. **Simple easily understood variable equations and units.** After adding a new node to the model, give it a good name and units. Then add the equation as soon as possible. Careful choice of nodes and arrows will lead to simple variable equations. These can be so obvious that you don't have to inspect a need to see its equation. For example: (1) *influence per degenerate x Supporters Due to Degeneration = degenerates influence* and (2) *undetected false memes = false memes – detected false memes*.

   Add a node whenever necessary so that your equations are simple and the model is easily read. For example, instead of A = MAX (B, C + D x (E/F)), add a node for the C + D x (E/F) calculation. The name of that node will describe what the calculation using the four variables means. Another node will describe what B means. Then consider adding a node for the D x (E/F) calculation. Now your model is much more understandable.

   However, for some situations adding nodes would clutter the model. An example is the twin nodes *degenerates infectivity rate* and *rationalists infectivity rate*. These share three variables (*memetic infectivity, incubation time,* and *one year*) and have other input variables. By designing the structure as shown, the model remains uncluttered and readable, at the slight cost of more complex equations for the twin rates.

   Use clear units like births/year. Units must agree with the variable equation and must be consistent throughout the entire model.

   Once a variable has a good name, proper units, and a good simple equation, it's self-descriptive. If not, add a comment in the equation editor.

9. **Well-designed model pages.** Simple models fit on one page. Most models for difficult problems require multiple pages. These pages should be carefully designed to be subsystems, with the first page having the main model. Large models will have subsystems of subsystems. Each page should be well named.

**10. Clearly designed output graphs**. Model builders and published model results will use the output graphs a lot, so they must tell their story well. Use different colors, line thickness to discriminate between lines. This allows many lines to be on a single graph without becoming confusing. Use a clear graph title. Make all graphs consistent.

# 5. Model validation requirements

## *5.1. Solving the missing data problem with tendency models*

What does the modeler do when key behavior data cannot be or has not been accurately collected? This occurs frequently in soft data like people's attitude, preferences, happiness, susceptibility to deception, and so on. It also occurs in problems where certain data has not been measured, cannot be measured, or is too expensive to collect, like a list of all proposed solutions to a difficult social problem for the last 50 years and their outcomes, including whether they were implemented and how much the proposed solution was changed during implementation. Another example is level of criminal activity in a population, like income tax evasion and fraud, spouse abuse, and cocaine use. Self-reporting, even with face-to-face interviews, is widely known to have low accuracy on behavior of this type, making accurate measurement difficult, too expensive, or impossible.

The problem of inability to collect data (both time series and constants) is frequently solved by **estimation**. But now when a model is tuned and behavior validation is performed, one is comparing model behavior to estimated data. The model can only be as good as the estimates. This results in models with low credibility unless the estimates are provided by experts.

However, estimates from experts are not always available. What does the modeler do then? Our solution follows that of Aracil (1999), who feels this void can be filled by "the modern theory of nonlinear dynamical systems. This theory is particularly concerned with the qualitative aspects of the system's behavior." Aracil defines **qualitative** as "concerned mainly with *dynamic tendencies: whether the system is growing, declining, oscillating, or in equilibrium.* Qualitative, in this sense, has a fuzzy meaning that covers those aspects that are less well defined than the strictly quantitative aspects, but which characterize the system's behavior patterns."

Since "qualitative" model has a strict definition in the SD literature (it means causal loop diagrams), we will use the term dynamic "**tendency**" model. Forrester's urban decay model is a tendency model, as it models an idealized representative city and its data is estimated. All Thwink.org models so far are tendency models and use estimated constants and lookup tables, and are compared to mostly estimated time series data, since measurement of so many soft factors has never been done. There are exceptions. For example, the rising ecological footprint serves as a broad measure of growing environmental unsustainability.

Most importantly, tendency models can be used for *comparing the relative effectiveness of different leverage points*. Forrester did this by evaluating the relative effectiveness of the four most popular policies for solving the urban decay problem. The existing SIP analysis does this by measuring the relative amount of leverage in different leverage points.

## *5.2. Validation and model types*

Validation occurs during model iteration. Homer (1983) defines the term:

> "**Validation** of a system dynamics model can be viewed broadly as a process of demonstrating that both the *structure and behavior* of the model correspond to existing knowledge about the system under investigation."

Validation centers on the concept of ensuring that the model produces "the right behavior for the right reasons." Here "the right behavior" means model behavior must agree with real world data to the desired level of accuracy. "The right reasons" means the model structure produces model behavior for logically sound reasons, as determined by inspection by model builders and problem experts. Thus, validation is best divided into two main steps: **structure validation** and **behavior validation**. To be through, we have added a minor third type: technical validation.

The approach to model validation testing depends on to the purpose and type of the model. If only a general idea of the causal structure is needed, a *qualitative* causal loop diagram will suffice. If only the general dynamic tendencies must be understood, a dynamic *tendency* SD model will do. But if exact dynamic behavior must be understood, then a *calibrated* SD model is required. A spectrum of model types exists, ranging from low to high ability to exactly mimic the system of interest, as diagramed below. The latter two types are quantitative.

Qualitative CLD Models → Dynamic Tendency SD Models → Calibrated SD Models

As a model or model section is constructed, it frequently goes through all three types. Quick *qualitative* causal loop diagrams are followed by a *tendency* SD model, to check that the dynamic hypotheses of model behave as expected and to begin to explore the model for insights and unexpected behavior. Some data may be available at this point. If so, it's used instead of estimated data. As the model is built, the need for data is clarified, more data is collected, and the model is tuned to agree with the data to the desired level of accuracy. This leads to a *calibrated* SD model, the normal endpoint for most serious problem-solving SD models.

## *5.3. Technical validation*

This covers technical aspects of SD models that must hold regardless of the structure or intended behavior of the model. Fortunately, these are few in number. This list assumes Vensim is the SD modeling tool.

1. **Avoid divide by zero.** Design constant ranges and lookup table values to avoid this.
2. **No isolated variables or subsystems**. All variables must be connected to at least one other variable. All subsystems must be connected to the main model.

3. **Run the units check frequently** when constructing the model. This checks for unit consistency between connected nodes, which reduces logical errors.

## *5.4. Structure validation*

**Structure validation** determines if model behavior arises for "the right reasons." Model behavior arises from model structure. In these tests the model is not running, since we are only inspecting its structure.

These steps must ideally be done by both model builders and problem experts. However, model builders will perform these steps in more detail. **Makes sense** means something makes strong logical and factual sense.

1. **Does every node-to-node relationship make sense?** This means it must correspond to problem behavior. Constants and lookup tables are included. These must agree with the real world.
2. **Does the arrangement of the stocks make sense?** Do they elegantly capture the behavior of key physical items like housing aging, escalating levels of illicit drug use, or the progress of proposed solutions?
3. **Does every important feedback loop make sense?** Do this by walking around the loop one node at a time and telling a story as you go.
4. **Does the feedback loop structure as a whole make sense?** Do this by walking along the causal paths that connect the loops, telling stories as you go.
5. **Does the structure of the model strongly support the analysis findings**? The key findings are logically structured as social force diagrams. Does the model strongly support every node on the diagram and the mode change, except the solutions? Solutions are not in SIP models. Instead, a model contains the leverage points that solutions push on. It's possible that large future models may need to contain some aspects of particular solutions.
6. **Is the boundary of the model correct? Exogenous** behavior is behavior external to the model that is included in the model by use of constants and lookup tables. An SD model's **boundary** (what's inside and outside) is thus defined by its constants and lookup tables.

   This test is important for models not developed using root cause analysis, since the model's dynamics hypothesis (the key structure) is created intuitively. It's not that useful for models developed using root cause analysis, since once the symptoms node is added to the model as the first node, all other nodes comprise the causal chain leading to the symptoms. This tends to automatically lead to correct boundary nodes, since the causal chain nodes (especially the all-important leverage points) must be variables that change. Everything else must be boundary nodes.

Many more structure validation tests are discussed in the literature. Those listed above appear to be the main ones and should suffice for our purposes. More tests will be added as necessary.

## *5.5. Behavior validation, the correspondence test, and "close enough"*

**Behavior validation** determines if model behavior agrees with real world data *to the desired level of accuracy*. During these tests the model is running. The main test is the **correspondence test**:

1. **Does model behavior correspond closely to collected data?** This is *the* key behavior test. The correspondence will never be perfect, since models are simplifications of reality. Instead, the model should track historical or estimated data to the desired level of accuracy. In particular, it must agree with the tendency of the dynamic data, including growth, decline, equilibrium, and oscillation. The model must also agree with measured constants and lookup tables.

In comparing model behavior to data, how close is close enough? The answer is *close enough to validate that the structure of the model is reasonably correct in terms of the model's intended use.* For SIP, the intended use is to use high leverage point knowledge to design solution elements.

If the model passes the "close enough" test, then one may have confidence that various leverage point scenarios are reasonably correct. It follows that policies based on these scenarios can be expected to succeed, within the range of how accurately the model mimics problem behavior for the right reasons, and within the range of confidence gained by solution element testing.

John Sterman (2000, p. 846) found that "Many modelers *focus excessively on replication of historical data* without regard to the appropriateness of underlying assumptions, robustness, and sensitivity of results to assumptions about the model boundary and feedback structure." In other words, many modelers focus excessively on behavior validation rather than structure validation. I believe one should focus far more on structure validation. *Behavior validation should be viewed as empirical confirmation that the structure validation is correct.* This is true because it's easy to build a model that mimics historical data for the wrong reasons.

Let's examine an actual SD model to illustrate how close is close enough. This model was discussed in Jack Homer's (1983) paper on *Partial-model testing as a validation tool for system dynamics*. The paper's Figures 7 and 10 are shown below.

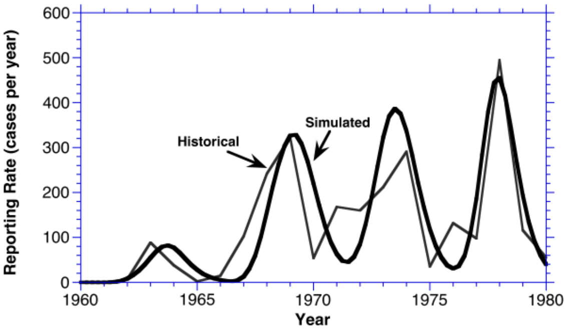



Fig 7. Partial-model test, third-order delay ($T = 1.25$)

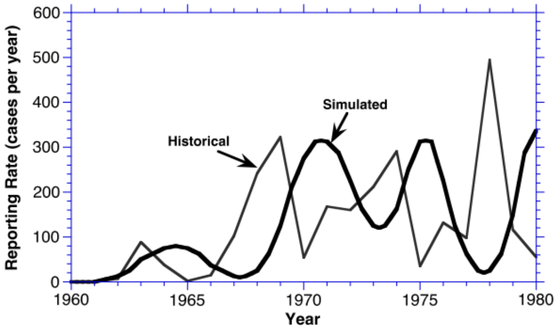



Fig 10. Whole-model simulation of the reporting rate. Source: Homer (1983, p. 431)

Both graphs contain the same historical time-series data. Note how the data points are connected with straight lines, giving the historical graph line a rough jagged appearance. By contrast, the simulated graph line has mostly smooth transitions.

The close match of behavior in Figure 7 was achieved by careful tuning of the model subsystem that calculated the *reporting rate* variable, while that subsystem was cut off from the rest of the model's behavior to allow partial-model testing. The key tuning aspects were use of a third-order delay in rate calculation and a *reporting time* (a model constant) of 1.25 years. This resulted in a very good fit. Model oscillation and growth corresponded surprisingly closely to real world data for a subsystem with only 13 nodes, including 1 stock, 5 constants, and 2 lookup tables. The subsystem is shown below.

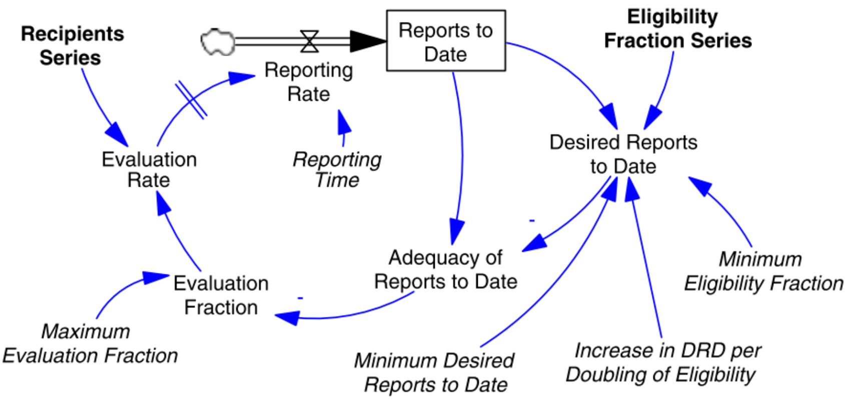



Fig 4. Evaluation and reporting subsystem. Source: Homer (1983, Ch. 5)

When the subsystem was hooked up to the rest of the model, the result was Figure 10. Now the simulated curve is not nearly as close to the historical data as it was before. Yet Figure 10 was acceptable. It was "close enough." Homer explained that due to the difference between Figures 7 and 10, one might conclude "that something is wrong with the model" because the timing of the model's oscillations is wrong. But "in real life, the precise timing of the oscillations is sensitive to random disturbances that can affect the evaluation and reporting process" used in the problem that was modeled." No model can predict random event timing precisely. Thus, the behavior validation was close enough.

## *5.6. Behavior validation, additional tests*

Here we list behavior tests that have a completely different purpose from correspondence testing. Instead of verifying model behavior accuracy, they look for behavior problems that indicate structure problems.

2. **Extreme condition testing**. Does the model exhibit reasonable behavior at a constant's end points? What if this is done with several constants at the same time? As you do this, does any unusual behavior offer new insights?

   This test is easily run by moving constant sliders to their lower and upper limits. My rule for setting these limits is that they be the limits found in the real world. These limits are usually estimated. The default value is that of the reference mode.

3. **Sensitivity analysis**. This test seeks to determine if model behavior varies in important unexpected ways when assumptions are varied over their plausible range. These assumptions can be constants, lookup tables, the level of aggregation used in stock aging chains, and "even the way people make decisions." (Sterman 2000, p. 884)

   If a lookup table must be easily tested for different assumptions, it's usually possible to add constants controlling the table's graph, such as its slope, starting, and ending points, or even all its points. I've had to do this only a few times. I've also dragged table graph nodes while the model was running to do simple testing, as well as tuning.

   Commonly only constants are tested dynamically. The other types of assumptions are usually tested by inspection. A single constant is easily tested manually by dragging it slider. Simple testing of multiple constants at a time is frequently done to test potential weakness one can spot, given the model's structure. Testing many constants at a time in a complete manner is so laborious that most SD modeling tools offer automated sensitivity analysis.

   However, even with automated testing, complete sensitivity analysis of all possible constant permutations is impossible, unless the constant ranges are restricted to a small number of discrete values. To solve this problem, Sterman (2000 italics in the original) recommends that "sensitivity analysis must focus on those relationships and parameters you suspect are *both* highly uncertain *and* likely to be influential. A parameter around which no uncertainty exists need not be tested. Likewise, if a parameter has but little effect on the dynamics it need not be tested…."

Sensitivity analysis is also used to look for what we call high leverage points. Here, instead of using root cause analysis to find the high leverage points, the modeler assumes the model already contains the root causes (usually without using that term) and relies on sensitivity analysis to find the unique combinations of parameter values that would solve the problem by providing the desired scenario. This approach will not work if the model does not already contain the root cause. This approach also does nothing to encourage looking for the root causes.

The behavior validation tests described above are sufficient for our purposes for now, since we are building relatively simple models. More tests will be added if needed.

### *5.7. SIP leverage point testing*

Not listed in the behavior validation tests is *testing the behavior of the model's leverage points*. This occurs as a normal part of applying SIP. Does this low or high leverage point behave as expected? Of these two leverage points, which has the highest leverage? Can pushing on this one high leverage point cause the desired mode change, or must multiple points be used? And so on. This type of testing is where most testing time goes.

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