2

Modeling of Dynamic Business Systems

> His driving curiosity was apparent when, in his last media interview, he told the *Boston Globe* last year that his work on the shuttle commission had so aroused his interest in the complexities of managing a large organization like NASA that if he were starting his life over, he might be tempted to study management rather than physics.
>
> —Quotation from the obituary of Richard P. Feynman
> in the *Boston Globe,* 16 February 1988

2.1 Introduction

The eminent theoretical physicist, Richard P. Feynman, served on the committee that investigated the Challenger disaster in 1986. As a physicist, Feynman was used to the complexities associated with the world of subatomic particles or the motions of stars and galaxies. However, his experience on the committee opened his eyes to the complexities of managing a modern organization, as is shown by the quotation from Feynman's obituary in the *Boston Globe*.

Feynman recognized that managing an organization had become a complex problem and, for a person with his intellectual curiosity, the management of such organizations provided a stimulating area of study.

But where does this complexity come from? An organization is basically a system, which can be defined as "a regularly interacting or interdependent group of items composing a unified whole."

Organizations are composed of a number of interconnected component parts (many of which are people). Like any other system, in order to operate successfully, these component parts must work in a coordinated fashion. The interconnections must be managed. Therefore, the difficulty in operating an organization is directly related to the complexity of individual interconnections and to the number of interconnections that must be managed. Both the number and complexity of the interconnections have changed over time, in part because of the following trends:

- Business size—many organizations have grown in size (through mergers and acquisitions) in order to compete or satisfy the ever-growing expectations of shareholders.[1] Indeed, "merger mania" has been common over recent years. These mergers or acquisitions mean that more interconnections must be managed in order for the new organization to be successful and reap the benefits of the growth in size.

- Globalization—this has added the issues of language, culture, currency, local legal regulations, and so forth, which has made some of the individual interconnections more complex.
- Improving efficiency—the pressure to improve the bottom line ultimately leads to fewer resources being available to buffer components from each other. The typical example here is the impact of removing inventory from supply chains. With lower inventories, an organization has greater difficulty reacting to unexpected production delays, customer demands, and so on. This means that components of the organization that could previously be treated as independent must now be coordinated in order that unexpected situations can be handled successfully.
- Competition/customer expectations—customers expect more and more every day. They have more choice in what is available to them and they can switch suppliers on a whim. In bygone days, a company could survive if communications between research and development, manufacturing, marketing, and sales were poor. But this is clearly no longer the case.
- Technological advances—for example, improvements in the field of communications mean that now it is easy to connect parts of the organization. Use of the Internet in business is a testimony to this. Although these connections may give an organization an advantage initially when they are set up, eventually the organization changes so that it depends on these connections to operate. The Y2K situation was a global-scale example of this dependency not only on individual computers but also on the networks and interconnections they manage.

Whatever the reason for growth in organizational complexity, it is a fact of life and it must be managed. What exactly do we mean by managing a system? The dictionary defines *management* in general as "the judicious use of means (resources) to achieve an end."

This can be translated into a business context as the optimal allocation of resources to achieve the goals of the business.[2] Therefore, the key question that must be asked continuously in order to manage an organization is this: If we allocate our resources in a certain way, what will the impact be on the organization's performance? Given a range of options for allocating resources, we can then choose the option that gives the best results. Put another way, we must be able to predict the performance of an organization under a given set of conditions. Management thus reduces to the ability to predict the future performance of the or-

1. Examples are AOL/Time Warner or Pfizer/Warner-Lambert Pharmacian.
2. And as Goldratt and Cox (1992) point out in *The Goal,* the end in mind for any business organization is to make money!

ganization under a given set of conditions.[3] Furthermore, in order to make a prediction, a manager must create a model of the system.

A model of a system is simply a representation of the system that anyone can use to predict the performance of the system—without having to use the actual system. Such models can range from simple mental models to sophisticated computer simulations. The value of a model is not measured by its sophistication but by its ability to predict the real system performance. In this book, we provide readers with insights and tools to model and then predict the performance of an organization so that they can improve their capability of managing the organization. We approach this objective with a definite strategy, which can be outlined as follows:

1. Break up the organization into smaller, more manageable parts.
2. Choose an appropriate modeling technique.
3. Build the model.
4. Validate the model by predicting known historical behavior.
5. Make new predictions.
6. Propose and implement changes to the organization using the new predictions.

Steps 1 and 2 will be discussed in this chapter. In particular, we will look at the role of dynamic modeling in business.

2.2 Making the organization more manageable: Systems and processes

Given the complex nature of the entire organization when viewed as a single system, it is natural to try to break the system into smaller, more manageable units using organizing principles. For example, organizing by skill set leads to an organization in which activities emphasize functional abilities. The business has engineering activities, financial activities, and so forth. A business that is supply chain-focused will organize by product or product group.

In general, no single organizing principle will suffice for the whole business—the business is just too complex. More often, multiple organizing principles are used, which leads to the concept of the matrix organization. People working in such a matrix organization will see their roles from multiple perspectives. For example, a person might be an engineer from a functional perspective but a member of a product team from a supply chain perspective. This can present a difficult work environment for people because it may appear that their loyalties are divided. Am I an engineer first or a supply-chain person first? Hammer (1996, 128) discusses the issues around the matrix organization, where he refers to management with this organizing principle as "notorious matrix management."

3. Of course, these conditions may involve assumptions about the world outside the organization.

In more recent years, the strategy of using process as the key organizing principle has received more attention. In fact, Hammer (1996, xii) has said that in his definition of reengineering—"the radical re-design of business processes for dramatic improvement"—the original emphasis was on the word *radical* but it really should have been on the word *process.* On top of this, most if not all of the major quality improvement approaches focus on process, defined in the dictionary as "a series of actions, activities or operations conducing to an end," as the key organizing principle.[4]

This process focus is also the organizing principle favored in this book. To apply this approach, we must break up the system into its component processes. For example, consider the system consisting of an automobile, the driver, the road, other drivers and pedestrians, and environmental conditions. Within this system, the driver wants to drive from point A to point B. The driver can identify a number of processes to help accomplish this overall goal: starting the car, accelerating the car, braking, keeping the car in the lane, avoiding other traffic, and so on. Similarly, looking at a business system or organization, we can identify the major processes within the organization and study these processes individually.

There are many ways to break an organization into its major processes. The one favored by the authors is to start by looking at the value chain of the organization. This allows us to identify the main value adding processes, which add value to the products or services that the organization sells to customers to make money. A typical value chain is shown in figure 2.1.

Therefore, we have major processes for market research, product development, and so on. These processes are still large. Typically, these major processes will be subdivided into smaller processes. For example, process development might be broken into processes such as manufacturing route selection, process optimization, validation, and so forth.

Next, we can consider the business value adding processes. These are processes that must be executed in order for the value chain to operate successfully but do not add any value to the products or services of the organization. For example, in manufacturing, production must be planned, people must be trained, safety must be managed, and so on.

Finally, we must identify the non-value adding processes. These are processes that add no value but consume resources. (Consequently, the organization would prefer not to have to do them). This group includes rework processes, inspection processes, and so on.

Be aware that breaking down the organization into its component processes does not solve the interdependency problem. It is still there, and it shows up in the way the processes are interconnected. Outputs of one process become inputs to other processes. In analyzing a particular process, we must know of any other connected processes so that we can take account of them in our analyses. In ana-

4. For example, the six-sigma approach developed by Motorola and popularized by GE.

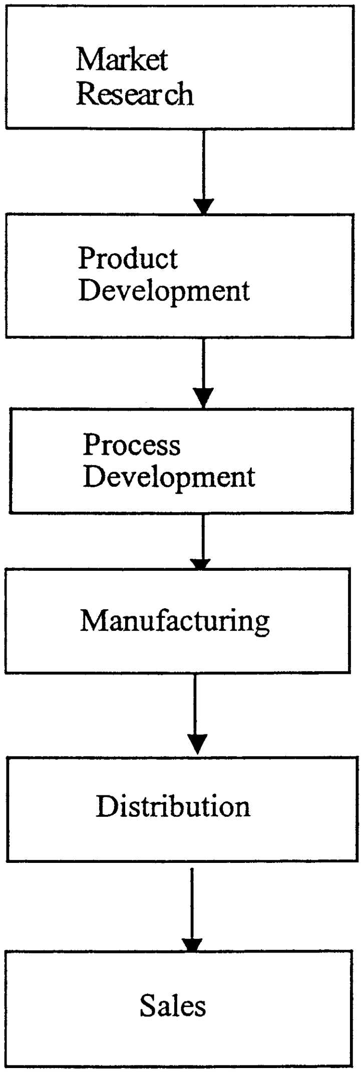

FIGURE 2.1. Typical value chain for an organization

lyzing a process, it is helpful to have a common description of a business process. A simple but useful general description of a process is the supplier input process output key stakeholder (SIPOKS) description, shown in figure 2.2.

In this model, the flow of the process is from suppliers who give us the required inputs to our process. These inputs are used in the process. The process then produces a set of outputs that are used by the key stakeholders. This model is discussed fully by Scholtes (1998). In his description, he uses "customer" instead of "key stakeholder," giving the acronym is SIPOC. However, using the notion of a

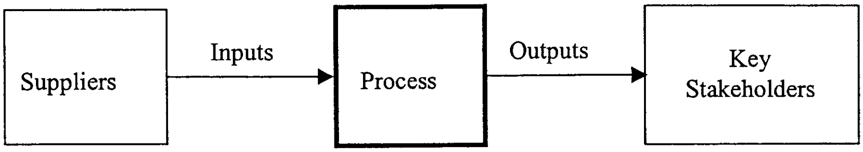

FIGURE 2.2. The SIPOKS description of a general process

key stakeholder is more general than that of a customer. A stakeholder is defined as any group that is impacted or interested in the performance of the process and the word key denotes the important stakeholders. Thus, a customer is an obvious key stakeholder. Also, the public may be a key stakeholder. If the organization potentially can pollute the environment, then the public will be keenly interested in the performance of the process from an environmental perspective. The key stakeholders are the ultimate evaluators of organizational and/or process performance. In general, we can divide the key stakeholders into three groups:

1. Compliance Key Stakeholders—these groups regulate the operation of an organization. They represent and protect the public. Examples are the Environmental Protection Agency (EPA), the Food and Drug Administration (FDA), and the Occupational Health and Safety Administration (OSHA). Being compliant means meeting all key stakeholder requirements.
2. Effectiveness Key Stakeholders—these are the customers of the product and/or services provided by the organization. Being effective means meeting all customer requirements.
3. Efficiency Key Stakeholders—this group includes management and shareholders who are interested in the financial performance of the organization. Being efficient means using resources efficiently. Of course, this group realizes that the financial performance depends on being compliant and effective as well and will be interested in them, too. We will return to the stakeholders again when we discuss performance measures in chapter 3.

Once we have defined a process according to a description like SIPOKS, we can create a model of the process.

2.3 Creating and using a model

It would be nice if people could create system models and make predictions from them using their mental capabilities alone. However, in general, the human mind does not have the capability to make predictions from a model using pure mental reasoning alone. Processes have inherent computational complexities that prevent the human mind from being able to take a model and infer behavior from it. For this reason, people need help. Traditionally, this help has come in the form of mathematical modeling methods. More recently, computer-based modeling techniques have become more popular, and we use the latter approach in this book. The advantage of using computer-based techniques is that people can create sophisticated models without having advanced mathematical knowledge. In this book, we purport that there are four different types of complexity in a real system as shown in figure 2.3.

The following discussion will focus on each of the four types of computational complexity: size of solution space, physics, uncertainty, and structure.

Size of the Solution Space

Here the number of possible configurations of the resources available to the manager is immense, but only one of these configurations leads to an optimal system. The system manager is faced with the task of identifying the one optimal configuration from the immense number of possibilities. One of the classic problems in this area is the Traveling Salesperson Problem (TSP). In the TSP, a salesperson must make a trip regularly to a number of cities to visit customers. Starting from a home city, the salesperson visits each customer city just once, ending up back at the home city again. In order to achieve the goal of minimizing time on the road, the salesperson must find the most time-efficient route. The salesperson

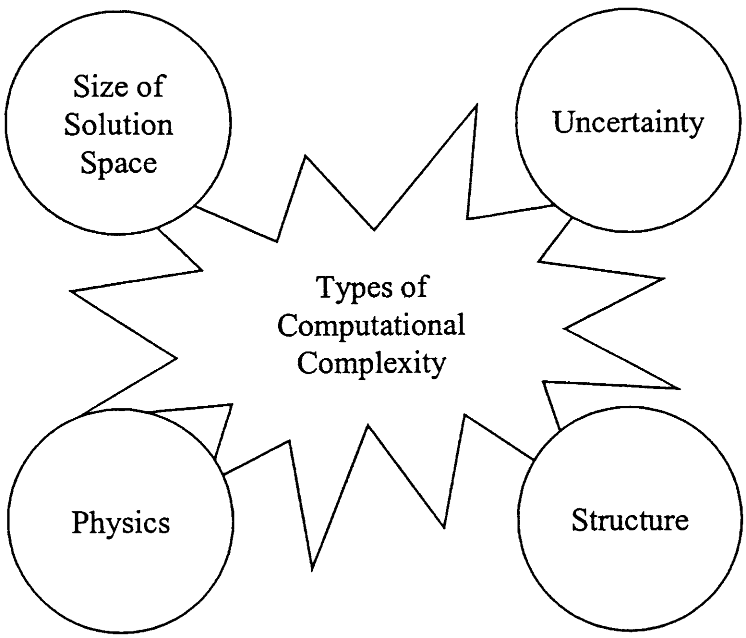

FIGURE 2.3. Types of computational complexity

knows the time it takes to travel between each city. Suppose that 19 customer cities are on the route. There are 19! (factorial 19)[5] possible ways to visit all the cities, ending back at the starting point. How is the salesperson going to choose the optimal route? One could try to enumerate all the possibilities. However, even if the salesperson could evaluate one million tours a second, it would take 3,857 years to evaluate all routes. Clearly, entire enumeration is not a practical option. Models that incorporate this type of complexity are referred to as normative models. These models allow us to answer this question: "If we want the system to give a certain output, how should the system be set up; that is, how should the inputs be specified?" This is an optimization problem and arises in many areas in business—from scheduling a factory to optimizing an entire supply chain. Among the tools available to help manage this complexity are linear and nonlinear programming and integer programming. For more details, see Winston (1994).

Physics

Here the basic relationships in the system are complex. This usually means that we must be able to represent complex physical relationships in order to predict the system behavior. An example would be an engineer trying to understand the behavior of a complicated series of chemical reactions. The engineer may have to use complicated relationships from chemistry and thermodynamics to specify the relationships and, hence, predict the system behavior. Generally the models used to represent these relationships are referred to as predictive models.

Uncertainty

Here some aspects of the inputs are not fixed or known. Uncertainty in an input implies that there is a probabilistic aspect to input. Uncertainty can show up in two distinct ways.

An input may be uncertain if it varies every time an activity or task is repeated, because it is not possible to repeat an activity exactly the same every time. For example, the time it takes typically to complete a task would have some uncertainty associated with it. The best we can do is to say that the task time will be within some range with some probability. So we might be able to say that there is a 90 percent chance that a task time is in the range of 5 to 10 minutes. This type of uncertainty is referred to as random variation: we say that the input has random variability associated with it.[6]

By contrast, an input can also have uncertainty associated with it if it has a definite value but that value is unknown to us. This lack of knowledge may be because we do not have enough information about the input or because the input is based on an event that will happen in the future. An example of the former could

5. $19! = 1 \times 2 \times 3 \times \ldots \times 17 \times 18 \times 19 = 1.216451004088 \times 10^{17}$.
6. In fact, the impact of random variation is so important that Hopp and Spearman (1996) include a chapter titled "The Corrupting Influence of Variability."

be the average salary of people in a certain country. Unless we get the data for each person and calculate the average, we must take a sample of people and estimate the average. An example of the latter case is the price of a stock at some future date. We can guess what it might be and make a decision based on that guess, and when the date actually occurs, the stock will have a definite value.

Irrespective of the type of uncertainty involved, models that incorporate this type of complexity are called *stochastic models.* In this book, the models that we will discuss will involve only random variation. In order to create such models, we must be able to describe the uncertainty in the input. This involves the use of probability distributions. Although readers can use this book without getting involved in the details of these probability distributions, it is beneficial to understand these distributions and where they tend to occur. This will ensure that incorrect probability distributions are not used when readers create their own models. Appendix C contains a discussion of some of the more common probability distributions, where they occur, and how they can be implemented in ithink.

Note that Hopp et al. (1996) make the important point that any source of variability, whether it is random or deterministic, will have an impact on the performance of a process. Such deterministic sources of variation can be related to nonuniform staffing levels, production levels, and so on. Dynamic models make it easy to separate the impact of these two sources of variation. One can simply turn off all sources of random variation and run the model to see the best performance possible if all random variation could be removed (remembering that this is an interesting ideality only). In this book, we consider the impact of both random and deterministic sources of variation.

Structural Complexity

In this case, the structure of the system makes it difficult to see what the output of the system might look like. Structure refers to the relationships between the various parts of system. The outputs of the system depend on these relationships, and the evolution of the outputs in time becomes complex because of these relationships. However, it is known that people cannot look at the structure of a system and reliably predict its evolution in time.[7] Three major structural relationships that can exist in a system make it difficult to predict the behavior of a system over time. These are feedback, time delays, and nonlinearity.

Following are definitions and some brief discussion of how each of these elements can affect a system.

Feedback

Feedback occurs when a variable within a process is used to modify the value of another variable in the process. The variable is “fed back” from one part of a process to another. This feedback can be of two types: *reinforcing feedback*, which

7. See Senge 1990.

causes a variable to increase or decrease in a sustained fashion, or *balancing feedback,* which causes a variable to return to a target value if a change has moved it away from target. Suppose that a company's profits go up. Then it has more money to invest in research that leads to new products, new sales, and more profits. Of course the opposite could also happen. A decrease in profits leads to less investment in research, fewer new products, fewer new sales, and hence reduced profits. Now, suppose a manager controls costs closely. If costs rise above plan, the gap is noted and activities are put in place to reduce the costs. If the costs go below plan, the system might look for ways to use the extra cash for unfunded activities. Balancing feedback is critical to the notion of management controls. Such controls are used by management to keep performance at a target (expenses on budget, projects on track, and so forth).

Time Delays

In real systems, a time delay always occurs between taking an action and seeing the result of this action. Many people consider time delays to be one of the primary difficulties in managing systems. When managers make changes to a system to create improvement, normal business pressures force them to look for instant results. When this does not happen, they feel compelled to keep doing other things that may undermine the original action. The original action may have been the right thing to do; they just did not give it enough time to see the results. In effect, such managers end up tampering with the system. Also, they may erroneously conclude that the original action was incorrect and reverse their original decision.

Nonlinearity

A *linear relationship* is one where the sensitivity of an output to an input is constant over the entire range of possible values of the input. Suppose a change of one unit of input changes the output by 2 units: then the sensitivity would be 2/1 = 2. If this value of 2 does not change as the input value is changed, then the relationship is linear. A linear relationship is an idealization. It is a useful approximation to the real world. In general, relationships will be *nonlinear* (although the error introduced by assuming linearity may be negligible). Relationships involving people are notoriously nonlinear. For example, if the gap between actual performance and target is small, a manager may well ignore the gap. This may continue until a threshold value is reached. Then the manager takes a huge action.

These three elements of system structure make it difficult to predict how a system will behave over time. That is, it is difficult to predict the dynamics of the system. Models used to predict the behavior of a system over time are referred to as descriptive models. In particular, models used to predict the dynamics of a system are referred to as dynamic models or simulations. We set up the model structure, give it a set of initial conditions, and then run the model (simulation) to see the predicted behavior.

While all four types of computational complexity (size of solution space, physics, uncertainty, and system structure) appear in business organizations, the main focus of this book is on system structure. We focus on business organizations as comprising of processes whose dynamics must be modeled so that performance can be predicted. Random variation is included because it can have a significant impact on the dynamics. In general, any relationships between variables are described with simple mathematical formulas to avoid any computational complexity because of physics. An example of optimization is included in appendix D, which is based on the models used in chapter 8, but the reader can omit this appendix if desired.

To justify our claim that structure and random variation introduces computational complexity, we now discuss two examples illustrating these complexities.

2.4 Structural complexity: A market share model

In order to show how structural complexity can make it difficult to predict the behavior of a system, consider a marketing department that is getting ready to launch a new product. The department wants to study the process by which the product is taken up by the market. The total marketplace for the product is given the value of 1 so that uptake in the marketplace is represented by a number from 0 (no uptake) to 1 (maximum uptake). The market uptake, or market share, is represented by the variable M. The time horizon of the model is divided into equally spaced segments, and the model should predict the value of the market share at a period T+1, M_{T+1}, from the market share at period T, M_T. Initially, the company intends to invest in creating a small seed market, so that $M = M_0$ at time 0.

Once the product is launched, two opposing mechanisms will change the market share from its initial value of M_0:

- As the product gets used, satisfied users of the product will spread the word so that the value of M_{T+1} will be proportional to M_T.
- As the market uptake grows, less of the marketplace remains. It becomes harder to gain more share. This means that the value of M_{T+1} will be proportional to $(1 – M_T)$.

We can summarize this model with the following equation:

$$M_{T+1} = RM_T (1 - M_T) = RM_T - RM_T2 \qquad 0 \le M_T \le 1 \qquad (2.1)$$

The first term is the growth term for the market share and the second term is the decay term. R is a constant that will vary from system to system. It is a combination of how much effort the company puts into marketing the product and how much resistance there is to growth as the market share gets closer to 1. If the company invests in marketing the product or if the resistance to growth is large, then R will be large. Equation 2.1 is nonlinear because of the M_T squared term. Equation 2.1 is now cast into a model as shown in figure 2.4.

The market share at time T is represented as a stock, MT. This stock is set up so that it cannot go negative and its initial value is set to the value of the converter M_0. Every time period, an amount DELTA M is added to this stock. The equation for this flow connector follows:

$$R*MT*(1 - MT) - MT$$

This is equation 2.1 with M_T subtracted from both sides. Note that the flow connector is configured to be a biflow because the population can decrease as well as increase. The constant R is represented by a converter with a constant value. Figure 2.4 illustrates the feedback in the market share model. The current value of the market share is fed back to determine the market share at the next time period. The parameter R is now seen to represent the strength of the feedback. That is, the larger the value of R, the greater the amount of feedback. Figure 2.5 shows the profile for the population M over 500 time periods with M_0 set to 0.1 and R set to 0.9 (profile 1) and 2.5 (profile 2).

This chart shows that in both cases the market share quickly reaches a steady state value. In fact, it is easy to predict this value directly from equation 2.5 by setting $M_{T+1} = M_T = M_\infty$. This gives the following equation:

$$M_\infty = RM_\infty(1 - M_\infty) \quad \text{which simplifies to} \quad M_\infty = (R - 1)/R \qquad (2.2)$$

From this it can be seen that if $R <= 1$ then the steady state value M_∞ is 0,[8] which is in agreement with profile 1 in figure 2.5. This means that if the effort that the company puts into the product is low, then the market share will decay to

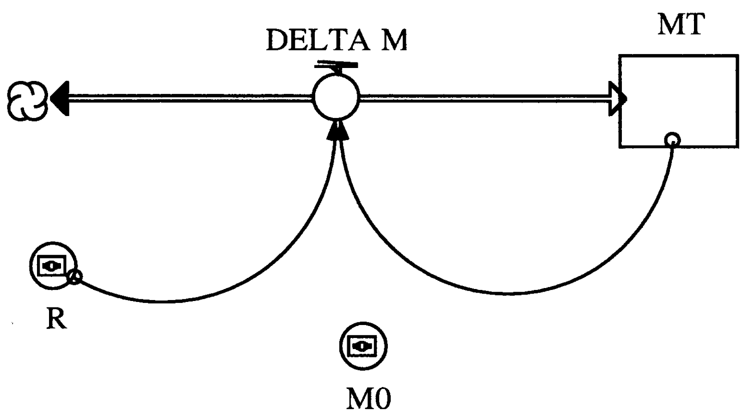

FIGURE 2.4. Model for market share equation 2.1

8. The equation for the steady-state market share gives a value < 0; but, because the market share cannot be negative, the model gives a steady state value of 0.

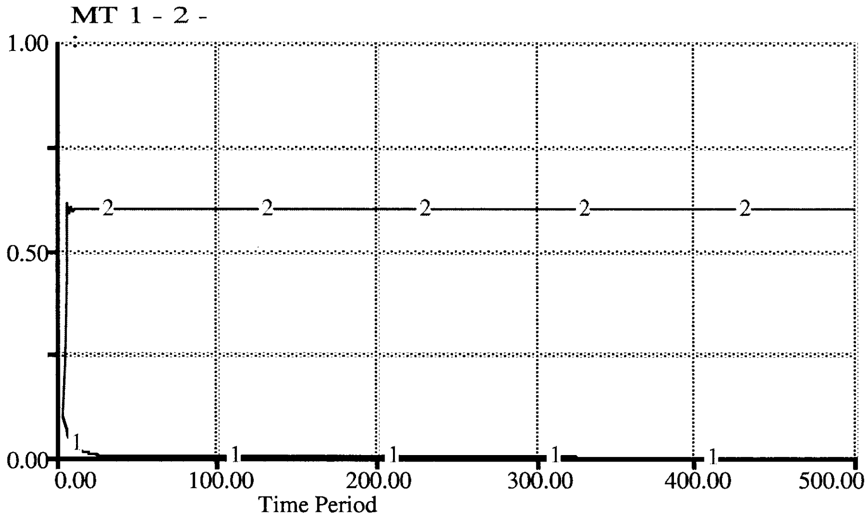

FIGURE 2.5. Profiles of market share $M_0 = 0.1$ and $R = 0.9$ and 2.5

the point that the product loses all market share. This certainly makes sense. Setting R to value of 2.5 gives $X_\infty = 0.6$ as seen in figure 2.5, in agreement with profile 2 in figure 2.5. This means that if the marketing effort is large enough, eventually a constant market share is obtained where the resistance to growth in the marketplace balances the growth effort. Again, this appears to be a reasonable result.

At this stage, it appears that the system as defined by equation 2.1 or the model in figure 2.4 is simple. So where is the complexity? If our understanding of the role of feedback is correct, then increasing the amount of feedback may introduce complex behavior in the system. To increase the amount of feedback, we must increase the value of R. Figure 2.6 shows the profile for the market share with R set to 3.9.

Now the complexity is revealed. The steady-state value for the population with this value of R should be $(3.9–1)/3.9 = 0.744$. However, there is no evidence from figure 2.6 that a steady state will ever be reached. The reader can increase the amount of time periods in the model to verify this. The profile in figure 2.6 is reminiscent of random variation but there is no random variation in the model. In fact, the market share profile shows evidence of chaotic behavior.[9] It is difficult to imagine how a profile as complex as that shown in figure 2.6 could be predicted by looking at the simple structure in figure 2.4. Essentially, the high value of R means that the market share keeps bouncing quickly between high and low values. It is as if the high growth and resistance means that the market is never still

9. For more information on chaos, see Gleick 1998.

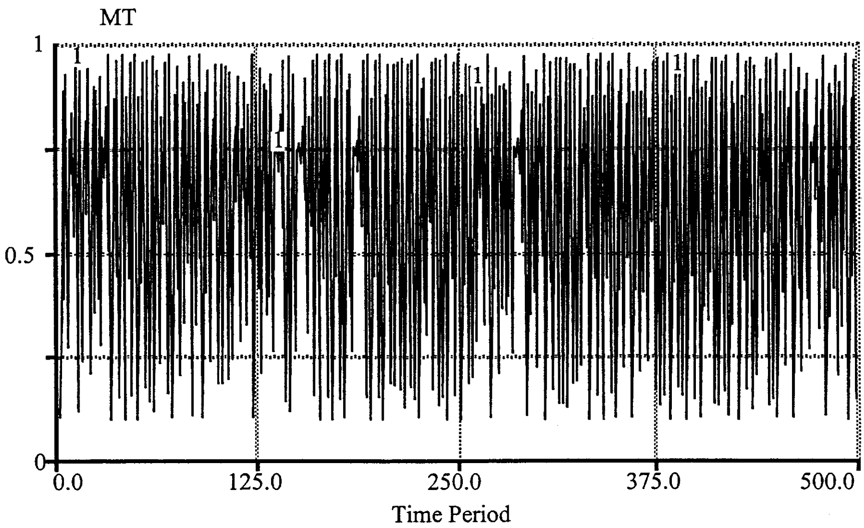

FIGURE 2.6. Profile of market share with R = 3.9 and $X_0 = 0.1$

long enough for a steady state to be reached. Detailed analysis of the behavior of the model shows that the reason for the complex behavior at the higher values of R is the nonlinear term in equation 2.1.[10] So it is the combination of the nonlinearity and feedback in the model that leads to the complex behavior.

It must be pointed out that the profile in figure 2.6 would never be seen in a real marketing situation. No sane organization would ever have a product marketed with this profile. What the model does point out, however, is that if the marketing department uses an aggressive marketing plan, or if the product takes off quickly, the initial fast growth rate may turn to decay rapidly. Perhaps we have seen some of this behavior in the rapid growth and demise of the dot-com companies.[11]

We can add further complexity to the system in figure 2.4 by adding time delays. These time delays can occur because the market may not react immediately to changes. The time delay for the growth term and the decay terms may be different. Consequently, separate time delays are added to the model. The modified model for this system is shown in figure 2.7.

Converters have been added between the stock and the flow to allow for the time delay. Following are equations in the delay converters:

DELAY(MT,GROWTH_DELAY_TIME)
DELAY(MT,DECAY_DELAY_TIME)

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10. Bequette 1998.
11. Senge (1990) discusses the case of the rapid growth and subsequent demise of the People's Express airline company, which also may be an example of this behavior.

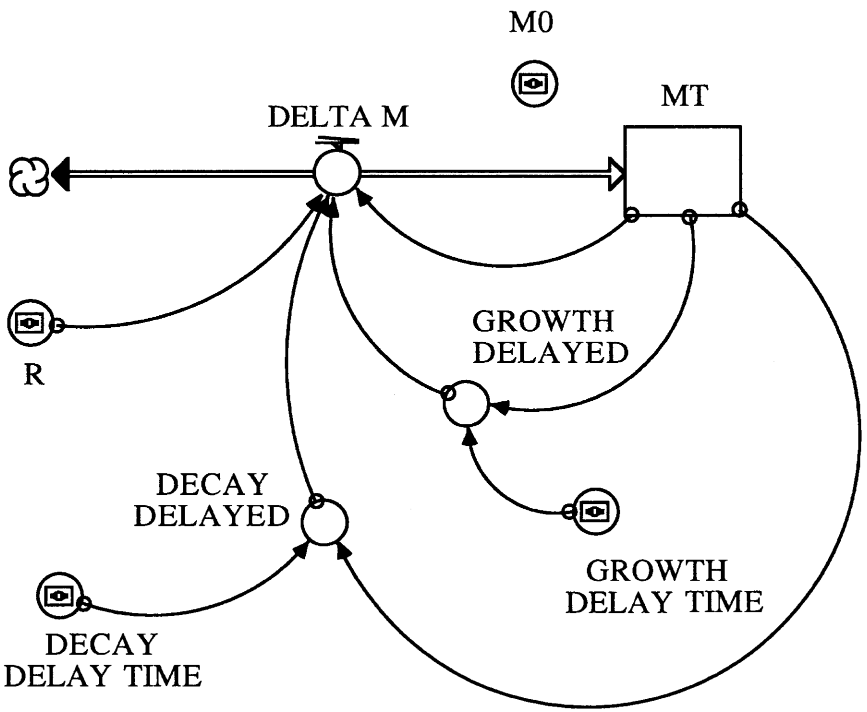

FIGURE 2.7. Market share model with time delay

By increasing the value of the converters—GROWTH_DELAY_TIME and DECAY_DELAY_TIME—we can increase the amount of time delay in the model. The equation in the inflow is

R*GROWTH_DELAYED-R*DECAY_DELAYED*DECAY_DELAYED-MT[12]

We will now look at the behavior of the model for the three cases, R = 0.9, 2.5, and 3.9. Figure 2.8 shows the profile with R = 0.9 and with delays of 10 in both growth and decay.

Comparing figure 2.8 to profile 1 in figure 2.5 shows that the time delays have not changed the profile by much. The steady state value is still 0. The only impact of time delays appears to be that the decay to 0 is slower when time delays are present. In effect, the time delays slowed the response of the market. This makes sense. By running the model with different combinations of the time delay values, readers can also verify that having different values for the time delays does not change the general behavior of the market share profile.

Figure 2.9 shows the profile for the case of R = 2.5 and both time delays set to 10.

12. Readers should satisfy themselves that the last term, MT, should not be delayed.

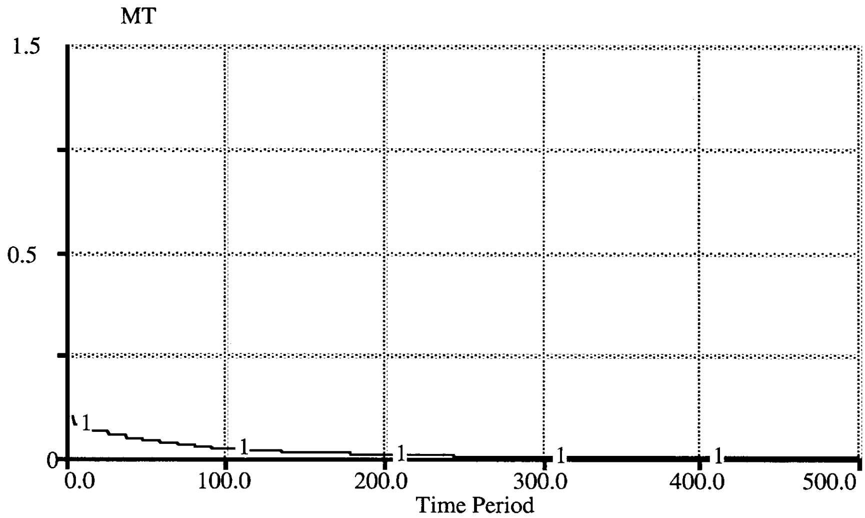

FIGURE 2.8. Market share model with R = 0.9 and delays of 10 time periods

Again, we see that the behavior in figure 2.9 is the same as for profile 2 in figure 2.5, except that it takes longer to reach the steady-state value. Further investigation shows, however, that this situation only holds when the time delays in both growth and decay are the same. If the time delays are different from each other (even by 1 time period only) then the profiles become unstable and the market

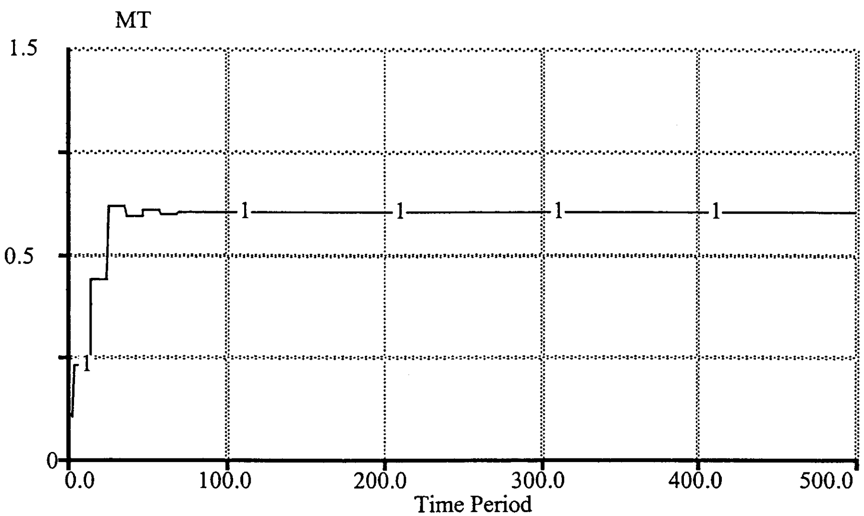

FIGURE 2.9. Market share model with R = 2.5 and delays of 10 time periods

share profile oscillates in ever-increasing cycles. Readers should verify this by running the model with various combinations of the time delays. It would appear that when a time delay is present, it introduces instability into the model. When both time delays are the same, they effectively cancel each other out. It should not surprise us that the time delays have a different impact on the behavior of the model. After all, the growth time delay enters through a linear term and the decay time delay enters through a nonlinear term.

Figure 2.10 shows the market share profile for R = 3.9 with both time delays set to 10. As in the previous two cases, if the growth and decay time delays are the same, the basic profile is the same as when there was no time delay. The only impact of the time delay is to slow down the response of the market. In figure 2.10, this slowing down is seen as a stretching out of the oscillations. If the time delays are not the same, then the market share profiles depend on the relative values of the time delays. It is left as an exercise to the readers to investigate the impact of the time delays by running the model.

This analysis can be summarized with the following learning point.

> Learning Point: The structure of a system (feedbacks, time delays, nonlinearities) adds computational complexity to a system and makes it difficult, if not impossible, for a person to infer the dynamic behavior of a system by mental modeling alone.

It should be pointed out that the earlier model for market share (figure 2.7) is not presented as an accurate model for market share dynamics. As we have already said, all models are only approximations to the real world. The ultimate jus-

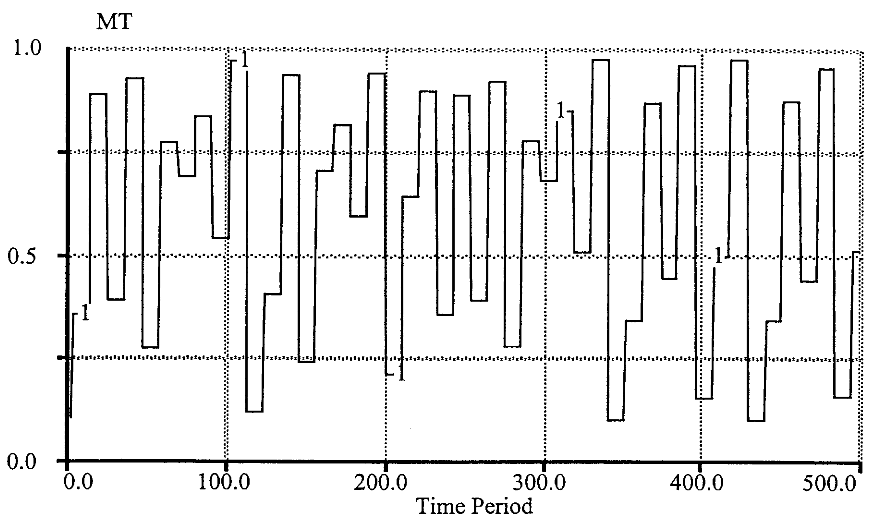

FIGURE 2.10. Market share model with R = 3.9 and delays of 10 time periods

tification for any model will be its usefulness to the user. Various modifications to the model presented here could be proposed and investigated. In particular, consider a model where the growth rate term and decay rate term have different constants, R_1 and R_2, instead of a single constant, R. This modification could be made in two ways, as shown by equations 2.3 and 2.4:

$$M_{T+1} = R_1 M_T \left(1 - \frac{M_T}{R_2}\right) = R_1 M_T - \frac{R_1}{R_2} M_T^2 \qquad 0 \le M_T \le 1 \qquad (2.3)$$

$$M_{T+1} = R_1 M_T \left(1 - \frac{R_2}{R_1} M_T\right) = R_1 M_T - R_2 M_T^2 \qquad 0 \le M_T \le 1 \qquad (2.4)$$

These two models are basically the same. These models are not analyzed here. However, the second model is included as model 2.7a to enable readers to investigate their properties as a function of R_1, R_2 and the time delays.

2.5 Complexity due to random variation: An order control process

In order to understand how random variation can make it difficult to predict the behavior of a system, consider the following example. You are employed in an order entry process in which orders arrive from customers and are processed. The downstream part of the process can only handle one order per minute, but orders do not necessarily enter the process at this rate. It is your job to adjust the upstream part of the process so that the rate of flow of orders moving downstream is one/minute. Based on the input order flow rate, you are able to adjust the rate to get it back to 1. A model for this system is shown in figure 2.11.

The base order input rate is modeled using the stock BASE INPUT RATE. It might seem strange that a rate is modeled as a stock. In theory, this model could be set up using only flows and converters. However, within the ithink architecture, this would show up as problem with a circular reference.[13] The converter INPUT RATE VARIATION allows us to add a change to the input rate, so that the converter ORDER INPUT RATE adds the variation to the BASE INPUT RATE. The actual input rate that the process sees is the converter ORDER INPUT RATE. It is this number that must be kept at the target. Once a change occurs because of the value in INPUT RATE VARIATION, we must decide on an adjustment. This adjustment should depend on how far the ORDER INPUT RATE is from target. The equation in the INPUT RATE ADJUSTMENT converter is

IF TIME < = 500 THEN 0 ELSE (TARGET - ORDER_INPUT_RATE)

13. See MODEL 2.11A.STM for an example of trying to make this model work without a stock.

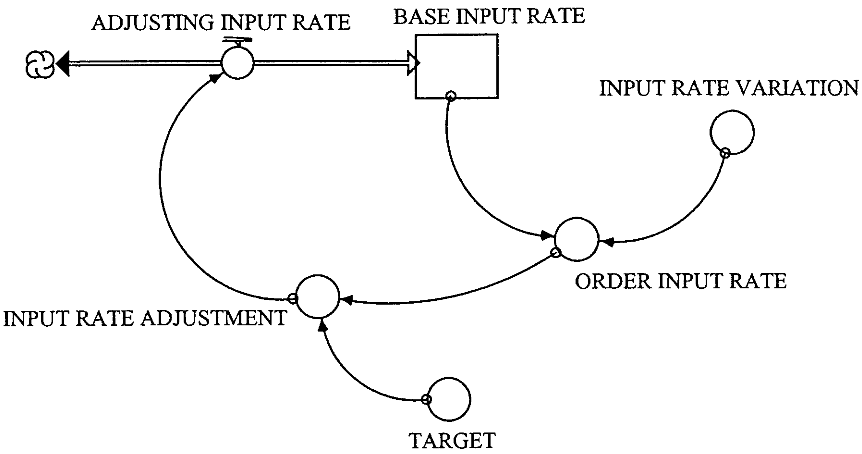

FIGURE 2.11. Model for the order rate adjustment process

The reason for the IF statement with TIME < = 500 is that we will not turn on any adjustment strategy until time = 500 minutes. This will allow us to see the impact of the adjustments on ORDER INPUT RATE. Once the order input rate is off target, an adjustment will be made. Note that the measurement and control of ORDER INPUT RATE is considered to be part of the process because you cannot understand the behavior of the process without understanding how the process is being adjusted when it is off target.

To show how the model reacts to a change, we use the equation STEP(0.5,200) in INPUT RATE VARIATION. This will cause the order input rate to jump from 1.0 to 1.5 orders/minute at the 200th minute. The profile for ORDER INPUT RATE is shown in figure 2.12.

The input order rate stays at 1.5 until the 500th minute, when the adjustment strategy is engaged. The input order rate is immediately adjusted back to the target of 1.0. The reader is invited to try different functions for the input rate variation to see the impact of the adjustment strategy. The behavior of the order input rate is easy to understand, and it behaves as expected.

Now we modify the input variation using the function RANDOM(-0.5,0.5). This function adds random variation that is uniform in the range –0.5 to +0.5. The resultant profile for the order input rate is shown in figure 2.13.

Until the 500th minute, the order input rate varies randomly about the target of 1.0. Because the additional variation is in the range –0.5 to +0.5, the input order rate varies in the range 0.5 to 1.5. It remains in this range until the 500th minute, when the adjustment strategy is engaged. We would now expect the variation in order input rate to be reduced and eliminated. The graph shows a completely different behavior. Not only is the variation not reduced, it actually increases! The data in figure 2.13 are also contained in table 2.13 in the model. If these data are copied into a spreadsheet, the standard deviation of the data can be calculated for

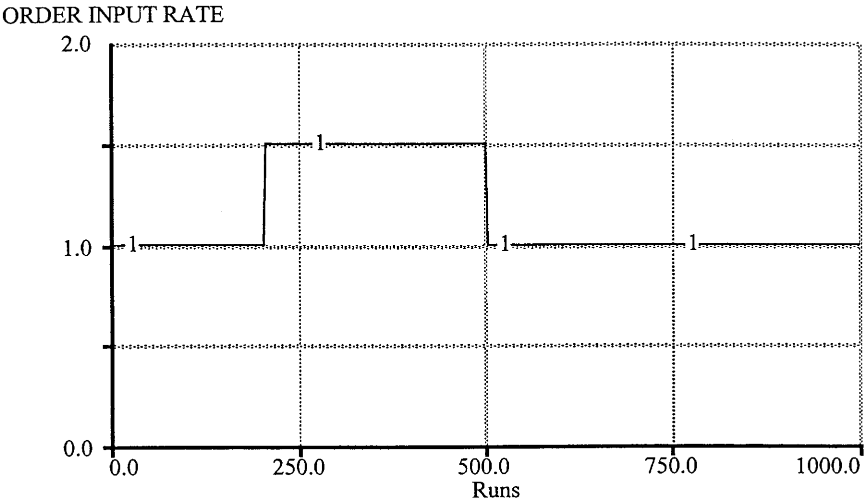

FIGURE 2.12. Profile for order input rate with a step change at t = 200 minutes

the time periods before and after 500 minutes. The values thus obtained are .29 before and 0.40 after. This represents an increase of 40 percent in the standard deviation. Thus, the addition of an adjustment strategy that was designed to eliminate the variation actually increased it. This leads to another learning point.

> Learning Point: When a measure is subject to random sources of variation, it is not possible to reduce the variation in the parameter by making adjustments based solely on the last value of the parameter. Such adjustment strategies actually increase the variation!

In fact, this principle is a key part of the process adjustment strategies used in statistical process control (SPC).[14] It is not difficult to see how a lack of understanding of this principle can impact a manager. When random variation exists in the process measure, the measure will never be on target. If the manager responds to every gap by taking a control action, the manager only ends up making things worse! Suppose the measure represents the average unit cost over a month and is reported on a monthly basis. The value this month is $12, whereas last month it was $11.50. The manager is asked to explain why costs have risen, and therefore tries to find some reason for the increase—in effect, valuable people resources must be used to track down the problem. However, any actions the manager might take based on just this one measurement could actually make things worse.

14. For example, see McConnell 1997 or Deming 1986.

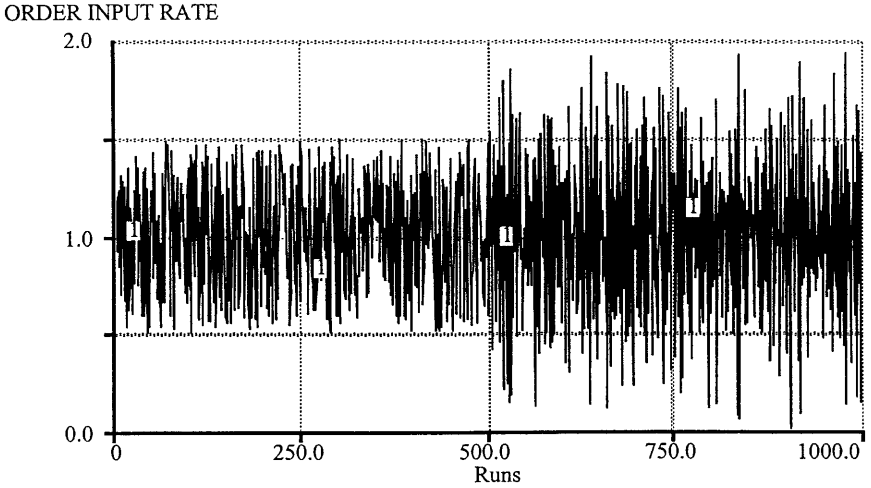

FIGURE 2.13. Profile for order input rate with random variation

Suppose next month the unit cost drops, as it might because the measurement is affected by random variation. Then the manager might attribute this drop to interventions that were made during the month. This convinces the manager to take further action because the interventions appear to be working. The following month, the manager is expecting the unit costs to drop again, but instead the value increases again. Now the manager is confused. More interventions must be identified—and quickly. What the manager is failing to realize is that the control system being used is reacting to pure random variation. The only change that will result is that the variation in the measure will increase.

Of course, the manager cannot simply ignore the values of the unit cost altogether. Some of the changes in the unit cost might represent a genuine trend in the unit cost. For example, a drop in productivity may result in an upward trend in the unit cost. This is a genuine signal to which the manager should react as soon as possible. Therefore, the manager needs a way to separate the real upward trend from the "normal" background random variation and must be able to do this as soon as possible after the trend has started, or the business will suffer a loss in profitability for a longer period of time. Again, the ability to differentiate between trends and random variation is the subject of statistical process control.

> Learning Point: In order to operate a business as successfully as possible, a manager must be able to differentiate between changes in a measure due to genuine trends in the measure and random variation in the measure.

Figure 2.11 shows the feedback that is involved in the control strategy used for the input order rate. The value of the order input rate is fed back to calculate the

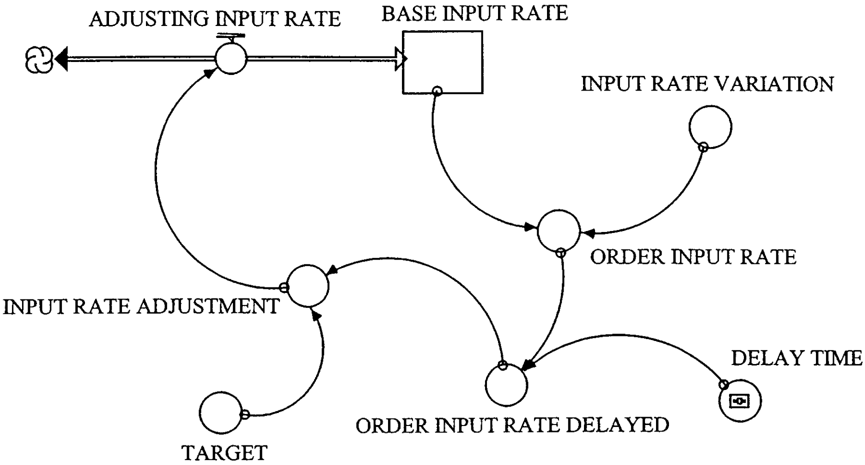

FIGURE 2.14. Model for the order rate adjustment process with time delay

adjustment. There is no time delay involved. The model in figure 2.14 is similar to figure 2.11 except that a time delay has been added.[15]

The model in figure 2.14 contains the time delay explicitly. However, the presence of random variation is equivalent to a time delay when the monitoring of a process for control is part of the process. Consider figure 2.11 again, in which the system changed at t = 500. The change in the profile was immediate and there would be no discussion as to where the change occurred. However, what about figure 2.13, which has random variation included? How quickly could we decide that an increase in variation had occurred? Figure 2.15 shows the same profile as figure 2.13, except that it shows only the range t = 490 to t = 510.

Now it is more difficult to answer this question: "Where did the change occur?" Perhaps by time 503 or 504, one might be prepared to say that a change in the amount of random variation has occurred. This delay in our ability to detect a change will delay our ability to react to that change. Thus in effect, the random variation has introduced a time delay into the process.

Learning Point: Random variation in a process introduces a time delay in our ability to monitor change in a process.

2.6 Further benefits of dynamic modeling

There are other benefits that can be gained from the dynamic modeling of business processes. These include the following:

15. This model will not be discussed here and is provided to readers so that they can assess the impact of the time delay.

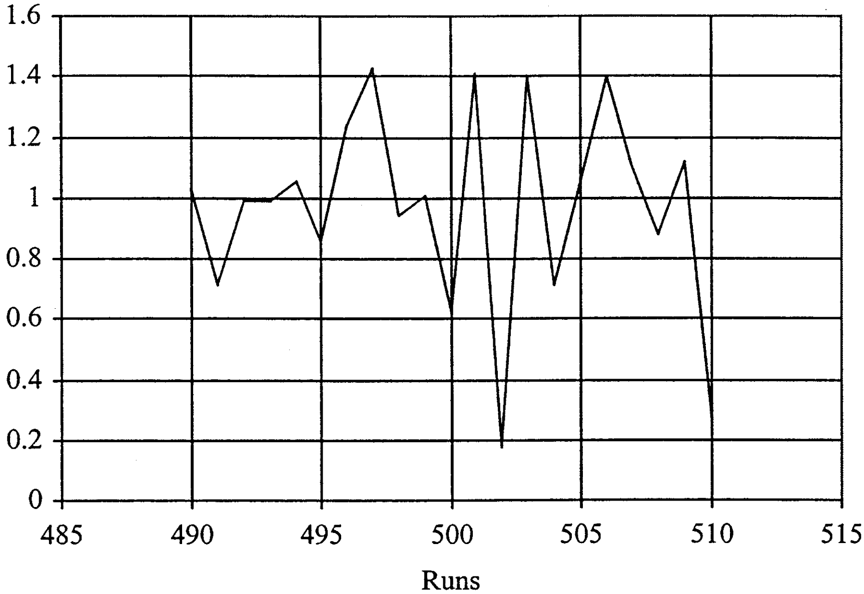

FIGURE 2.15. Profile for order input rate with random variation

• Find possible emergent properties of a system. Even though managers have been working with particular systems for a considerable time, they may not have seen all the possible ranges of behaviors that a system can exhibit. This emergent behavior may take a long time to occur in the actual system, that is, in real time. Dynamic models provide a way to explore such emergent behavior because such models can cover these real-time spans in the short time it takes to run the model. We can model five years of behavior in 60 seconds of real time!

• Provide quantitative assessments of qualitative ideas. Generally, most systems are only understood at a qualitative level. A model can allow the user to turn qualitative understanding into quantitative understanding. For example, we all qualitatively understand that compounding interest can cause an investment to grow rapidly over time. However, without a model, we cannot quantitatively understand just how large it will grow.

• Allow the identification of the most important parameters in a system. In any real system or process, many inputs are typical. In theory, all of the inputs can have an impact on the output. However, if we have to monitor all of the inputs to manage the outputs, we are in big trouble. We hope that we can use the Pareto Principle. This principle states that 80 percent of the output is affected by 20 percent of the inputs. Said another way, all inputs are not created equally. In general, there will be a subset of these inputs that have the greatest impact on the output. If we know what inputs are in this subset, we can focus on these inputs. But how are we to identify these inputs? If we have a model available for the process, we can perturb each input and see how it affects the output. Then we can rank the inputs in terms of their impact on the output and pick those that have the highest impact. This is called a *sensitivity analysis.* We will say more about this in chapter 3.

• Allow testing of “what-if?” scenarios. When planning how we can improve a process, we generally propose some specific improvement actions and then set up some tests to see which action leads to the biggest improvement. In effect, we set up some experiments and carry out some “what-if” scenarios. Traditionally, such experiments have been physical in nature. We set up a physical model of the system or process and test the changes on the physical model. This can be an expensive way to test, however. If we have good computer model of the system or process, the computer model becomes the equivalent of the physical model. The main expense for the computer model is typically the initial set up. After that, testing these ”what-if” scenarios is relatively cheap.

• Facilitate communication through both model results and the model structure. After “what-if” scenario tests have been carried out, it is important that results of the testing can be communicated easily to those who are interested but have not been involved in the testing directly. Models can be useful to communicate the structure of a system and the results obtained from testing. Also, and perhaps just as important, models help show people why the actions taken lead to the results obtained.

• Provide a system memory. When we learn something about how a system works, we may be able to use this immediately to create improvement. As well as the immediate use of learning, it is also important that we provide some way to archive the learning so that sometime in the future, the information is easily available. It is not unusual in organizations to find situations where an issue arose because something that was once learned was forgotten. Models provide a way to create system memory. A model can be set up to contain current knowledge about a system or process. Any changes to the system or process must be tested in the model, and if the real system or process is modified, then the model is modified as well.

• Use as a training tool. It would be great if we could train a person on a process and then be sure that this person would always work on the process. However, in reality, people move around an organization and new people must be trained. A model can be invaluable in helping train to new people, especially if the model is also being used as an important part of the overall learning strategy as described in the previous paragraph. In fact, a popular idea today is the management flight simulator. A model of a system is created and then set up so that a user can interact with the model to make decisions and see the impact of these decisions. The model is set up to give feedback when the user takes actions that are not optimal.[16] By running the model multiple times, the user can try different approaches to managing the system. Of course, if wrong decisions are made, only a virtual

16. High Performance Systems, the company that produces the ithink software, also produces what they refer to as learning environments—these are essentially the same as management flight simulators

business is affected. It is better to make these mistakes on this virtual system than on the real system!

• Facilitates the formation of a dynamic hierarchy of exploration within a group. In many situations, getting management to commit to giving resources to create a detailed model of a system is difficult. They want to see some benefit before they make the commitment. A compromise can be reached by starting with a high-level model that has just enough detail to make the model useful. Then as management sees the usefulness of the model, they might commit resources to add more detail to the model. In fact, reluctance on the part of management has some positive benefit. By forcing us to start off at a high level, we get a feel for where greater detail will be most useful. Sometimes, addition of detail to a certain part of a model may involve a lot of work but add little or nothing to our understanding. Knowing how much detail to add to a model in order to make it useful is a skill that can be obtained only through experience.

2.7 Organizing principle of this book

The remainder of this book focuses on the application of dynamic modeling to business systems. Chapter 3 is devoted to the modeling of performance measures. In keeping with the approach of starting simple and then expanding to more complicated models, chapter 4 discusses the simplest process possible, a single-step process. Then, between chapters 5 and 10, we expand this to cover multistep processes, supplier and customer interfacing, multiple business objectives, and supply chains. Think of this as expanding the simple process in a single dimension. In chapter 11, we show how to expand into a second dimension by considering the relationship between strategy and tactics. Finally, in chapter 12 we consider how organizations improve their process performance. Improvement is a process in itself; it can be modeled like any other process.

Validation of models will not be covered in this book. Readers will do this as they apply models to their own organizations. Instead, we will use the models presented throughout this book to explain the general behavior of organizations. The principles that we uncover can be applied to the many different types of organizations found in business today.

Model Equations

```
MODEL 2.4.ITM
{ INITIALIZATION EQUATIONS }
M0 = 0.1
INIT MT = M0
R = 0.9
DELTA_M = R*MT*(1-MT)—MT

{ RUNTIME EQUATIONS }
```

```
MT(t) = MT(t—dt) + (DELTA_M) * dt
DELTA_M = R*MT*(1-MT)—MT

MODEL 2.7.ITM
{ INITIALIZATION EQUATIONS }
M0 = 0.1
INIT MT = M0
R = 0.5
GROWTH_DELAY_TIME = 0
GROWTH_DELAYED = DELAY(MT,GROWTH_DELAY_TIME)
DECAY_DELAY_TIME = 0
DECAY_DELAYED = DELAY(MT,DECAY_DELAY_TIME)
DELTA_M = R*GROWTH_DELAYED-R*DECAY_DELAYED*DECAY_
DELAYED-MT

{ RUNTIME EQUATIONS }
MT(t) = MT(t - dt) + (DELTA_M) * dt
GROWTH_DELAYED = DELAY(MT,GROWTH_DELAY_TIME)
DECAY_DELAYED = DELAY(MT,DECAY_DELAY_TIME)
DELTA_M = R*GROWTH_DELAYED-
R*DECAY_DELAYED*DECAY_DELAYED-MT

MODEL 2.11.ITM
{ INITIALIZATION EQUATIONS }
TARGET = 1.0
INIT BASE_INPUT_RATE = TARGET
INPUT_RATE_VARIATION = RANDOM(-0.5,+0.5)
ORDER_INPUT_RATE = BASE_INPUT_RATE +
INPUT_RATE_VARIATION
INPUT_RATE_ADJUSTMENT = IF TIME < = 500 THEN 0 ELSE
(TARGET- ORDER_INPUT_RATE)
ADJUSTING_INPUT_RATE = INPUT_RATE_ADJUSTMENT

{ RUNTIME EQUATIONS }
BASE_INPUT_RATE(t) = BASE_INPUT_RATE(t—dt) +
(ADJUSTING_INPUT_RATE) * dt
INPUT_RATE_VARIATION = RANDOM(-0.5,+0.5)
ORDER_INPUT_RATE = BASE_INPUT_RATE +
INPUT_RATE_VARIATION
INPUT_RATE_ADJUSTMENT = IF TIME < = 500 THEN 0 ELSE
(TARGET- ORDER_INPUT_RATE)
ADJUSTING_INPUT_RATE = INPUT_RATE_ADJUSTMENT

MODEL 2.14.ITM
{ INITIALIZATION EQUATIONS }
TARGET = 1.0
```

```
INIT BASE_INPUT_RATE = TARGET
INPUT_RATE_VARIATION = RANDOM(-0.5,+0.5)
ORDER_INPUT_RATE = BASE_INPUT_RATE +
INPUT_RATE_VARIATION
DELAY_TIME = 0
ORDER_INPUT_RATE_DELAYED =
DELAY(ORDER_INPUT_RATE,DELAY_TIME)
INPUT_RATE_ADJUSTMENT = IF TIME < = 500 THEN 0 ELSE (TARGET-
ORDER_INPUT_RATE_DELAYED)
ADJUSTING_INPUT_RATE = INPUT_RATE_ADJUSTMENT/DT

{ RUNTIME EQUATIONS }
BASE_INPUT_RATE(t) = BASE_INPUT_RATE(t—dt) +
(ADJUSTING_INPUT_RATE) * dt
INPUT_RATE_VARIATION = RANDOM(-0.5,+0.5)
ORDER_INPUT_RATE = BASE_INPUT_RATE +
INPUT_RATE_VARIATION
ORDER_INPUT_RATE_DELAYED =
DELAY(ORDER_INPUT_RATE,DELAY_TIME)
INPUT_RATE_ADJUSTMENT = IF TIME < = 500 THEN 0 ELSE (TARGET-
ORDER_INPUT_RATE_DELAYED)
ADJUSTING_INPUT_RATE = INPUT_RATE_ADJUSTMENT/DT
```

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