Proceedings of the 2010 Winter Simulation Conference
B. Johansson, S. Jain, J. Montoya-Torres, J. Hugan, and E. Yücesan, eds.

IMPROVING MODEL UNDERSTANDING USING STATISTICAL SCREENING

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ABSTRACT

Models of dynamic systems are often constructed to improve system performance by identifying and modifying structures and parameters that drive system behavior. Once identified, these can be used to design and test policies for performance improvement. A preliminary step in developing policies is the identification of high leverage parameters and structures, the influential model sections that drive system behavior. The current work describes the use of statistical screening as a tool to improve model understanding, explanation, and development with a six step process. Statistical screening offers system modelers a user-friendly tool that can be used to help explain how model structure drives behavior.

1 INTRODUCTION

Modelers often focus on identifying mechanisms within a system that offer explanations of system behavior (Sterman, 2000). Once identified, these mechanisms can be used to design and test policies for altering the system's behavior. An efficient method for developing these policies is to focus on portions of the model that exert the greatest influence on the behavior of the variable or variables of interest, i.e. the high leverage parameters and structures. Changes in high leverage parameters and structures can dramatically alter system behavior.

Causal feedback structures are one particularly potent type of model structure (Sterman 2000). Model analysis methods for identifying high leverage parameters in feedback structures have seen increased attention from researchers in recent years. For example D. Ford (1999) describes behavioral model analysis, Mojtahedzadeh et al. (2004) describes the pathway participation method, and Kampmann and Oliva (2006) and Guneralp (2006) describe loop eigenvalue analysis. We describe and demonstrate the statistical screening approach to identifying high leverage parameters in feedback model structures as an example of the application of statistical screening to dynamic simulation models. See Ford and Flynn (2005) for a comparison of statistical screening with pathway participation and loop eigenvalue analysis. We illustrate the application of statistical screening with the tipping point model developed by Taylor and Ford (2006; 2008). The relevant portions of the tipping point model are shown in
Figure 1.

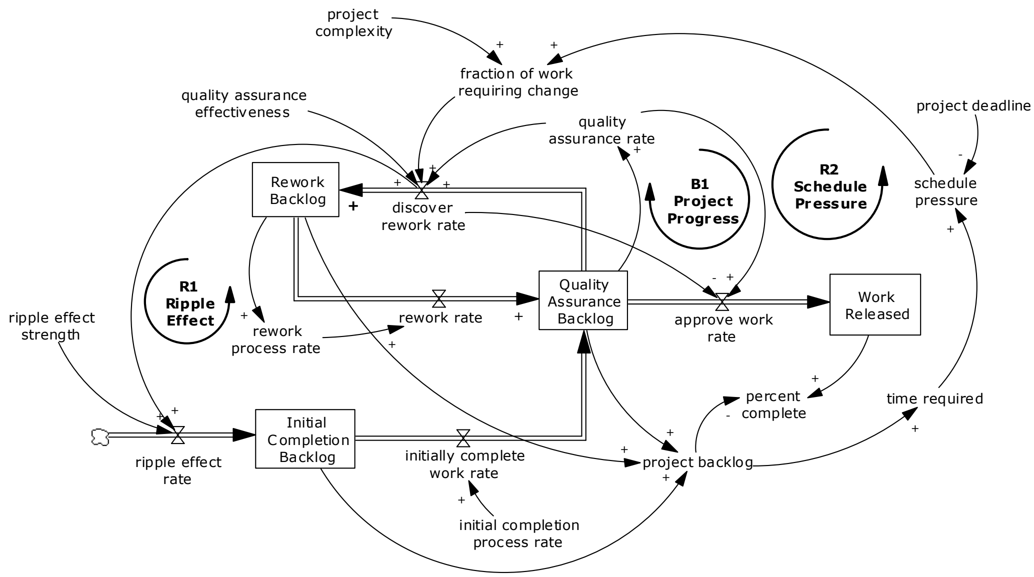

Figure 1: Feedback in a tipping point project model (Taylor and Ford 2006, 2008)

The tipping point model simulates a single development project subject to feedback dynamics that can create both rework of original project scope and the addition of work to the project beyond the original scope through ripple effects. The discover rework rate is the product of the fraction of work requiring change, the quality assurance effectiveness, and the quality assurance rate (
Figure 1). The quality assurance effectiveness describes the ability of quality assurance personnel to identify work packages that contain errors. For the simulations presented here quality assurance is assumed to be 100% effective (i.e. all work packages requiring rework are identified by quality assurance). The fraction of work requiring change can be exogenously increased by increasing the project complexity and endogenously increased by increasing schedule pressure (Loop R2,
Figure 1). The discovery of rework can also add work to the project in addition to the initial project scope. This additional work is represented by ripple effects (
Figure 1) and can be exogenously increased by the ripple effect strength and endogenously increased through the ripple effect loop (Loop R1,
Figure 1). Detailed information on the tipping point model structure, equations, testing, and use is beyond the scope of this note. See Taylor and Ford (2006) and Taylor and Ford (2008) for more detail on the tipping point model. The model is available for download at <http://ceprofs.tamu.edu/dford/>.

The feedback dynamics of the tipping point model can create two very different behavior modes for projects with the same feedback structure and very similar characteristics. For example, Figures 2 – 4 each show the behavior of the percent of the project work completed over time for 200 individual projects simulated using the tipping point model. For all 600 simulations the values of 13 of the 14 model input parameters were selected from a uniform parameter value distribution with a range of + 20% of the base case value. The variation in parameter value of ±20% is selected to simplify the illustration of the method. Modelers should assign uncertainty to input parameter values that reflect the uncertainty in the actual system. The only difference among the simulations in Figures 2, 3, and 4 is the value of the final exogenous model parameter, the project deadline. The project deadline was 300 months for the simulations in Figure 2, 75 months for the simulations in Figure 3, and 130 months for the simulations in Figure 4. A late deadline allows all 200 projects to reach 100% complete (Figure 2), an early deadline prevents any of the projects from being completed (Figure 3), and an intermediate deadline allows some of the projects to reach 100% complete (Figure 4).

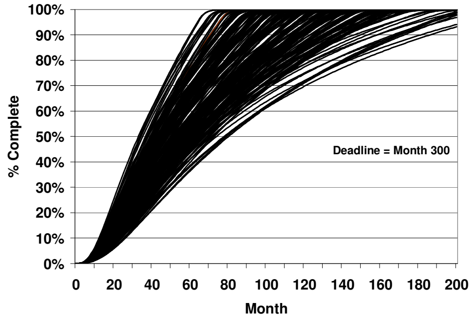

Figure 2: Behavior of 200 simulated projects with deadline = month 300

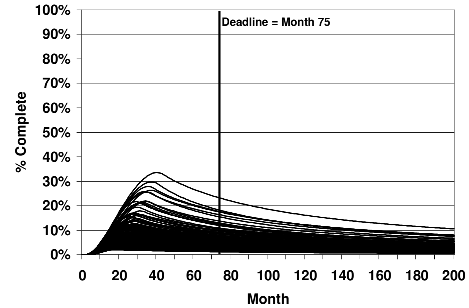

Figure 3: Behavior of 200 simulated projects with deadline = month 75

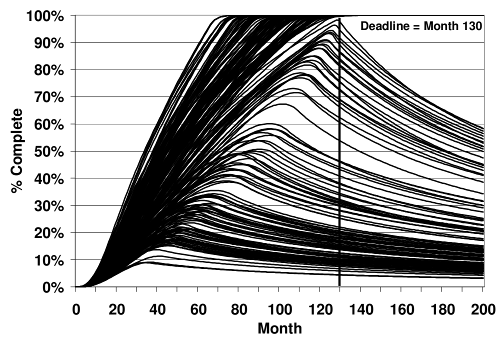

Figure 4: Behavior of 200 simulated projects with deadline = month 130

Statistical screening examines model behavior to identify high leverage parameters. Examining the behavior modes in Figures 2 – 4 reveals the project deadline as a high leverage parameter for project performance. Clearly this information would be valuable to the manager of such a project. How can a modeler identify the project deadline and other high leverage parameters in this model?

Statistical screening (Ford and Flynn, 2005) offers a simple, structured, and user-friendly means of identifying high leverage model parameters. Statistical screening quantifies parameter influence throughout a simulation, thereby describing the evolution of exogenous impacts on behavior. In addition, statistical screening provides modelers with the objective model analysis results required to generate clear behavior distinctions such as those shown in Figures 2 – 4. Statistical screening does this by allowing a modeler to simultaneously test many model parameters.

Appendix A (based on Ford and Flynn 2005) describes the use of statistical screening analysis to quantify tolerance intervals for the most influential model input parameters. The current work extends the use of statistical screening by presenting a six step method that utilizes statistical screening as a tool to improve model understanding and as a tool that can highlight sections of model structure for further analysis. To illustrate its use, the method is applied to the tipping point model (Taylor and Ford, 2006; 2008).

2 THE SIX STEPS OF STATISTICAL SCREENING

Statistical screening uses multiple simulations generated by varying model input parameters to calculate correlation coefficients that measure the direction and strength of the relationship between input parameters and a user defined system performance variable.

The correlation coefficient (r) used here is the linear correlation coefficient in the form of:

$$r = \frac{\sum\left(x-\bar{x}\right)\left(y-\bar{y}\right)}{\sqrt{\sum\left(x-\bar{x}\right)^2 \sum\left(y-\bar{y}\right)^2}} \qquad \text{(Ford and Flynn, 2005)}$$

Values of correlation coefficients vary between -1 and +1, with the polarity denoting the direction of impact. Parameters with correlation coefficients with a value of "1" are perfectly correlated with the performance variable, correlation coefficients of "0" indicate no correlation, and correlation coefficients of "-1" indicate a perfectly inverse correlation. The method calculates correlation coefficients for each time unit of the simulation for as many exogenous parameters as the user selects. This provides a time series of correlation coefficients for each selected exogenous variable (demonstrated next). The detailed steps of calculating correlation coefficients for statistical screening are described in Ford and Flynn (2005) and Appendix A.

The six steps of statistical screening, described next, are designed to guide and assist model investigation.

1. Select a specific set of exogenous model parameters and a performance variable for analysis. Select a range of possible exogenous parameter values based on data from the real system.
2. Perform statistical screening of the model to calculate correlation coefficients for the selected exogenous model parameters as described in Ford and Flynn (2005). Plot both the correlation coefficients and the behavior of the performance variable.
3. Select a time period for analysis by examining time series of the performance parameter and the correlation coefficients.
4. Create a list of high leverage parameters. The high leverage parameters are those parameters with the highest absolute correlation coefficient values during the selected time period.
5. Identify the high leverage model structure(s) for each parameter identified in step 4 as those that are directly connected to the high leverage parameter. If multiple parameters from step 4 are directly connected to the same model structure add each parameter set to the list.
6. Use additional structure-behavior analysis methods to explain how each parameter or set of parameters and the structures they influence drive the behavior of the system.

The six-step process is next applied to the tipping point model. The example reveals that a mix of analysis, interpretation, and judgment is required in a model investigation.

3 AN EXAMPLE APPLICATION: THE TIPPING POINT MODEL

Step 1: Select Parameters, Parameter Ranges, and Performance Variable

All fourteen model input parameters for the tipping point model were analyzed. For large models with many exogenous inputs the modeler may need to use their judgment when selecting input parameters for analysis. See Ford (1990) for an example of developing a process to select relevant parameters for analysis. "Percent complete" was selected as the performance variable. The fourteen exogenous parameters were varied uniformly + 20% from base case values. The variation in parameter value of $\pm$20% is selected to simplify the illustration of the method (similar to range selection methods described in Ford and Flynn, 2005). When analyzing a model, modelers should assign uncertainty to input parameter values that reflect the uncertainty in the actual system. However, modelers should be wary of their confidence in parameter range estimates when estimating uncertainty. As Sterman (2000) notes, "people are grossly overconfident in their judgments" (p. 272).

Step 2: Perform Statistical Screening to Calculate Correlation Coefficients
To generate data for the statistical screening analysis 200 simulations were run based on the range of possible exogenous parameter values. Data from the 200 simulations was downloaded into Excel® and the correlations coefficients tabulated using the Excel® template described in Ford and Flynn (2005) and available at http://www.wsu.edu/~forda/. Figure 5 shows the time series of the correlation coefficients of the four parameters with the highest absolute correlation coefficient values and therefore the highest leverage on percent complete. Percent complete behavior for the same set of simulations is shown in Figure 4.

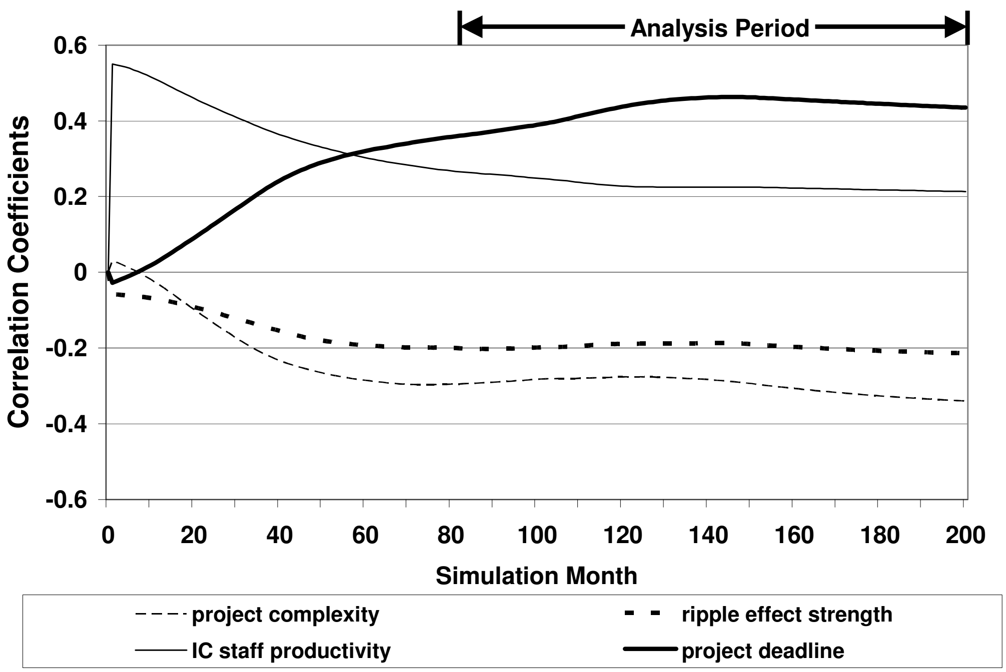

Figure 5: Statistical screening of the tipping point model (based on 200 simulations)

Step 3: Select Analysis Time Period
The period between months 80 – 200 was selected for analysis because the percent complete behavior modes bifurcate during this time period as shown in Figure 4.

Step 4: Identify Parameters with High Absolute Correlation Coefficients Values
Between months 80 – 200 the parameters "project deadline" and "project complexity" have the highest influence on percent complete as evidenced by their high absolute correlation coefficient values during the analysis time period. The number of parameters with high absolute correlation coefficient values investigated is based upon the authors' judgment. The influence of parameters decreases as their correlation coefficients approach zero. For example, we first identified parameters with low correlation coefficients [-0.15, 0.15] and then tested whether they had low influence by adding dummy variables to the model that were not connected to any part of the model structure and therefore were known to have no impact on performance. Correlation coefficients for these dummy variables had a maximum range of [-0.15, 0.15].

Step 5: Connect High Leverage Parameters with Model Structure
An examination of
Figure 1 shows the parameters "project deadline" and "project complexity" individually and directly impact the schedule pressure loop (R2 in Figure 1) and the ripple effect loop (R1 in Figure 1). This analysis

indicates that these parameters and their associated model structure have a strong influence on percent complete between months 80 – 200. **Table 1** explicitly identifies three parameter-structure pairs for possible further analysis based on the results of step 4.

Table 1: High leverage parameters and the model structure they directly influence

Parameter	Model Structure Directly Impacted
project deadline	Constrains loop R2 through schedule pressure.
project complexity	Constrains loop R2 through the fraction of work requiring change. Also constrains loop R1 through the fraction of work requiring change.
project deadline & project complexity	Constrains loop R1 and loop R2

The pair of parameters are also identified for additional analysis because they both impact the same model structure.

Step 6: Additional Analysis

In this example, manual feedback loop analysis is used to link structure and behavior. The final step of the six step process is where the modeler is required to exercise most of their judgment in analyzing the behavior of the system. This judgment can be reinforced by adding more rigor to this step by employing structured analysis methods (e.g. behavioral analysis). The schedule pressure loop (R2) impacts percent complete by altering the level of rework on a project. The "fraction of work requiring change" determines how much work is completed correctly and released or completed incorrectly and adds work to the project backlog due to ripple effects through loop R2. Schedule pressure can increase the amount of rework on a project by increasing the "fraction of work requiring change." Increasing the value of the "fraction of work requiring change" by increasing "project complexity" strengthens the ripple effect loop (R1) and weakens the project progress loop (B1). Changing the relative strengths of loops B1 and R1 can dramatically alter project percent complete because if the "fraction of work requiring change" increases past the tipping point feedback loop dominance is shifted from the project progress loop (B1) to the ripple effect loop (R1) and the percent complete switches from steadily increasing to steadily decreasing (Figure 4).

Although both "project complexity" and "project deadline" impact the schedule pressure loop (R2) the statistical screening analysis reveals that "project deadline" has a higher impact on percent complete then the "project complexity." This difference in parameter leverage can be better understood by examining the model equations that describe the amount of rework on the project. Combining the equations for the "fraction of work requiring change" and the "schedule pressure" (
Figure 1) yields the following equation:

$$f_r = f_{r-m} + s\left[\left(\frac{T_r}{DL-T}\right)-1\right] \qquad (1)$$

where:

- f_r fraction of work requiring change (percent)
- f_{r-m} project complexity (percent)
- s sensitivity of rework to schedule pressure (percent)
- T_r time required to complete remaining tasks (month)
- DL project deadline (month)
- T simulation time (month)

Examination of Equation 1 reveals that a change in the project complexity results in a shift in the fraction of work requiring change whereas a change in the project deadline changes the size of the scaling of the fraction of work requiring change. This relationship helps explains why the parameter "project deadline" is a higher leverage parameter then "project complexity."

The negative impact of schedule pressure as described here is consistent with the results of Nepal et al. (2006). The verbal reasoning analysis presented here is supported by the results of behavioral analysis (Ford 1999) of the tipping point model. See Taylor et al. (2005) for details on the behavioral analysis of the tipping point model. The feedback simplicity of the core of the tipping point model provides the basis for a clear example of the application of the six steps of statistical screening. With additional judgments the steps can be applied to larger and more complex models. See Taylor et al. (2007) for an application of the basic six step process to the Bass Diffusion and the World3 models.

4 DISCUSSION

Statistical screening analysis can improve model development by identifying specific model parameters and structures for additional development. Previous work has described the importance of "endogonizing" parameters that have a strong influence on system behavior as a part of model development. A. Ford (2009) notes that converting exogenous parameters to endogenous model structure is a "pragmatic approach" to improving model structure (p. 142). Sterman (2000) notes that "each candidate for an exogenous input must be carefully scrutinized to consider whether there are in fact any important feedbacks from the endogenous elements to the candidate" (pp. 95-96). The screening process described here can identify high leverage exogenous parameters that may be endogonized to improve model validity.

Statistical screening can also aid in explaining how structure drives behavior. Using the six step process and the tipping point model example the modeler could identify the project deadline and schedule pressure as key drivers of percent complete. The modeler could then illustrate the importance of the project deadline and schedule pressure to the project manager by showing Figures 2 – 4 to the project manager. Figures 2 – 4 illustrate that, despite the variation in the 13 other model parameters, a change in the project deadline (and therefore a change in the amount of schedule pressure) can dramatically alter the performance of a project. The graphs present the results of the analysis in a form that the project manager is familiar with, project progress as tracked by percent complete. The graphs also make clear how an overly aggressive deadline (Figure 3) can lead to poor project performance while a more relaxed deadline (Figure 2) can reduce the chance of project failure due to schedule pressure. Similar benefits may be available for any model in which changing the value of a single parameter causes a dramatic change in the behavior mode of a system performance variable. This presentation method has proven useful in practice in discussions of land use policies that influence Sage-grouse populations in central Washington (Beall et al. 2006). The presentation method allowed the Sage-grouse team to more easily explain how the ecological system affected the population of Sage-grouse to wildlife management professionals.

Though a potentially useful tool for improving model understanding, the six step process presented here has limitations. The effectiveness of the process relies heavily on the judgment of the modeler to interpret the results of the analysis. While the correlation coefficients identify high influence parameters, it does not identify specific high influence structures. The identification (and verification) of the influence of these structures is left to the modeler. Ford and Flynn (2005) noted several limitations in the correlation coefficient analysis. Correlation coefficients may not recognize a high influence parameter because the pattern of influence is not linear across the range of uncertainty. Also, the analysis has difficulty handling models that produce oscillatory behavior. Despite these limitations the six step process can provide modelers with a method of improving model understanding. Future research in this area should focus on the interaction of high leverage parameters on the performance variable, applying the six step method to additional models, and incorporating additional statistics measures into the screening process (e.g. correlation coefficient significance).

5 CONCLUSIONS

The current work describes and clarifies the use of statistical screening as a model analysis tool by presenting a six step process for using statistical screening to provide insight into how model structure drives system behavior. The process was demonstrated by analyzing the bifurcated behavior produced by the tipping point model (Taylor and Ford 2006; Taylor and Ford 2008). The process facilitates improved model understanding, explanation, and model development by providing a method to analyze multiple model parameters over the course of a simulation. Statistical screening offers an easy and objective method to efficiently identify high leverage model parameters. With good modeler judgment these high leverage parameters can be connected with key model structure, leading to improved understanding of the existing model as well as productive avenues for model improvement.

A APPENDIX STATISTICAL SCREENING

Statistical screening (step 2 of the six step process) can be performed as follows:

- 2-A. Select uncertain model input parameters and a single performance variable for analysis.
- 2-B. Specify a distribution (e.g. uniform with maximum and minimum values) for each uncertain model input identified in step 1.
- 2-C. Simulate using combinations of values from the distributions specified in step 2. For example, Vensim's® "Partial Simulation Tool" can be used to perform a Latin Hypercube sampling of values. Save the analysis results, for example in a Vensim® "Sensitivity Save List" file.
- 2-D. Export the results of the analysis performed in step 3 to an Excell® spreadsheet, such as by saving to a .tab file using Vensim's® "Export Dataset" tool.
- 2-E. Download one of the available Excel® templates from `http://www.wsu.edu/~forda/CCTemplate`.
- 2-F. Import the data saved in step 4 to the selected Excel® template. Once the data is imported into the Excel® template click on the worksheet tab "CC Graph" to view the correlation coefficients for the model analysis.

Example Application: Analysis of the Bass Diffusion Model

This appendix presents the Bass diffusion model (Figure C-1) analysis results. For a full description of the model see Sterman (2000).

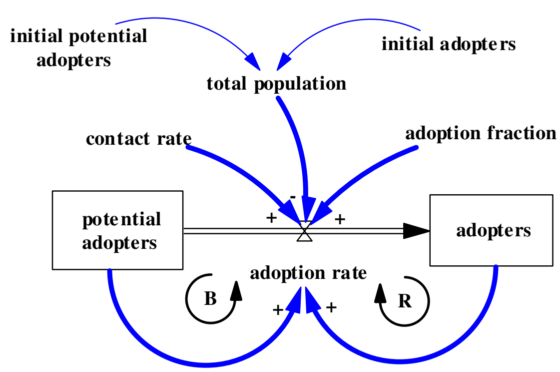

Figure C-1: Bass diffusion model (Sterman 2000), adoption rate = contact rate*adoption fraction*potential adopters*[adopters/total population]

Step 1: Select Parameters and Performance Variable

All four model input parameters for the Bass diffusion model were analyzed (Table C-1). "adoptors" was selected as the performance variable.

Table C-1: Exogenous Bass diffusion model parameters and their range

Exogenous Variable	Range
initial potential adopters	[495, 1485]
initial adopters	[5, 15]

contact rate	[0.25, 0.75]
adoption fraction	[0.25, 0.75]

Step 2: Perform Statistical Screening to Generate Correlation Coefficients

The four model input parameters selected in step 1 were varied uniformly ± 50% from base case values. Data from the 200 simulations was downloaded into Excel® and the correlations coefficients tabulated using the Excel® template described in Ford and Flynn (2005) and available at <http://www.wsu.edu/~forda/CCTemplate>. The number of adopters for each of the 200 simulations is shown in Figure C-2. Figure C-3 shows the time series of the correlation coefficients of the four parameters. The shaded region of Figure C-3 represents the threshold value for correlation coefficients, below which the value is assumed to be zero.

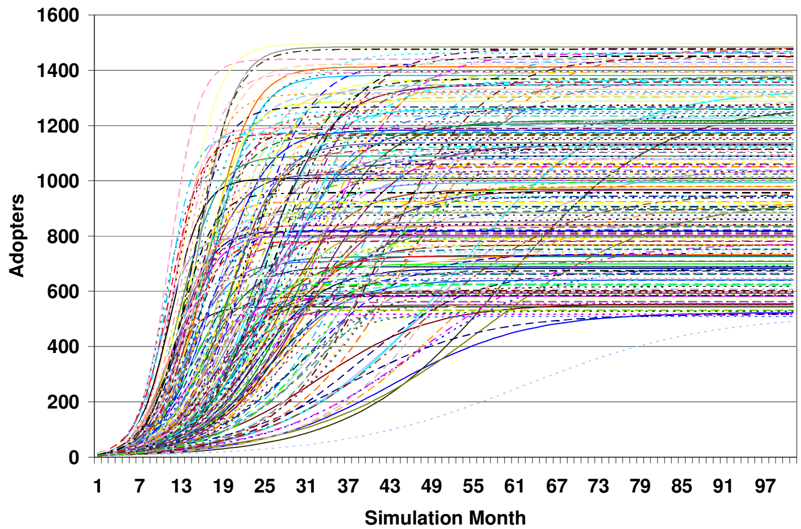

Figure C-2: Adopters for 200 simulations

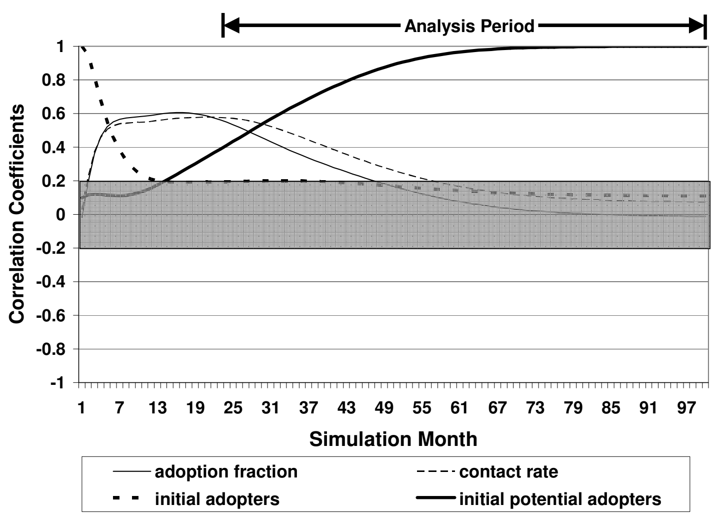

Figure C-3: Correlation coefficients for Bass diffusion model

Step 3: Select Analysis Time Period

Suppose you are interested in why the number of adopters of a new product peaks after a couple of years. Therefore you select months 35 – 100 for your analysis period.

Step 4: Identify High Magnitude Correlation Coefficients
Between months 35 – 100 the parameter "initial potential adopters" has the highest influence on the number of adopters of the new product as evidenced by it having the highest magnitude correlation coefficient value over the time period.

Step 5: Connect High Magnitude Correlation Coefficients with Model Structure
An examination of Figure C-1 shows the parameter "initial potential adopters," which is identified as a high leverage model structure between months 35 – 100, directly impacts the variable "total population."

Step 6: Additional Analysis
Verbal reasoning is used to link structure and behavior. Figure C-1 shows that the number of adopters is increased or decreased by the adoption rate. Since the number of adopters in Figure C-2 begins to level off somewhere between months 25-50 for most of the 200 simulations the adoption rate during this time must approach zero. The high leverage parameter "initial potential adopters" impacts the adoption rate through the total population and the number of potential adopters by constraining the adoption rate through the balancing feedback loop. The total population remains constant throughout the course of the simulation and therefore cannot cause the adoption rate to approach zero during a simulation. The number of potential adopters does change throughout the course of the simulation. As the simulation progressed the number of potential adopters decreases until the stock is emptied. At this point, there are no potential adopters left to acquire the new product. Therefore, the adoption rate approaches zero after a number of years and the number of product adopters levels off.

NOTE: See Ford and Flynn (2005), Taylor Ford and Ford (2007), and Taylor, Ford, and Ford (2010) for additional details on the application of statistical screening and tools to facilitate its use.

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