Model-based Policy Design that Takes Implementation Seriously[1]

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Introduction

Low-cost and low-risk policy experimentation is an acknowledged virtue of simulation models of complex public issues (Ghaffarzadegan, Lyneis, & Richardson, 2011). But the virtue can become the vice. It is often too easy to ask, "What if this parameter value could be changed?" and get a quick quantitative answer. Model-based analysis that relies exclusively on parameter sensitivity testing may ignore how parameter changes in a computer model can be implemented by public organizations in the real world. Of course, testing a model's sensitivity to variations in policy parameters is an important exploratory step in model-based policy analysis. Too often, however, there is no next step. A content analysis of three decades of articles published in the *System Dynamics Review* found that policy analysis has been limited to parameter sensitivity testing in nearly 75 percent of models of public issues (Wheat, 2010). This situation has developed despite admonitions from experienced modelers. Richardson and Pugh (1989) warned that "policies represented as parameter changes frequently tend not to be very effective in system dynamics analysis" (p. 332) and Sterman (2000) reminded modelers that "policy design is much more than changing the values of parameters" (p. 104).

To illustrate the limits of parameter-based policy analysis, suppose simulation results show that a flu epidemic might be avoided by vaccinating 20 percent of an at-risk population monthly (i.e., the monthly vaccination parameter equals 0.20). What assumptions about institutional arrangements, organizational capacity, and public cooperation are implicit in that simulation experiment? When is it advisable to model some of those assumptions explicitly--to reveal the "plumbing" of a policy and how it functions in the model? And what modeling tools, policy concepts, and literature guidance would be helpful? To answer such questions, we encourage model-based implementation planning and analysis during the policy design stage of system dynamics simulation modeling. This continues our quest for a synthesis of system dynamics and the implementation paradigm in the public policy literature (Wheat, 2010). The goal is to encourage more *operational think*ing during model-based policy design and produce models that are less reliant on wishful thinking and more useful to policy makers.

We begin with a brief description of system dynamics explanatory modeling as a prerequisite for policy modeling. The focus then shifts to implementation planning and the importance of operational thinking during the policy

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[1] This paper is a merger and revision of papers presented at the 2011 conferences of the International System Dynamics Society (Wheat & Shi, 2011) and the Association of Public Policy and Management (Wheat, 2011). Several models serve as illustrations but discussion of equations is kept to a minimum and full explanatory models are not shown. Readers with questions about specific equations or any other topic should contact the author at david.wheat@uib.no. [Later published as a chapter in *Governance in the Information Era*, ed. E.W. Johnston (Routledge, 2015)]

modeling stage. The entire process is illustrated with models of two public health issues: a flu epidemic and automobile pollution. The final section highlights the application of useful modeling insights gleaned from implementation literature.

The System Dynamics Modeling Process

It is useful to think of system dynamics (SD) modeling in terms of two high-level tasks: *problem explanation* and *policy design*. More than 40 years ago, Forrester (1969) emphasized the practical value of this distinction and recently reiterated it (Forrester, 2009). The goal of *problem explanation* modeling is to identify the historical systemic reasons for a pattern of behavior widely viewed as a serious issue (e.g., increasing traffic congestion or declining employment). *The policy design* task is to explore and evaluate ways to alleviate the problem; that is, to improve the dynamic performance of the model system in ways that suggest feasible, cost-effective policies in the real world system that the model represents.

Problem Explanation. The first task is to build and test an *explanatory model*. Although SD scholars emphasize different details of the modeling process, there is a consensus about the key steps when developing the explanatory model: (1) specify the symptomatic problem in terms of its dynamic behavior, (2) develop a hypothesis in the form of a model that offers a structural explanation of the problematic dynamics, and (3) analyze the model with various validation tests aimed at discovering whether it provides a robust endogenous explanation of the problematic behavior (Randers, 1980; Richardson & Pugh, 1989; Coyle, 1996; Sterman, 2000; Barlas, 2002; Morecroft, 2007; Roberts, 2007; Ford, 2010).

An explanatory SD model uses functionally interdependent variables to simulate problematic behavior patterns (e.g., undesirable trends in crime or pollution) that have been observed in the past. Bardach (2005) concludes that policy analysts will find a "good causal model . . . especially [useful] . . . when the problem is embedded in a complex system of interacting forces, incentives, and constraints--which is usually the case" (p. 17). Forrester (2009) states it more bluntly: "Only by clearly understanding what is causing the problem can one begin to see where [policy] attention should be focused." Moreover, a policy has a better chance of acceptance and adherence when its underlying causal theory resonates with those whose cooperation is needed for adoption or implementation (Mazmanian & Sabatier, 1981; Hogwood & Gunn, 1984).

A simple example of an explanatory model is displayed in Figure 1, which shows two central concepts in an SD model: a stock and its flows.[2] In this example, productivity and resource are parameters, the values of which are determined out side the boundary of a model. The inflow could be defined as the product of those parameters. A stock accumulates (or dissipates) over time as the net flow determines its rate of change.

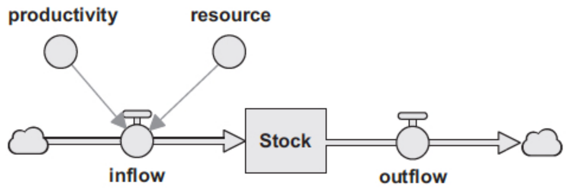

Figure 1. Example of a simple system dynamics stock-and-flow model

Examples of stocks include patients in a hospital, pollution in the air, and housing in a community. Corresponding inflows would be the rate of patient admissions (patients/month), pollution emissions (pollutants/ hour), and housing construction (houses/year), while outflows would be the rate of patient discharge, pollution dispersion, and housing demolition. When revising a simple explanatory model so that it reflects more realistic complexity, the modeler reformulates some of the exogenous *parameters* as *vari*ables. Those variables, in turn, would be functionally dependent on a combination of other parameters and variables along chains of causality. The process of modeling backwards from a flow along a particular causal chain continues until (a) it ends with an exogenous parameter, or (b) it traces a circular path all the way back to the flow, thus forming a feedback loop--the third central SD concept--that provides an endogenous explanation of the observed dynamics.

Policy Design. The next task is to build and test a policy model. Policy modeling requires representing a real-world policy option in the form of new structure added to the explanatory model. The potential for alleviating problematic behavior is then evaluated with simulation analysis. The SD literature provides examples of adding policy structure (Richardson & Pugh, 1989; Sterman, 2000; Ford, 2010), but more conceptual and technical guidance is needed. That is our purpose in this chapter. We build on the feedback tradition in SD policy design in a way that integrates parameter and structure analysis, prompts operational and politically insightful questions when implementation planning is needed, and facilitates adding implementation constraints to a policy model when it is useful to do so.

[2] Models have been created with Stella® Professional Modeling and Simulation Software, available from www.iseesystems.com.

The Feedback Approach to Policy Design

Integrating Parameter and Structure Analysis. Parameter testing is necessary and useful, even if it is insufficient as a sole policy analysis method. Making an exogenous adjustment to a parameter value and then simulating is a quick and easy way for a modeler to estimate the potential impact of a general strategy for influencing key feedback loops in a problematic model system, and find what Richardson and Pugh (1989) call "leverage points" in the system (p. 322). What is needed, however, is a way to use parameter testing as a springboard to structural design of policy options, i.e., to integrate parameter and structure analysis.

The behavior of the model in Figure 1 would depend, in part, on the values estimated for the parameters: *resource* and its *productivity*. Simulating with alternative values for the resource would enable preliminary testing of the impact of a policy initiative aimed at changing the acquisition and utilization of the *resource.* Figure 2 displays a simple policy model that extends the Figure 1 model and specifies a dynamic feedback decision process, in which changes in the resource depend on a *goal* for the *stock*. For our purposes, it highlights potential constraints on the impact of a policy due to implementation requirements.

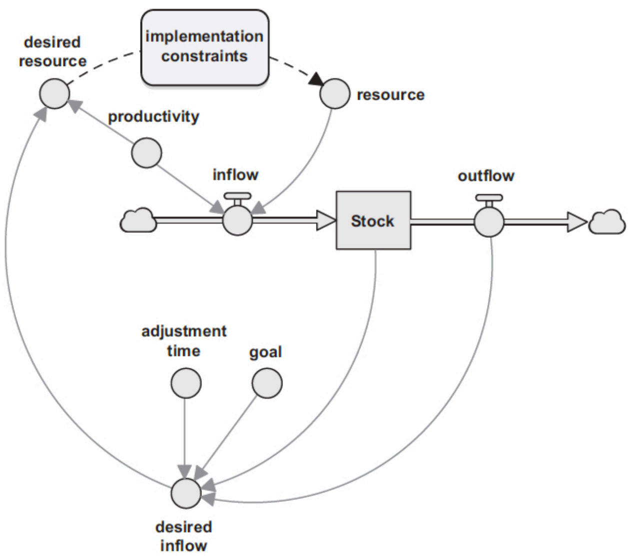

Figure 2. Simple policy model highlighting implementation constraints

The policy modeling process begins with specification of a *goal* for the stock and a realistic and politically acceptable *adjustment time* for closing the gap between desired and actual conditions. 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 receiving welfare assistance that corresponds to a politically acceptable fraction of all families in a society.

It is also necessary to choose a basic strategy for achieving the policy goal. Managing a stock toward a goal requires regulating at least one of its flows. Thus, generating a list of strategic options means specifying whether the inflow or outflow side of a stock will be the target of the policy initiative. For example, a business manager faced with declining 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 of both. A public health official fearing an epidemic 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 *(Wheat & Shi, 2011).* In Figure 2, the strategy focuses on regulating the *inflow by* modifying the *resource* level. The *resource* and its *productivity* will drive the *inflow* and, after some delay, the *stock* will have a feedback effect--increasing or decreasing the *desired resource*, as needed to move toward the policy goal.[3]

Next, it is necessary to test the policy feedback loop to see *if* the model performs as expected and *why*. Does the stock adjust to its goal during the simulation? If not, the "desired" equations are either inaccurate or incomplete and must be corrected before beginning any other task. Of course, the right result could be achieved for the wrong reason. That is why behavior analysis is only one of several validation tests in the SD modeling process. Each equation must be scrutinized theoretically and empirically, parametric *stress tests* should be conducted to enable assessment of a model's behavior under extreme conditions, and feedback loops should be analyzed to understand the source of endogenous dynamics.

Operational Questions for Implementation Planning. A big assumption along the policy feedback loop is that a *desired* resource can be transformed into an *actual* resource. Sterman (2000) emphasizes the importance of distinguishing between *desired* and *actual* quantities in a

[3] If we assume that the inflow is the product of the resource and its productivity, then in re-arranged terms, resource = inflow/productivity. Expressed in goal-directed terms, desired *resource = desired inflow/productivity.*

model:

> Modelers should separate the desired rates of change in system states from the actual rates of change. Decision makers determine the desired rates of change in system states, but the actual rates of change often differ [from desired rates] due to time delays, resource shortages, and other physical constraints (p. 519).

In Figure 2, the dashed link signifies that transforming the *desired resource* into an *actual resource* is not an automatic, self-executing step. It requires further actions, necessitates use of real resources, and takes time even under ideal conditions. Moreover, policy initiatives usually generate resistance during the implementation phase, and carrying out real-world policies is often constrained by institutional arrangements and organizational and social capacities for change (Hill & Hupe, 2009; Howlett, Ramesh, & Perl, 2009; Knoepfel, Larrue,Varone, & Hill, 2007). Therefore, we refer to the dashed link as a *wishful thinking* link (Wheat & Shi, 2011) because it ignores the operational requirements for transforming desires into reality. Computer-generated policy results are unlikely to be achieved in real life with the same effectiveness, at the same cost, and in the same timely manner.

In Figure 2, the oval-shaped box overlaying the wishful thinking link represents a set of implementation constraints that can be expected to impede progress toward a policy goal. As explained more fully in the next section, it is desirable to formulate the set of constraints as a sub-model (i.e., the box should contain additional stock-and-flow structure to represent how the constraints might work). The input to the sub-model would be the *desired resource* and the output would be the *actual resource.*

Anticipating and planning for policy constraints requires what Richmond called *operational thinking*--thinking about how things actually work in the plumbing of the problematic system (Richmond, Peterson, & Vescuso, 1987; Richmond, 1993, 1994, 2000).As modelers, we cannot know all the answers regarding a policy's feasibility; thus, it is necessary to consult policy domain experts during the modeling process. Insights gleaned from public policy implementation literature can help modelers pose useful questions to the experts (Wheat, 2010). Therefore, before attempting to model the constraints, we should express them as answers to questions that highlight the implementation challenges inherent in a particular policy option.

The questioning process begins by asking where our implementation analysis is located on the *policy timeline*. Has legislation already been passed establishing general policy goals and authorizing (and funding) a government agency to design and execute a specific program of action? If so, implementation means "carrying out a basic policy decision" that has been made by government officials exercising formal authority (Mazmanian & Sabatier, 1983, p. 1). On the other hand, if a policy has yet to be authorized, implementation planning means anticipating what needs to happen (Ferman, 1990). Placing our policy analysis on a timeline reveals the nature of the constraints (legislative, budgetary, managerial, technical, social, cultural, etc.) a particular policy is likely to encounter. The expected benefits of any policy option should be discounted if formal authorization (or adequate funding) is uncertain.

Other questions shift attention to distant points on our policy timeline and require working back toward the present. Elmore (1979, p. 604) urges analysts to ask about "specific behavior at the lowest level of the implementation process that generates the need for a policy," and from there urges analysts to use *backward mapping*--"to back up through the structure of implementing agencies" with questions about requisite organizational capacity along the implementation path. Using the model in Figure 2 as an example, we would say that the inflow is the behavior targeted by the policy, and that changing the *resource* quantity applied to that inflow is the strategy to be analyzed. We then need to envision implementing agencies that are likely to be involved, the extent to which their operating procedures could generate the *desired resource*, the decisions and actions needed to activate those procedures, and the capacity and incentives for those decisions and actions. There may be a hierarchy of key agencies and actions, and mapping backwards requires sequential attention to each.

Elmore's (1979) "backward mapping" provides an operational approach to questioning how government agencies function in particular issue settings--a prerequisite for informed policy feasibility estimates. A complementary, if less operational, approach is suggested in Table 1, which contains a checklist of feasibility-relevant questions, compiled by surveying the works of Allison (1969, 1971), Mazmanian and Sabatier (1981,1983), Hogwood and Gunn (1984), Linder and Peters (1989), and Bardach (2005). For particular types of policies, some questions will be more significant and the answers more critical. In general, however, each "Yes" answer provides a reason to challenge the feasibility of a policy option.

TABLE 1 A checklist of feasibility-relevant questions
"Yes" answers indicate potential constraints on policy implementation.

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1. Does the policy require future legislative action by elected officials?

2. Do responsible agencies lack the capacity (budgetary or human resources, technology, or legal authority) to do what the policy requires?

3. Do responsible agencies have discretionary authority to decide what to do and when to do it?

4. Does the policy require a high level of coordination among different agencies within a single government or across jurisdictions?

5. Does the policy require responsible agencies to perform new tasks, develop new procedures, or hire and train new personnel?

6. Do key personnel in the responsible agencies reject the causal theory implicit in the policy, the moral or social justification for the policy, or the basic goals of the policy?

7. Are key officials within responsible agencies distracted by other pressing issues and unlikely to give adequate attention to this policy?

8. Is the policy opposed by organized interest groups with access to the media, the courts, or the responsible agencies?

9. Is the general public sharply divided over the policy?

10. Does the policy conflict with traditional cultural norms and values held by a politically significant segment of the population?

Answers to both operational and feasibility questions help modelers flag potential constraints on a particular policy option. The answers also facilitate distinguishing between policy options that otherwise suggest similar benefits and costs during wishful thinking simulation experiment. Moreover, both types of questions are helpful when building a sub-model of policy constraints, a simple illustration of which is presented in the next section.

Modeling Constraints on Policy Implementation. Policy design requires more than testing parameters, constructing wishful thinking links, and raising questions about the feasibility of a policy option. It requires adding stock-and-flow structure that transforms wishful thinking links into operational links. When Forrester discussed policy modeling in *Urban Dynamics* (1969), he emphasized the need to ". . . restructure the system so that the internal processes lead in a different direction" (p. 113). Richardson and Pugh (1989) explain that "policy improvement . . . involves the addition of new feedback links" and their examples reflect a feedback perspective on policy design (pp. 332, 337359). Sterman (2000) emphasizes that "policy design . . . includes the creation of entirely new . . . structures and decision rules" and he provides detailed feedback-based formulation guidelines for effective decision-rule design (pp. 104, 513550). Ford (2010) encourages "constructing a stock-and-flow diagram to describe the details of policy implementation" and provides numerous examples (p. 158).

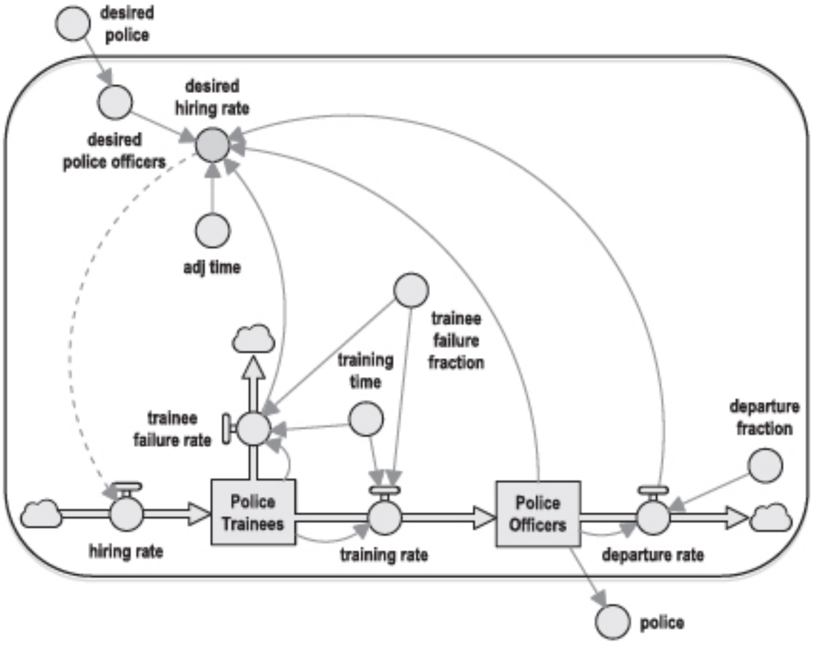

Figure 3. Inside an Implementation Constraints Sub-Model

Figure 3 displays a simple example of modeling implementation constraints when the requisite resource is a force of police officers. The input to the sub-model is desired police. The actual number of *police officers* is determined within the sub-model and is the output to the *actual police.*

The sub-model in Figure 3 operationalizes at least part of the process of changing an actual resource to its desired level. Operationalizing the constraints enables a more realistic simulation assessment of the expected impact of a policy that requires changing the number of police officers. At a minimum, the constraints in the sub-model delay the impact; it will take longer to achieve the desired number of officers than the wishful thinking link would suggest. The stock-and-flow structure reflects the need to train new recruits for some time before they become officers and operate with the expected level of productivity. Additional delays are due to continuous recruitment and training as officers depart the police force and some trainees fail to become officers. Moreover, if the failure rate were high, the constraints in this example could generate oscillations--too few officers in one time period followed by too many officers later on.[4]

Note that a new wishful thinking link appears in Figure 3: a change in the *desired hiring rate* would be instantly implemented in the actual *hiring rate*. Only a little armchair brainstorming is needed to recognize that nothing has been said about the budget for hiring new officers or whether there is a ready supply of recruits. More implementation modeling could be done and, in this case, should be done. In the public health modeling examples discussed below, more is done. One reason for leaving the example in Figure 3 unfinished is to keep it simple for explanatory purposes. Another reason is to underscore a key point: there is a limit to what can (or should) be modeled explicitly. Even large, complex finished models will contain some wishful thinking links (whether modelers acknowledge them or not). Taking implementation seriously does not mean modeling minutia or modeling past the point of diminishing returns for the user of the model. Rather, it means being vigilant when closing feedback loops--always aware of unstated assumptions implicit in a link and conscious of the next step: whether to add more stock-and-flow structure, raise more red flags with insightful questions, or both.

Public Health Issue Examples

The use of the policy design framework will be illustrated with two examples. The first draws on a classroom exercise that introduces the modeling process to students in the international system dynamics master's degree program at the University of Bergen in Norway.[5] A physical simulation game generates data that, along with the rules of the game, provide sufficient information to build an explanatory model that reproduces the behavior observed in the game. All of this is done during the first lecture to provide students with an overview of the skills they will develop during the course. During the second lecture, we demonstrate designing a policy model to control the epidemic.

The second example concerns auto pollution in Zimbabwe. The model has been adapted from a student research project in which Madoma (2011) developed an SD model to explain the growth of auto pollution in Zimbabwe's urban centers from 1990 to 2010. She also developed a policy model to test the impact of inspecting cars and impounding those that emit

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[4] The potential for oscillations is due to multiple delays along the negative feedback loop that seeks to close the gap between the desired and actual number of police officers.

[5] "Systems Education at Bergen" is available at Systems 2014, 2(2), 159-167; http://www. mdpi.com/2079-8954/2/2/159.

pollutants at a higher rate than allowed by law.

Although contrived, the epidemic model is a simplified version of SD epidemic models that have been developed for real-world situations (Dangerfield, Fang, & Roberts, 2001). Here, its simplicity makes it accessible to a wide range of readers. The auto pollution example, although adapted from a complex model of a messy real-world situation, has also been simplified to facilitate exposition.

The Epidemic Game.[6] Before the game begins, one anonymous student is discreetly designated as "infected." During the game, each student has one random "daily" contact (handshake) with another student. When an infected student and uninfected student make contact, there is a chance of a new infection based on the outcome of a coin toss. Eventually, an "epidemic" occurs. The cumulative number of infected persons grows at different rates over time: slowly during the first few days, then rapidly, then slowly again, and finally no growth at all after everyone becomes infected.

Explanatory Model of the Epidemic. We conceptualize the epidemic game data in terms of two stocks--*Susceptible Per*sons and *Infected Persons*--and a flow called the *infection rate* that is the daily rate of new infections. As infections occur during the game, people flow from a *Susceptible* Persons stock to an *Infected Persons* stock. The epidemic grows due to the positive feedback loop between *Infected Persons* and the *infection rate*, and slows due to the negative feedback loop between *Susceptible Persons* and the *infection rate*. When graphed, the stock of *Infected Persons* follows an s-shaped growth pattern.

[6] The Epidemic Game described here has been adapted from the original version (Glass-Husain, 1991).

Policy Design for the Epidemic Game Model. After the dynamics of the problem are understood, we explore policy options to combat an epidemic. We begin by selecting a broad strategic option for analysis, in this case a vaccination strategy. Figure 4 displays a sub-model of constraints that could impede a vaccination strategy. To keep the focus on the policy model (left side of the diagram), the explanatory model (bottom right) is highly simplified with only the feedback loop effects on the infection rate shown.

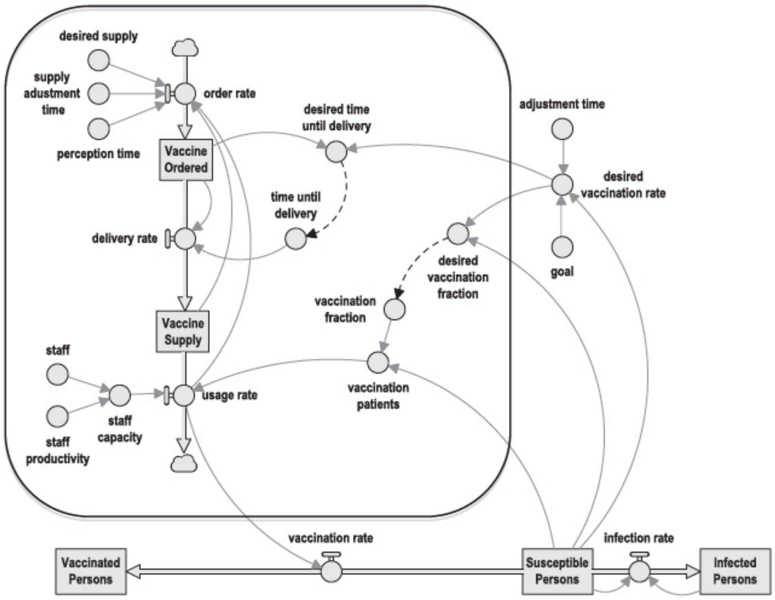

Figure 4. Illustrative implementation constraints on a vaccination policy

Susceptible Persons is the stock to be managed and, in Figure 4, a new outflow--*vaccination rate*--has been added to the explanatory model. The strategy is to drain the stock of *Susceptible Persons* before they have contact with *Infected Persons*. The *vaccination rate* is the flow to be regulated and in the absence of constraints on policy implementation would be instantly equal to the *desired vaccination rate*. But that is wishful thinking.

Modeling Implementation Constraints on the Vaccination Policy. Vaccinations occur when there is a demand for vaccine, a supply of vaccine, and adequate human resources to administer the vaccine. These conditions determine the vaccine usage rate and, therefore, the *vaccination* *rate*. The demand for vaccine is the number of persons who show up to get vaccinated, whether voluntarily or through coercion. The *vaccine supply* on-site and ordered--often problematic under real-world epidemic conditions--is represented as a supply chain. The human resource capacity constraint is represented by parameter values for *medical staff* and *staff productivity.*

Various simulation scenarios, each designed to reflect different assumptions about the constraints, are used to test the impact of the vaccination policy. The best-case scenario is that the number of infections is reduced by nearly half if the vaccination policy can be carried out as desired, i.e., without constraints. If fewer-than-desired people step up to be vaccinated, if there is insufficient medical staff capacity, or if the vaccine is not produced and delivered quickly enough to be useful, the policy will not be as effective as the best-case scenario suggests.

One of the wishful thinking links is a reminder that a vaccination strategy must include a program designed to encourage susceptible persons to get vaccinated. Another highlights the need for pharmaceutical firms to deliver sufficient quantities of vaccine in a timely manner. Neither requirement is a foregone conclusion. Whether to continue building this model (i.e., replace these two wishful thinking links with operational links) is a judgment call. The alternative is to highlight both issues in discussions with policy makers or program administrators and be sure that remaining implementation obstacles are not overlooked. No matter where we stop, there will always remain some wishful thinking links; not everything will be modeled. There is value, however, in surfacing hidden assumptions and highlighting constraints that remain.

Auto Pollution in Zimbabwe. In contrast with the contrived epidemic example, the auto pollution example is based on Madoma's (2011) study of actual conditions in Zimbabwe. From 1990 to 2010,vehicles in urban centers increased by 150 percent and air pollution attributed to vehicles rose even more, indicating that emissions per vehicle were increasing.

> Most are poorly maintained low-cost second hand vehicles that do not meet strict emission standards of the countries of their origin. Zimbabwe has become a dumping ground for used cars because people rely heavily on importing second-hand vehicles as they cannot afford new vehicles sold in the country. As a result, vehicle emissions have become a major source of pollution in the cities. (*Madoma, 2011, p. 5)*

In SD terms, auto emissions add to the stock of air pollution while the dispersion rate subtracts, and the pollution level grows when the inflow is greater than the out- flow. Specifically, the auto emissions rate is due to the number of cars and the average emissions per car. The dispersion rate is a function of the auto pollution level and the time required to disperse the pollutants under local atmospheric conditions.

Policy Design for Auto Pollution Model. To slow the growth in the auto pollution stock, its net inflow must be decreased. The outflow is assumed to be beyond the control of public authorities, because it depends on the properties of the pollutants in the air and the dispersing influence of local atmospheric conditions. The proximate cause of the inflow, the emissions rate, is the combined effect of the number of cars and the emissions per car, either or both of which might be the target of policy initiatives. Madoma evaluated the strategy of impounding imported cars that violate Zimbabwe's emissions regulations. The strategy aims to influence the emission rate in two ways. First, it could reduce the total number of cars because some drivers who lose their used imports in the impoundment process could not afford more expensive replacement cars. Secondly, with the reduction in the number of used imports, the weighted average emissions per car would decline.

Figure 5 displays a simplified version of Madoma's implementation constraints sub-model, which receives an input from *desired impoundment rate* and generates the *actual impoundment rate* output. Within the sub-model, organizational, technological, and social constraints hinder achievement of the policy goals. The sub-model structure focuses on the funding, hiring, training, and equipping of inspectors who would be responsible for impounding used imports that are in violation of Zimbabwe's auto emissions standards. [7] A stock-and-flow feedback approach is used to model the dynamics of the *inspectors* stock and the *wage budget* on which it depends. A key question is how much of the desired wage budget might actually be funded. Instead of attempting to model the budgetary process in Zimbabwe, Madoma uses a parameter, *fraction funded*, to test the sensitivity of the model to various assumptions about program funding. Another important parameter, *probability of corruption*, has a negative influence on *inspector productivity*, and reduces the actual *impoundment rate.*

[7] The sub-model in Madoma's (2011) original work includes additional constraints, primarily relating to the funding, acquisition, and use of the gasoline analyzers needed for the inspections. Those are aggregated and simplified in Figure 5.

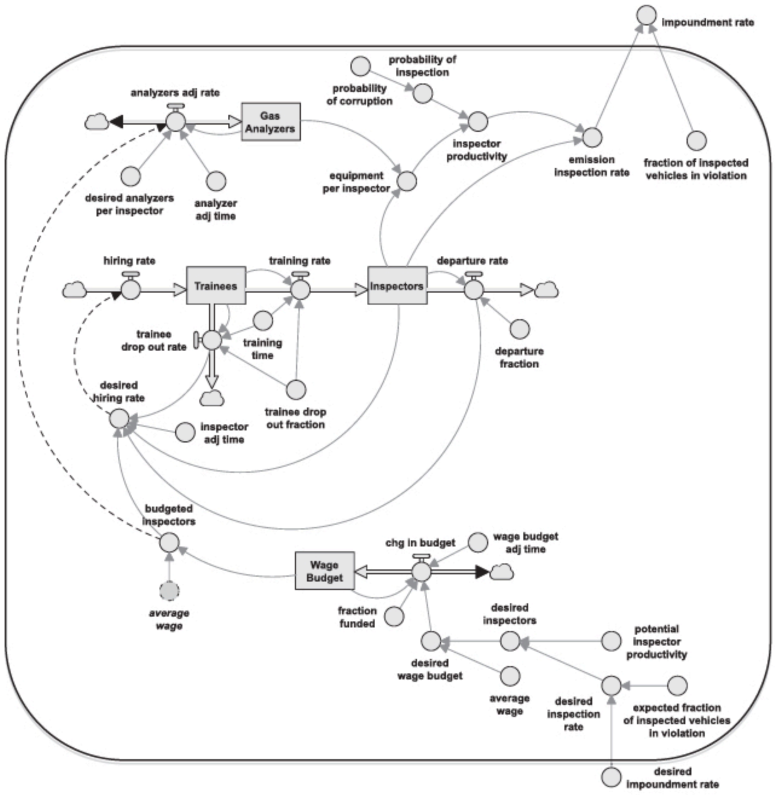

Figure 5. Illustrative implementation constraints on an impoundment policy

Simulation scenarios are used to facilitate an assessment of the expected impact of an impoundment policy in the auto pollution model.[8] Wishing away all constraints in the first scenario, the policy performs in its desired manner and stops the growth in auto emissions. The next scenario activates the implementation constraints sub-model and assumes a fully funded *Wage Budget* and no lack of inspections due to corruption. Compared to the best-case scenario, the results are not as good because delays occur within the budget and hiring processes and some trainees drop out. Although emissions slow dramatically, they continue rising because the policy sub-model is unable to impound the polluting cars at a rate that keeps pace with importation and use.

[8] Madoma (2011) developed the pollution index for Zimbabwe's urban centers by combining measures of five pollutants: sulfur dioxide, carbon monoxide, carbon dioxide, nitrogen oxides, and particulate matter.

The final scenarios reflect trouble at the government level and/or the street level. The third scenario assumes only half the budget requirements are funded but corruption is not a problem, while the last scenario makes the same budgetary assumption but assumes that inspections are cut by half due to corruption. The impact of the impoundment policy is weak in both cases. Lack of full support at either the top or the bottom of the policy chain undermines the policy, and the pollution level continues to rise near the business-as-usual rate. Should that occur, money spent on the program would be perceived as wasted. The high likelihood of a disappointing outcome means that weak links in the implementation structure must be strengthened or other policy options must be considered.

Discussion

Model-based policy design that relies exclusively on parameter sensitivity analysis raises questions about how parameter changes in a computer model could be implemented in real-world settings. In this chapter, we turn that question around--asking how implementation constraints could be embedded in a computer model--and provide an answer with a framework for model-based policy design that takes implementation seriously.

The framework builds on the traditional SD distinction between problem explanation and policy design. Policy design begins with a high-level perspective that ignores operational details, seeks the logical connection between the problem and the solution, and tests the potential impact of broad strategies. The result is a simulation model containing a series of feedback loops that regulate target flows of the stocks being managed. The loops contain wishful thinking links between desired and actual results, but motivate operationally and politically insightful questions about the feasibility of specific policy options.

Replacing wishful thinking links with stock-and-flow structure that represents operational thinking is the final task in the policy design process. Modeling the implementation process for a policy requires a street-level perspective, questions operational detail and feasibility, adds model structure to represent real-world constraints, and evaluates the policy in light of those constraints. But modeling everything is not possible. There will always be a need for wishful thinking links to highlight implementation constraints that are better addressed the old fashioned way--by constructive questioning and discussion.

To illustrate how the framework can be applied, we modeled two dynamic problems--a simple, contrived flu epidemic and a more complex, real-world auto pollution problem--complete with policy sectors containing stock-and-flow representation of practical details inherent in policy implementation. For both models, the value of the framework has been enhanced by reliance on key elements of the implementation paradigm in the public policy literature.[9] In this final section, we highlight pieces of that literature that can be useful for almost any policy modeling project and note their contribution to the particular examples illustrated in this chapter.

Foremost is Elmore's (1979) backwards mapping approach, which guides modeling for both the epidemic and pollution cases. Importantly, it is not limited to policy modeling; it also aids our *modeling backwards* approach to explanatory modeling.

When thinking about a vaccination strategy, it is useful to think in terms of policy outputs emerging from standard organizational processes (Model II perspective in Allison, 1969, 1971), both within public or quasi-public health institutions and within private pharmaceutical companies. In that context, feasibility of the vaccination strategy ranked high, with the main uncertainty relating to government's authority and determination to speed up production and delivery of vaccine. The impoundment strategy for the auto pollution problem, on the other hand, requires a new program with new budgetary claims in an unstable political culture. The losers under this policy will be identifiable and vocal; winners will be anonymous and silent. That will increase pressures for repeal within the government and pressures for evasive action, non-compliance, and corruption at the street level where the policy would be enforced. The bureaucratic politics perspective (Model III in Allison, 1969, 1971) and the policy feedback concept in the policy dynamics literature (Pierson, 1993; Baumgartner & Jones, 2002) are useful for thinking about the program's prospects for both passage and survival. These insights translate into low feasibility estimates reflected in the parameter assumptions about program funding and the probability of corruption.

Thinking about how governments function leads to thinking about the scope and limits of their power to deal with public issues. Linder and Peters (1989) show how the choice of the "instruments of government" facilitates or impedes implementation. Brainstorming policy options is more likely to remain hitched to reality if SD modelers have ready access to Bardach's (2005) list of "what governments do." In the contrived epidemic case, we have no reference to political culture; thus, the scope of formal authority is unknown. Nevertheless, a vaccination program is one of several standard ways that public health authorities in most countries respond to epidemics; thus, there is little doubt that the instrument of choice could be activated. An auto impoundment strategy, on the other hand, raises issues that would be insurmountable

[9] Essential roadmaps to the implementation literature are contained in Saetren (2005) and Hill and Hupe (2009).

obstacles in some political cultures. Even in Zimbabwe, the environmental laws passed in 2002 authorized fines (that were unenforced) but did not authorize impoundment. Legislative action is needed to bring the impoundment club out of the closet; thus, the importance of examining at least one simulation scenario that reflects a low conditional estimate of appropriations probability (given a low estimate on the chances for authorization).

Building bridges between the SD and public policy communities promises mutual benefits. The public policy literature is a valuable source of conceptual and empirical support for SD representation of delays, capacity limits, feedback effects, and nonlinearities that characterize complex policy systems notoriously resistant to change. And simulation modeling that takes implementation seriously can be a valuable addition to the policy analyst's toolkit. The framework presented in this chapter aims to encourage more operational thinking and less wishful thinking during model-based policy design. Ultimately, it aims to encourage building models that are more useful to policy makers.

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