Exploratory Policy Design

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This paper is the first of two that focus on the policy design phase of system dynamics modeling, when efforts are made to change a model in realistic ways to alleviate problematic behavior. The literature contains more examples of policy parameter analysis than structural modification, perhaps because the former can provide useful policy insights at a cost that is considerably lower than the latter. Building meaningful policy structure can be difficult and time-consuming. One reason may be the lack of a framework to guide the policy design process. Good examples of structural modification rarely reveal the method behind the masterpiece; indeed, the method often appears to be more craft than science. This paper proposes a framework to facilitate model-based policy design and thereby enhance the practice. A public health policy model is used to illustrate the first part of the framework: exploratory policy design. We conclude with a brief preview of the second part—implementation policy design—that is the subject of a companion paper.

Keywords: implementation, model, policy design, public policy, simulation, system dynamics

Introduction

In *Urban Dynamics* (1969, 113), Forrester lays bare the two essential stages of the system dynamics modeling process: "First … generate a model that creates the problem. [Next] … restructure the system so that the internal processes lead in a different direction." The first stage requires building an explanatory model that provides a useful theory of the structural causes of the problematic behavior pattern. When the source of that behavior is a complex feedback system, building an explanatory model is a challenging task. Nevertheless, there is ample guidance in the system dynamics (SD) literature. The iterative first stage is well described, albeit with different styles and emphases, in handbooks and textbooks such as Randers (1980), Richardson and Pugh (1989), Coyle (1996), Sterman (2000), and Ford (2010).

The focus of this paper, however, is on the second stage of the modeling process—policy design—which involves restructuring an explanatory model in ways that alleviate its problematic behavior. Often just as challenging, the task of policy design has not received equally cohesive attention in the instructional literature. This paper is one step toward redressing that imbalance; a companion paper takes another step.

Policy and policy design are elusive concepts used with various intents and purposes in diverse contexts; therefore, we must define our terms. In this paper, policy means *how governmental or business organizations deal with issues for which they are responsible*. This definition is consistent with long-standing usage in the SD literature, as this excerpt from *Principles of Systems* (Forrester 1968, 4.13) makes clear:

> A rate equation is a policy statement...[that] tells how a 'decision stream' or 'action stream' is generated. 'Rate equation' and 'policy' ... have the same meaning. A policy describes how the available information is used to generate decisions [and actions]. .... Decision and action are one and the same.

Policy design is a concept that also suffers from ambiguity, mainly because the identity of the "designer" is different during the two stages of the SD modeling process. When building an explanatory model of problematic behavior, we formulate decision rules for flows that reflect our understanding of policies developed (deliberately or subconsciously) by others. But *we become the designer* during the second stage, when we *modify, add, or delete decision rules in the explanatory model in ways designed to alleviate the model's problematic behavior*; and that's the meaning of policy design in this paper.

Model-based policy design usually begins with parameter analysis; i.e., testing the model's sensitivity to changes in parameters that could be influenced to some extent by policy makers. Too often, it also ends there. A survey of articles published in the *System Dynamics Review* found that nearly three-fourths of all public policy modeling articles contained *only* policy parameter analysis (Wheat 2010).[1] This situation—the relative absence of models containing policy-motivated structural modifications—exists despite clear and repeated guidance

[1] These findings should be interpreted cautiously. The survey was limited to public policy modeling articles published in the *SDR*. Journals specializing in public sector issues might have a higher fraction of models containing policy structure. In addition, mistakes could have been made during the subjective categorization process.

to the contrary in the SD literature. Forrester's (1969) counsel, cited in the opening paragraph of this paper, was only the first. Richardson and Pugh (1989, p. 332) explain that "policy improvement ... involves the addition of new feedback links" and their policy analysis chapter (pp. 321-359) includes both instruction and illustrations for structural re-design. Sterman (2000, p. 104) emphasizes that 'policy design . . . includes the creation of entirely new . . . structures and decision rules" and his chapter on decision-making modeling (pp. 513-550), in particular, provides detailed formulation guidelines for effective decision-rule design. Ford (2010, p. 158) encourages "constructing a stock-and-flow diagram to describe the details of policy implementation" and provides numerous examples. Case studies in Morecroft (2007) also illustrate structural modification during the policy design stage of modeling.

Notwithstanding decades of detailed guidance and some good examples in the literature, re-designing model structure remains difficult, time-consuming, and underutilized. The premise of this paper is that the policy-design stool needs three legs and one is missing. We have a treasure of insightful guidelines for formulating rate equations and many examples of good policy modeling. What's missing is a general method for getting started and staying on course. To address this issue, we propose a framework to facilitate and enhance the practice of model-based policy design. In the next section, we describe in general terms the first part of the framework: *exploratory policy design*. The broad-brush narrative is followed by a more detailed section that illustrates the application of exploratory policy design to a public health model. Finally, we preview essential features of the second part of the framework—*implementation policy design*—that is the focus of a companion paper.

Exploratory Policy Design: A Narrative

In our proposed framework, *exploratory policy design* lays the foundation for evaluating endogenous policy initiatives. The general method is to identify desired outcomes for at least one policy strategy and formulate the information feedback structure implicit in the strategy. The resultant exploratory feedback loops will contain "wishful thinking" links[2] that need to be operationalized in the second part of the framework—*implementation policy design*.

Table 1 lists four sets of steps in building and testing exploratory policy structure. Brief examples should clarify the discussion of each step, and a public health policy model will provide a more detailed illustration in the next section.

1. List broad strategic options and select one for exploratory analysis.
2. Specify policy goal, target flow, and desired flow.
3. Formulate desired flow, model backwards, close loops, and test.
4. Model backwards from target flow, close loops, and test.

Table 1. Steps in Exploratory Policy Design

The list in Table 1 is *not* intended to suggest that following a lockstep set of procedures will result in good policies. Sterman (2000, p. 87) warns that there is "no cookbook recipe for successful modeling" but he also underscores the need for a "disciplined process" to guide the creativity that each modeler brings to the task. And this is what our framework aims to do—suggest a disciplined iterative process for policy design that can complement the disciplined iterative process for explanatory model building that is already well articulated in the literature.

The discussion proceeds on the assumption that the first stage of the modeling process has been completed; i.e., that validation tests justify confidence in the explanatory model, that

[2] We thank our colleague, Max Kleemann, for attaching the "wishful thinking" label to links that show actual results following directly from desired results.

key feedback loops contributing to the problematic behavior have been identified, and sensitivity testing has identified policy parameters that represent what Richardson and Pugh (1989, p. 322) call "leverage points" for influencing the key feedback loops. "Only by clearly understanding what is causing the problem can one begin to see where [policy] attention should be focused." (Forrester 2009).

1. List Broad Strategic Options and Select One for Exploratory Analysis

After developing and studying the explanatory model, some broad strategic options can usually be identified in consultation with the client and key stakeholders. In SD models, when the objective is to alleviate problematic behavior, policy tasks are often expressed in terms of key stocks to be managed. And managing a stock requires regulating at least one of its flows. Thus, one way to generate a coherent list of strategic options is to specify whether the inflow or outflow side of the stock will be the target of the policy initiative. A business manager faced with falling demand and rising inventories might adopt an inflow strategy (lay off workers to cut production) or an outflow strategy (cut prices to spur sales), or some combination.

All viable strategic options should be analyzed, including some in the "doubtful feasibility" category if an improvement in prospects is conceivable. Elections can shift political power, economic growth can boost budgets, organizational capacity can grow, and social attitudes can change. For example, a city with an auto pollution problem may lack legal authority to limit the number of cars operating in the city. But in some political cultures, such authority might be attainable from the state if the expected net benefits were persuasive. The state might also grant authority for a city to inspect vehicles and impose fines for cars with defective emissions controls, while failing to provide the city with sufficient budget and workforce for the task. Yet, it is conceivable that budget priorities could change in response to deteriorating conditions accompanied by compelling policy analysis. While feasibility may be constrained initially, that may not be a permanent condition. Therefore, except for wildly unrealistic options, the feasibility criterion should not be used as a policy filter prior to analysis. Instead, during the implementation policy design stage of modeling, an option's feasibility should be reflected in its structure. For example, if a policy depends on availability of certain personnel who do not materialize from the policy structure, then the policy is likely to prove ineffective during the simulation. During the exploratory design stage, simple parameters representing expected delays and/or expected effectiveness can be used as proxies for preliminary feasibility estimates.

After brainstorming has generated a list of broad strategic options, pick one at a time for analysis. Later, combinations of strategies can be evaluated.

2. Specify Policy Goal, Target Flow, and Desired Flow

Pursuing a general strategy to alleviate problematic dynamic behavior requires specifying behavioral goals for the model—goals that a policy will be designed to achieve. Typically, policy goals are expressed as desired values of stocks that have contributed to the problematic behavior. For example, a fiscal policy goal could be a level of government debt that is considered sustainable. An environmental policy goal might be an air pollution concentration level that is deemed safe to breathe. A social policy goal could be the number of families needing welfare assistance that corresponds to a politically acceptable fraction of all families in a society.

Even when the headline goal is not a stock level, reaching the goal has implications for managing a stock. For example, the government debt goal mentioned above might be expressed in terms of a desired debt/GDP ratio, which is a ratio of a stock and a flow. In this case, a strategy for debt reduction implies a goal for the ratio's numerator—government debt. A non-arbitrary goal for a stock is almost always derived from the purpose of the stock and expectations about its flows. For example, desired inventory is typically a function of desired inventory coverage for production or sales; e.g., how much inventory is needed to satisfy expected demand for two months? A reasoned goal for a personal retirement fund would reflect the desired number of years it should provide expected retirement income; i.e., the stock goal follows from the desired coverage and anticipated yearly outflow.

Of course, picking a *single* goal is a luxury that almost never exists in the public policy arena. Even in private business, it is less common than economics textbooks imply. Multi-attributed issues are the rule rather than the exception, but that does not change the fundamental approach to policy design described here. However, multiple assessment criteria do require simulation experiments that show the various effects of each policy, so clients can confront trade-offs among performance criteria when selecting a policy or set of policies.

As mentioned, managing a stock towards a goal requires regulating at least one flow in or out of that stock. That's the target flow. Sometimes a new flow needs to be created, and it becomes the target. A public health official anticipating a pandemic might contemplate "draining the stock" of infected persons through an isolation strategy that reduces their contact with susceptible persons (Wheat 2010). A vaccination strategy, on the other hand, seeks to drain the stock of susceptible persons before many of them have contact with infected persons. And the target flow has its own goal, typically called the desired flow.

3. Formulate Desired Flow, Model Backwards, Close the Loops, and Test

After specifying the desired flow, the next step is to formulate it; i.e., write its equation. Because of the variety of explanatory models one might confront for re-design, there is no one-size-fits-all equation for the desired flow. However, there are some simple guidelines to consider in almost all cases before exploring more complex formulations. For example, the equation for a desired flow typically includes a desired stock adjustment, based on the current discrepancy between the stock and its goal and the desired time period for closing the gap.

When the desired flow equation includes only the desired stock adjustment, the stock will not reach its goal if it has other flows that are not regulated; in that case, simulation results will reveal a steady-state error (Sterman 2000, p. 671). Therefore, the desired flow equation must also include adjustments for the perceived values of the target stock's non-regulated flows. To illustrate, consider an inventory manager who orders supplies based on some goal for the inventory stock. If that manager fails to include an additional order amount for products flowing out as sales, the stock will stabilize at a level below the goal (and that level may be zero if sales are rapid and the stock adjustment time is long). Doubtless, such naive decision-making is not common for an experienced inventory manager. Policy design modelers must be as alert as good inventory managers.

Formulation of the desired flow, therefore, is dependent on links from the desired adjustment in the target stock and from its non-regulated perceived flows. The convergence of these links into the desired flow forms an incomplete policy feedback loop. Without further ado, close the loop by connecting the *desired* flow with the *target* flow—i.e., create a "wishful thinking" link. Then test whether the model performs as expected. Does the stock adjust to its goal? If not, the desired flow equation is either inaccurate or incomplete and must be corrected before beginning any other task.

Even when it works successfully, keep in mind that the policy feedback loop is still in its “desired” mode; closing the loop and reaching the stock goal does not mean a policy solution has been found. Real resources have to be activated to make something happen; e.g., the inventory manager’s phone call does not automatically add products to the inventory; it is merely the first step in activating a shipment from the supplier. The resources required in any particular case depend on the particular strategy for achieving the policy goals.

4. Model Backwards from Target Flow, Close the Loops, and Test

Attention now turns to the target flow. Delete the “wishful thinking” link and concentrate on the proximate influences on the target flow. If the target flow pre-exists in the explanatory model, there is already an equation that explains past behavior of that flow. The desired flow must somehow influence the target flow by changing the value of one or more of the variables in that equation. Uncovering that influence requires a method we call “modeling backwards” from the target flow to the desired flow.

Modeling backwards actually begins with the recognition that stocks—frequently our starting point in modeling—only change through their flows. Then we should ask: What causes the flows to change? If the answer is “X and Z” then the next questions are: What causes X to change? and Z to change? And so on, until we close a loop or reach the boundary of the model in the form of a parameter. In the present case, working backwards from the target flow aims to close the policy feedback loop by linking to the desired flow. The detailed model in the next section will illustrate the modeling backwards method, but a couple of examples here should help clarify the basic idea.

Recall the city with the auto pollution problem. In the explanatory model, the target flow might be the total auto emissions rate, in which case there would be a goal for total auto emissions—a desired flow. The target flow equation might be a production function involving the number of cars operating in the city and the emissions per car. Modeling backwards would reveal that desired emissions could translate into a desired number of cars or into a desired emissions rate per car, or both. Wishful thinking links could be established, and attention could turn to implementation requirements for one strategy or the other, or both.

Next, reconsider the fiscal policy issue of excessive government debt, and assume there is a goal for the debt, a target inflow called borrowing, and a desired inflow called desired borrowing. Modeling backwards from the target flow—borrowing—reveals two inputs to the flow equation: government spending and tax revenues. Controlling spending is one broad strategy, and a wishful thinking link could be established between desired spending and actual spending—leaving to implementation analysis how the wish could be realized. Another strategy would focus on the revenue variable. There, another modeling step backwards is required to reveal that revenue is a product of the tax base and tax rate, both of which are potentially influenced by fiscal policy actions. For example, a wishful thinking link could connect desired tax rate with actual tax rate.

After each wishful thinking link closes a loop, simulation runs should test the logic of the links and the formulation of the equations. The target flow should adjust towards the desired flow, and the target stock should adjust towards its goal. Thus, the product of exploratory policy design is a simulation model containing a series of feedback loops that regulate the target flow of the stock being managed. It is likely that each of those loops contains a link between a desired result and an actual result, which means the feedback structure represents a wishful policy and not an operational policy. Replacing those links with stock-and-flow structure that represents "operational thinking" (Richmond 1993) is the task of implementation policy design, the second part of our proposed framework.

Exploratory Policy Design: Applied to a Public Heath Policy Model

Several of the brief examples in the previous section were inspired by student projects in a graduate-level course on policy design and implementation at the University of Bergen. The students are required to select a peer-reviewed model from the SD literature that contains little or no policy design as that term is used in this paper. In most cases, policy analysis in the original published model is limited to parameter testing. After translating the original explanatory model into *iThink,*[3] replicating the original behavior, and thoroughly analyzing the model, the students complete a two-fold assignment. First, they use our framework to design a policy for the original model. Second, they develop an interactive policy learning environment as a communications tool for explaining their revised policy model.

One of those projects was conducted by co-author Lili Shi, and we present a revised version of her policy model here as an illustration of exploratory policy design. Shi selected a model from a paper presented at the 2010 International Conference of the System Dynamics Society in Seoul, South Korea. The paper, authored by Pruyt and Hamarat (2010), is titled "The

[3] *iThink* is a registered trademark of isee systems, inc. (http://www.iseesystems.com).

Influenza A(H1N1)v Pandemic: An Exploratory System Dynamics Approach"[4] and presents an innovative approach to SD modeling of epidemics. The authors engage in extensive policy parameter sensitivity analysis, including responsive policy analysis in which the value of a policy parameter (e.g., desired vaccine coverage of the susceptible population) is dependent on perceived conditions in the system (e.g., the infection risk after a contact between infected and susceptible persons). The *iThink* adaptation of the original Pruyt-Hamarat *Vesnim*[5] model is displayed in Figure 1.[6]

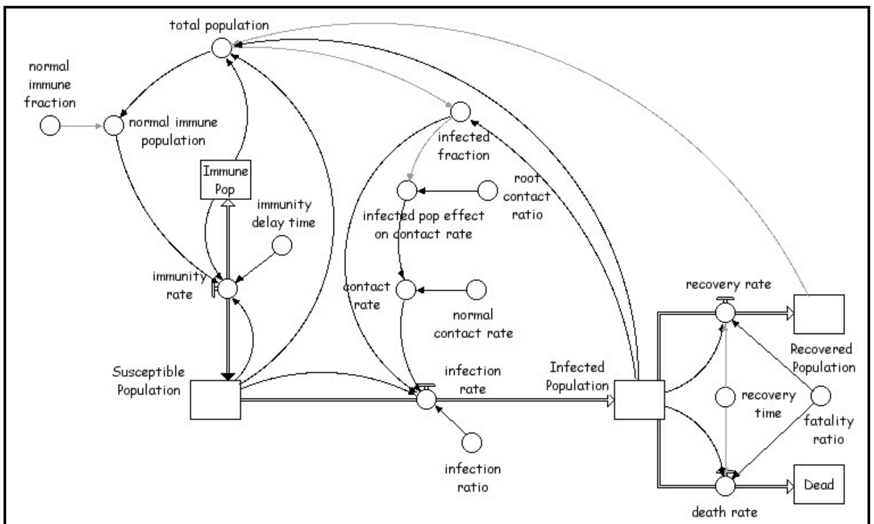

Figure 1. Epidemic Model Adapted from Pruyt and Hamarat (2010)

Notice the two key stocks: Susceptible Population and Infected Population, connected by the infection rate flow. The reinforcing loop driving the epidemic is in the center of the diagram, running from Infected Population to infection fraction to contact rate to infection rate and back to Infected Population. The Susceptible Population also drives the infection rate, but the

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[4] Coincidentally, the authors also described their approach to SD modeling as "exploratory."

[5] Vensim is a registered trademark of Ventana Systems Inc. (http://www.vensim.com/)

[6] In their paper, Pruyt and Hamarat modeled the interaction between the "Western World" and the "densely populated Developing World." For her project, Shi analyzed only the Western World portion of the model. Equations for the original model are available in the online conference proceedings. http://www.systemdynamics.org/conferences/2010/proceed/index.html

counteracting loop lowers the Susceptible Population stock. The structure that includes Immune Population is the Pruyt and Hamarat formulation of permanent and seasonal immunity, and the structure moves a portion of the people back and forth between the Immune and Susceptible stocks based on a sine wave function. The Immune Population fluctuates between 30 percent permanently immune and 70 percent immune during the summer months. This structure gives the model an exogenous oscillating stimulus.

1. List Broad Strategic Options and Select One for Exploratory Analysis

After studying the original model, Shi selected a vaccination strategy for her policy design work. Her decision was inspired, in part, because she had had personally received an A(H1N1) vaccination in Shanghai two years earlier and recalled the procedure. Also, Pruyt and Hamarat discussed vaccine policy parameter experiments in their paper.

2. Specify Policy Goal, Target Flow, and Desired Flow

A vaccination strategy seeks to drain the stock of susceptible persons before they have unprotected contact with infected persons. The Susceptible Population, therefore, is the stock to be managed. Figure 2 shows that a Susceptible Population goal was established. For our illustrative example, that goal was set at 180 million people. That's 30 percent of the entire "Western World" population of 600 million in the model; thus, the goal implies that 70 percent would be protected from the virus, either by vaccination or regular immunity.

The target flow is the vaccination rate in Figure 2. It is assumed that the vaccination eventually loses its effectiveness, causing a return flow of people to the Susceptible Population stock. Finally, Figure 2 displays a "desired vaccination rate."

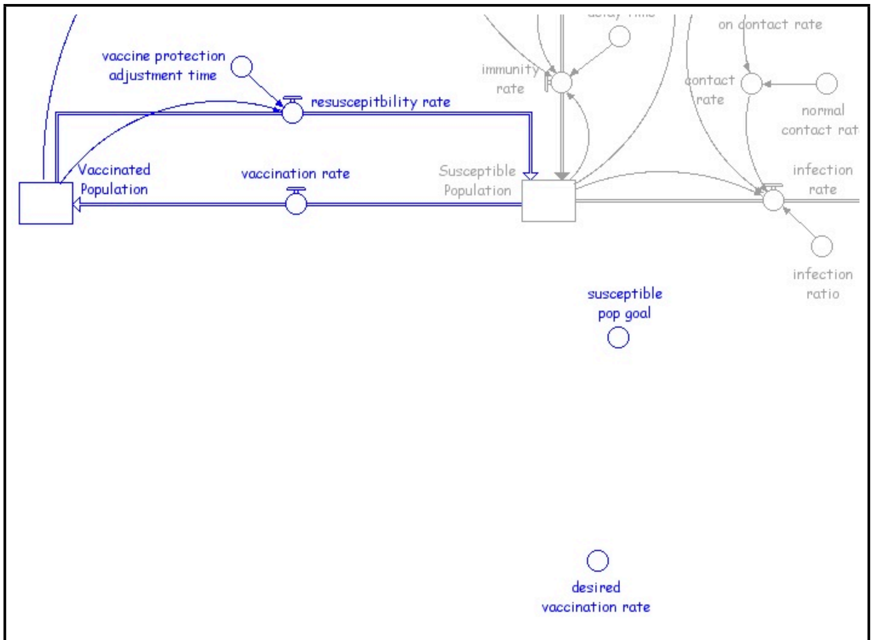

Figure 2. Policy Goal, Target Flow, and Desired Flow Specified in Modification of Pruyt and Hamarat (2010)

3. Formulate Desired Flow, Model Backwards, Close the Loops, and Test

Figure 3 displays the first exploratory policy structure tested for this model, after formulating the **desired vaccination rate** (units: persons/month) as follows:

max((susceptible pop gap adj + smth1(resusceptibility rate + infection rate - immunity rate, perception time)),0)

so that it incorporates the required adjustment implicit in the stock gap and accounts for the perceived values of the three unregulated flows of the Susceptible Population Stock. Note that the **susceptible population gap** (units: persons) is defined as

perceived susceptible population - susceptible pop goal

so that it has a positive value when it is higher than the goal; thus, the higher the required gap adjustment, the higher the desired vaccination rate.

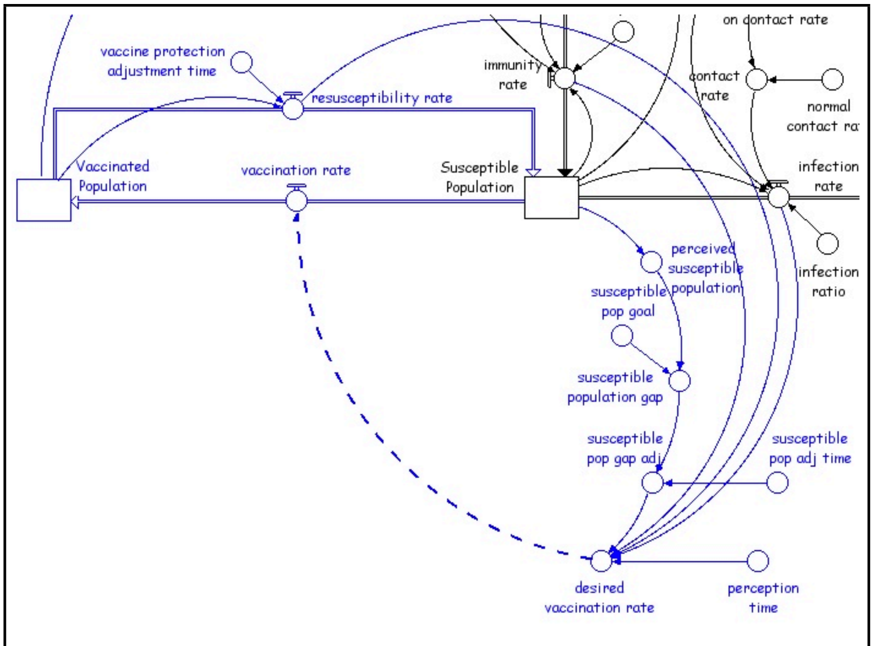

Figure 3. Formulation of Desired Flow and "Wishful Thinking" Test adapted from Pruyt and Hamarat (2010)

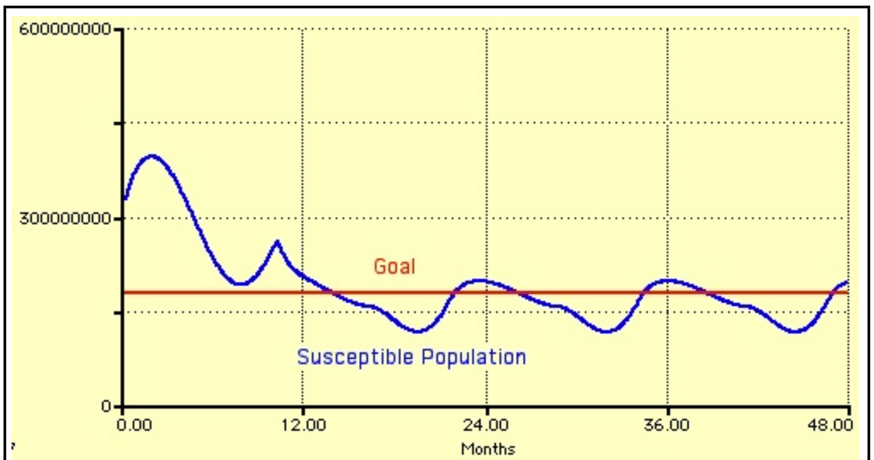

Figure 4. Simulation Results from Policy Model in Figure 3

Figure 4 displays the simulation results of the first "wishful thinking" test of the policy model after month 10, when the target flow (vaccination rate) equals the desired target flow (desired vaccination rate). The oscillatory pattern is due to the exogenous seasonal effect; without that effect, the Susceptible Population adjusts smoothly to its goal. This indicates that the desired vaccination rate is formulated correctly; i.e., that it accounts for the stock adjustment and all non-regulated perceived flows.

4. Model Backwards from Target Flow, Close the Loops, and Test

The first step away from wishful thinking is the recognition that vaccinations do not occur unless people get vaccinated, whether voluntarily or due to coercion. The new structure in Figure 5 shows a vaccination rate equal to vaccination patients, with the latter a first-order outflow from Susceptible Population based on the monthly "patient faction" seeking vaccinations.

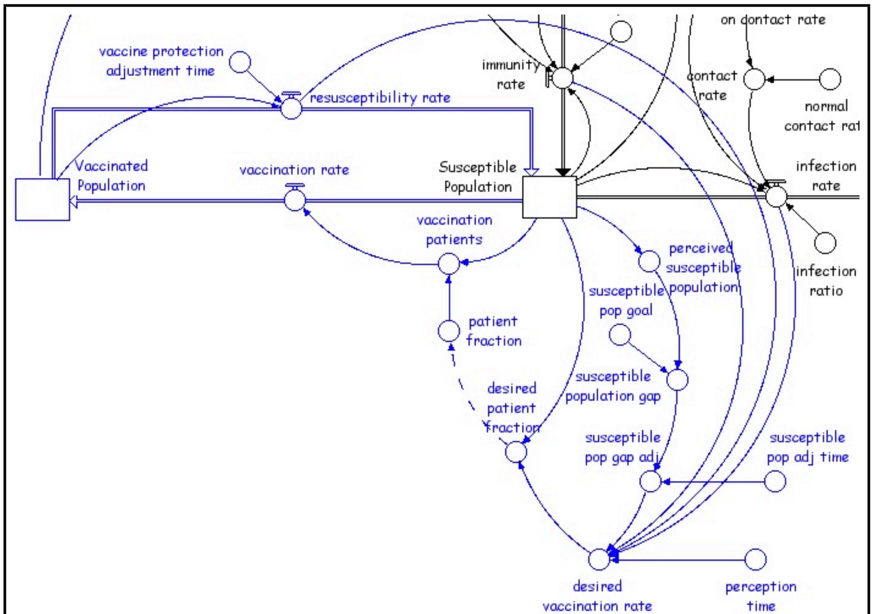

Figure 5. Modeling Target Flow: Patients Seeking Vaccinations adapted from Pruyt and Hamarat (2010)

Figure 5 also provides the first illustration of the "modeling backwards" method. Given the desired vaccination rate and the Susceptible Population stock, a **desired patient fraction** (units: 1/month) can be formulated as:

min(desired vaccination rate / Susceptible Population,1)

and a wishful thinking link (dashed arrow) connects desired patient fraction and patient fraction.

Figure 6 illustrates further refinement of the target flow—the vaccination rate. Vaccination capacity is added to the equation, and vaccination rate is now equal to the lesser of "vaccination patients" and "vaccination capacity." Shi formulated capacity in terms of nurses and nurse productivity. Thus, nurse productivity in Figure 6 is the monthly number of persons vaccinated by an average nurse.[7] Modeling backwards, a **desired nurse productivity** (units: persons/month/nurse) can be formulated:

if(nurses vaccinating = 0)then(0)else(desired vaccination rate / nurses vaccinating)

and a wishful thinking link is established between desired nurse productivity and actual nurse productivity.

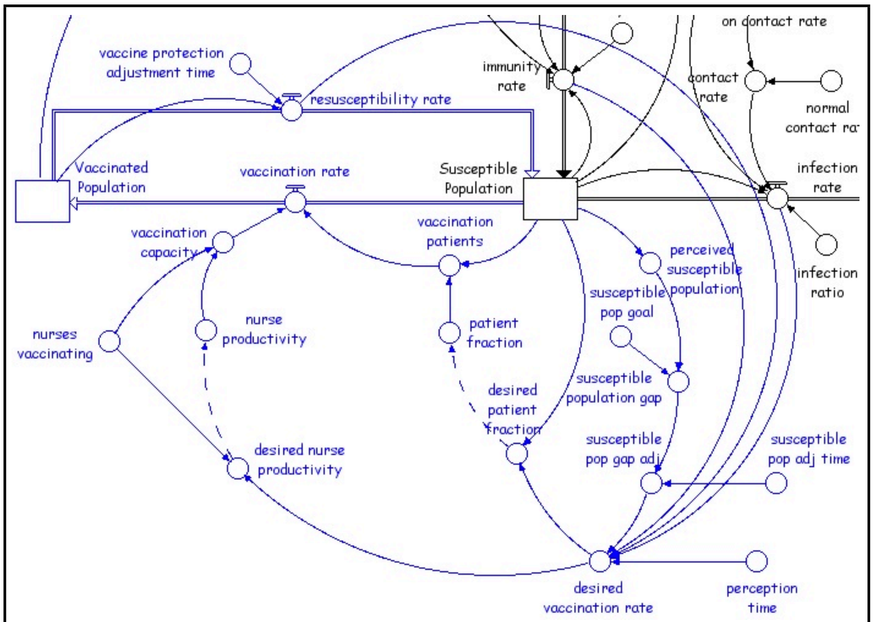

Figure 6. Modeling Target Flow: Vaccination Capacity adapted from Pruyt and Hamarat (2010)

[7] Because of its constraint potential, vaccine supply should be explicit in Shi's model, even in this exploratory stage.

Figure 7 displays the completed exploratory policy structure for this version of Shi's model. The last wishful thinking link connects desired nurses vaccinating and actual nurses vaccinating after formulating the equation for **desired nurses vaccinating** (units: nurses) as

desired vaccination rate / maximum nurse productivity

where maximum nurse productivity is assumed to be 3000 vaccinations per month.

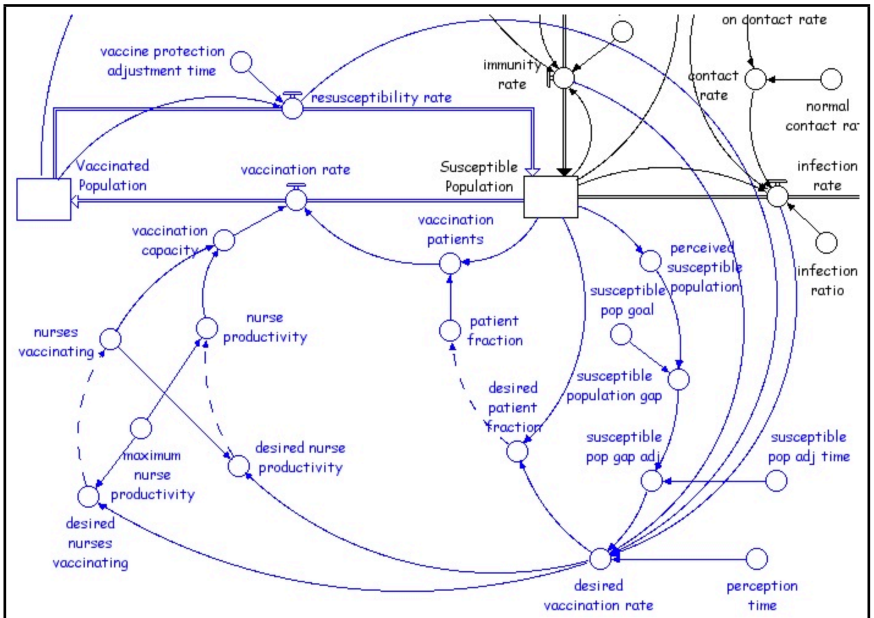

Figure 7. Modeling Target Flow: Nurse Supply adapted from Pruyt and Hamarat (2010)

Notice that there are no stocks-and-flows in the policy structure displayed in Figure 7.[8] This reflects the exploratory nature of this stage of the policy design process. Links are made under the (knowingly unrealistic) assumption of immediate desired effect. The dashed arrows linking "desired results" and "actual" results" serve the purpose of highlighting areas where implementation structure needs to be added.

[8] Except in the desired vaccination rate equation, where information stocks provide perceived values of the non-regulated flows in/out of Susceptible Population.

The dashed links also highlight three distinct components of a vaccination strategy. First, the strategy must include a program designed to encourage (or coerce) susceptible persons to get vaccinated. Also, a sufficient supply of nurses must be made available for the vaccination strategy to work. And, perhaps most critical, the strategy requires productive nurses; they must be supplied with sufficient vaccine and administer it at maximum feasible rates. In the implementation stage of policy design, each of these "programs" would be modeled with stock-and-flow structure.

We have not shown additional simulation results since Figure 4 because the results are all the same! The Susceptible Population stock adjusts smoothly to its goal when the exogenous oscillatory effect is turned off; otherwise, it fluctuates above and below the goal. The important insight is that, when there are no stock limitations or delays in the conversion of desires to results, the behavior of the policy model will be the same regardless of the myriad ways that desired vaccination rate is reformulated into other desired variables.

Conclusion

A story is told about American humorist and social commentator Will Rogers during World War I. When asked how the Allies should deal with the enemy submarine problem, he replied, "That's simple. Boil the oceans." When asked how to boil the oceans, he responded, 'I'm a policy man. I let others worry about implementation."

This paper has seemingly left implementation for others to worry about. The focus has been on a method called exploratory policy design, which encourages clear thinking about policy strategies, policy goals, and the fundamental policy feedback loop structure; but stops short of modeling the stock-and-flow structure needed to reveal implementation obstacles that hinder all policies. Implementation of real-world policies is constrained by feasibility considerations involving institutional arrangements and organizational and social capacities for change (cf., *Hill & Hupe 2009, Howlett et al. 2009, and Knoepfel et al. 2007*). Feasibility constraints should inform the design and evaluation of policy-motivated changes in the explanatory model, and a companion paper addresses these issues. There, the focus is on adding stock-and-flow structure that transforms wishful thinking links (such as those dashed arrows in Figure 7) into operational links that reflect awareness of institutional, organizational, and social constraints.

The *implementation policy design* paper extends the framework introduced here by drawing on the public policy implementation literature, including Elmore's (1979) method of "backward mapping." The method *begins at the end* “with a statement of the specific behavior at the lowest level of the implementation process that generates the need for a policy.” From there, backward mapping requires that we “back up through the structure of implementing agencies” with questions about requisite organizational capacity along the implementation path (Elmore 1979, p. 604). At the risk of making it sound like a cookbook recipe, backward mapping can be summarized in six basic steps:

- identify target behavior that the policy will be designed to change
- describe proximate actions that could affect that behavior
- describe the expected effect of those actions
- identify the resources needed for the expected effect to occur
- identify the behavior needed to provide those resources
- repeat for actions and resources “further back” along the loop.

Implementation policy design blends Elmore’s backward mapping with the method of modeling backwards introduced in this paper. Together, they seek to resonate with Richmond’s (1993) emphasis on “operational thinking” and advance the art and science of system dynamics policy design modeling.

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