6

Single-State Systems: The Complexity of Control

The basic building block of all systems dynamics models is a single-state variable (the "level") and the expression describing the causes of over-time variation in the state (the "rate"). A surprisingly large number of social science theories are concerned with the dynamics of systems that are composed of very few states and, in many cases have only a single "dependent variable." Such theories, however, are not necessarily simple, as they often specify quite complex hypotheses about the causes of variation in rates of change.

One theorist might, for example, be concerned with the dynamics of attitudinal intensity (as in the study of the strength of support for political candidates). The intensity of belief might be conceived of as a continuous (and conserved) state that changes over time at rates determined by the timing and intensity of propaganda, the subject's perceptions of the attitudes of members of their reference groups, and other factors. In this case, the system has essentially a single dependent state (attitudinal intensity), but this state may change over time at rates that are governed by quite complicated combinations of exogenous variables.

Another theorist might be concerned with the analysis of characteristics of aggregates, such as the number of organizations of a certain type existing in a given geographical space over time. In this case too, the theory is concerned with dynamics that are "simple" in one sense: There is a single dependent variable (the number of organizations). But, hypotheses that might be specified concerning the causes of increases in the organizational population (that is, the rate of organizational formation) and the causes of decreases in the organizational population (that is, the rate of failure) might be extremely complex.

There are many problems in each of the social sciences that may be usefully conceptualized as systems involving few states but complex rates. As the examples above illustrate, these problems are "simple" in the systems sense of the word, but hardly trivial. The dynamic behavior of "simple" systems is also not so easy to comprehend as one might expect. Depending on the complexity of the relationships expressed in the equations for the rates of change, and on the time paths of the exogenous variables, virtually any form of over-time behavior can be displayed by even the "simplest" of systems.

Systems analysis and systems theory provide an extremely powerful set of tools for describing and examining the complexity of the expressions for rates of change: "control structures." The expressions describing the causes of rates of change in states can be thought of as "mechanisms" controlling the speed at which processes that increase or decrease the level are occurring. These mechanisms can themselves be quite simple or quite complicated, and we can think about them in this way.[1] Some of the mechanisms governing change in patterns of social action and interaction may be quite "dumb" or simple, involving little more than responses to external stimuli. Other patterns of social action and interaction may be thought of as processes controlled by "self-referencing" mechanisms of "feedback" and "feedforward". Still more complicated control structures involve referencing goals, or even setting goals as part of the processes controlling action. As the complexity of the control structures that govern rates of change in a single-state increase, the range of possible behavioral responses increase as well. Systems with very simple control structures are capable of only a limited range of over-time behaviors, systems with complex control structures are capable of much more complex patterns.

In the remainder of this chapter we will examine "control structures" of increasing complexity, and look at some of the behavioral tendencies of single-state systems governed by such control structures. As will quickly become apparent, most theories of the dynamics of social action and interaction tend to use quite simple specifications of control structures. In most cases this is entirely appropriate, as many very important problems from all social science disciplines can be very effectively modeled as being relatively "dumb." An exposure to the range of possible control structures of greater complexity, however, should stimulate interest in the utility of more complicated specifications.

Types of Control Systems

In thinking about the ways in which the dynamic behavior of a variable might be generated or controlled, it is useful to keep in mind our earlier definition of complexity. The same ideas can be applied in discussing the complexity of the "control structures" of theories, as well as in discussing whole systems. A more complex control system is one that makes reference to more pieces of information about the system, utilizes more of this information simultaneously (i.e. the control system has high connectivity), and combines information according to functional and time forms of high order.[2]

It is possible to envision a continuum of control system types from less to more complex. At the simple end, the "control structure" governing the rate of change in some variable Y might consist of a single qualitative relation: If X, then Y. Rather nearer the other end or the possible spectrum of control system complexity are homeostatic mechanisms like thermostats: the "control system" here monitors the room temperature, compares its "perception" of the temperature to a "goal," and increases the rate of heating if the actual temperature is less than the goal.

For constructing theories about human social action and interaction, it is most useful to divide control systems into classes according to the complexity of the connections among pieces of information, rather than the number of pieces of information involved. The "simplest" control structures are describe patterns of action that are of a "stimulus-response" or "dumb" type. A DYNAMO diagram showing the basic structure of such a control structure is shown in Figure 6.1.

Control mechanisms of this simplest type receive stimuli from the environment (X1 and X2), which may be noise, constants, or functions of other variables, and produce automatic responses of increase (B1) or decrease (B2) with respect to time. A good deal of highly socialized human behavior can be effectively understood as involving only such simple mechanisms. Such dynamic models are often used, as well, to approximate more complex processes—as in the case of simple linear equations in exogeneous variables describing the behavior of aggregates.

A slightly "smarter" form of control system involves "self-referencing." Stimulus-response type control structures produce fixed responses to stimuli, regardless of the state of the system. Self-referencing systems' responses to stimuli depend on external stimuli and the current state of the system. The diagram in Figure 6.2 shows a prototype of a simple "self-referencing" control systems with feedback and feedforward.

Consider, as an example of such a "self-referencing" control system, the number of departments and hierarchical levels in a bureaucracy. One theory might hold that the "differentiation" (that is, the numbers of vertical and horizontally specialized units) of the organization increases

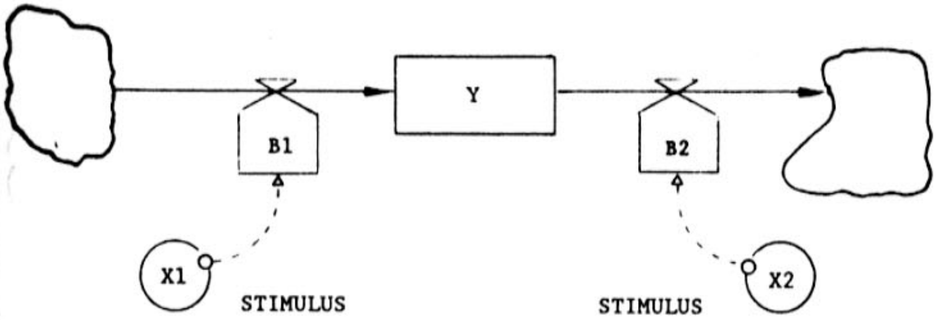

Figure 6.1: Stimulus-response control.

in direct proportion to the "carrying capacity" of the environment. This is a "stimulus-response" type of control. An alternative theory might suggest that the rate of addition of new units to a bureaucracy depends not only on the carrying capacity of the environment, but also on the existing level of differentiation: In the same environment with slack carrying capacity, it might be argued, organizations that are highly differentiated will increase their differentiation more rapidly than those that are less differentiated. In this example, the response to an environmental stimulus (slack carrying capacity in the environment) depends on the current state of the systems (how differentiated the organization already is). The behavior of the system might be said to be "self-referencing."[3]

Such simple mechanisms though, are often not sufficient to represent the control structures of many dynamic social processes. Many patterns of human social action and interaction are more usefully thought of as oriented toward the attainment of goals. Control systems in which information about goals as well as the state of the exogenous variables and the system itself are taken into account are, in some sense, "smart" systems. In goal-seeking control structures, the response of the system to a stimulus is contingent on the relationship between the current state of the system and some "desired" or goal state. A prototypical example of a goal-seeking control system structure is shown in Figure 6.3.

To return to our organizational differentiation example, suppose that the profitability of the organization depended on the "fit" between the carrying capacity of the environment and the differentiation of the organization. In a theory involving "goal-oriented" control, the organization's behavior in the face of an environment that has slack might be theorized to follow this process: The organization has a goal of increasing profit, and in each period of time the rate of addition (or elimination) of organizational units depends upon the level of current

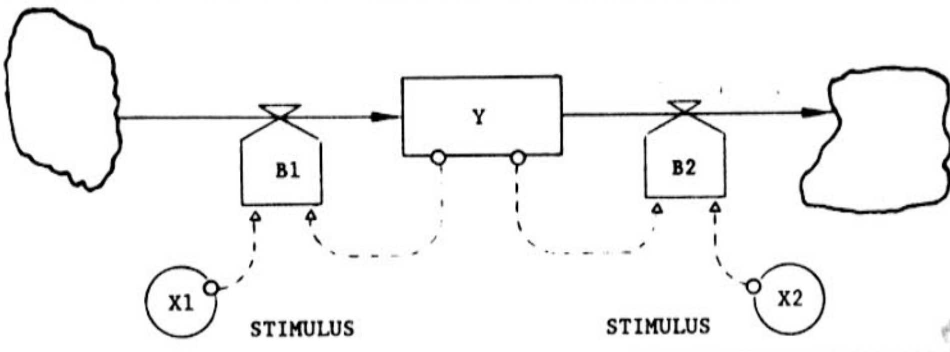

Figure 6.2: Self-referencing control.

profits. If profits are positive, organizational units are added; if profits are negative, organizational units are eliminated. In this control system, the rate of change in the number of organizational units is contingent upon a comparison between the current state of the system and a goal state. Rather than simply responding, or responding in a way that is conditioned by the current state of the system, the response is generated here by a much more complex process of comparisons to goals.

The next step up in the increasing complexity of control mechanisms should be rather easy to anticipate. Beyond "goal-seeking" mechanisms, we can readily imagine that much human social action and interaction can be usefully thought of as being governed by "goal-setting" or "adaptive" control. Such processes involve not only comparisons of the state of the system to goals, but also dynamic modification of the goals. A prototype of such a control structure is shown as Figure 6.4.

We can modify our theory of organizational behavior to make it "intelligent" (in the sense of goal setting) rather than simply rather "smart" (in the sense of goal referencing). Suppose that our organization's leadership monitors the environment and uses this information to set profit goals. The rate of addition or elimination of organizational units depend, as in the previous model, on the ratio of profits to profit goals. However, as the environment changes the goal for profitability is modified, and the organization is responding to environmental change both behaviorally and in the processes that set the goals that govern behavioral responses.

One could go on to consider even more intelligent mechanisms of control, but such mechanisms are beyond the scope of the current work—and are very rarely utilized in contemporary social science theorizing about the dynamics of systems. In fact, most theories of social action, in properly striving for parsimony, specify quite simple control

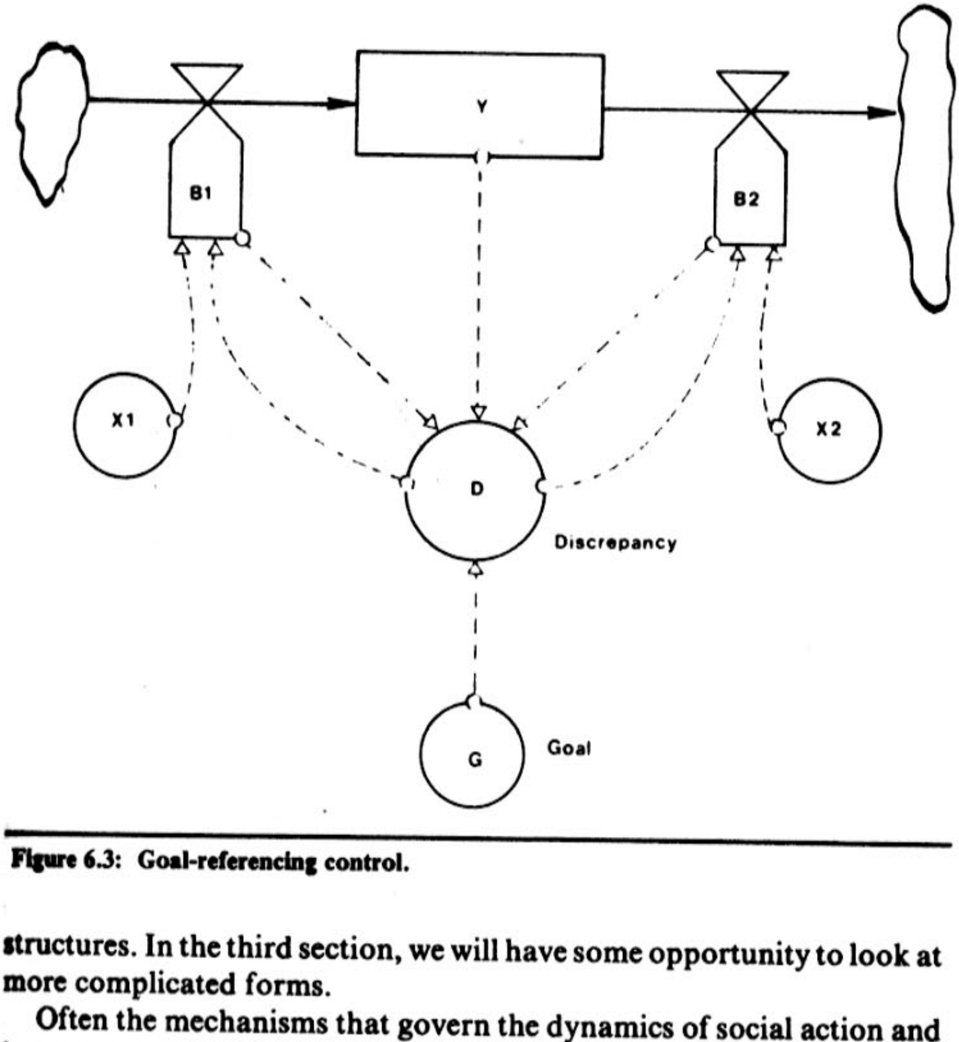

Figure 6.3: Goal-referencing control.

structures. In the third section, we will have some opportunity to look at more complicated forms.

Often the mechanisms that govern the dynamics of social action and interaction are quite complex, but can be approximated by simpler and hence more analyzable models. These "simple" control mechanisms themselves are capable of very complicated-appearing responses to stimuli, and are a good place to start in building theories of social dynamics.

The Dynamics of "Dumb" Control Structures

The dynamics of a very wide range of forms of social action can be very effectively described and analyzed as systems with quite simple control structures. Whether we are talking about an individual person, some other social actor, or the average tendency of a homogeneous aggregate of actors, many forms of social dynamics seem to be quite

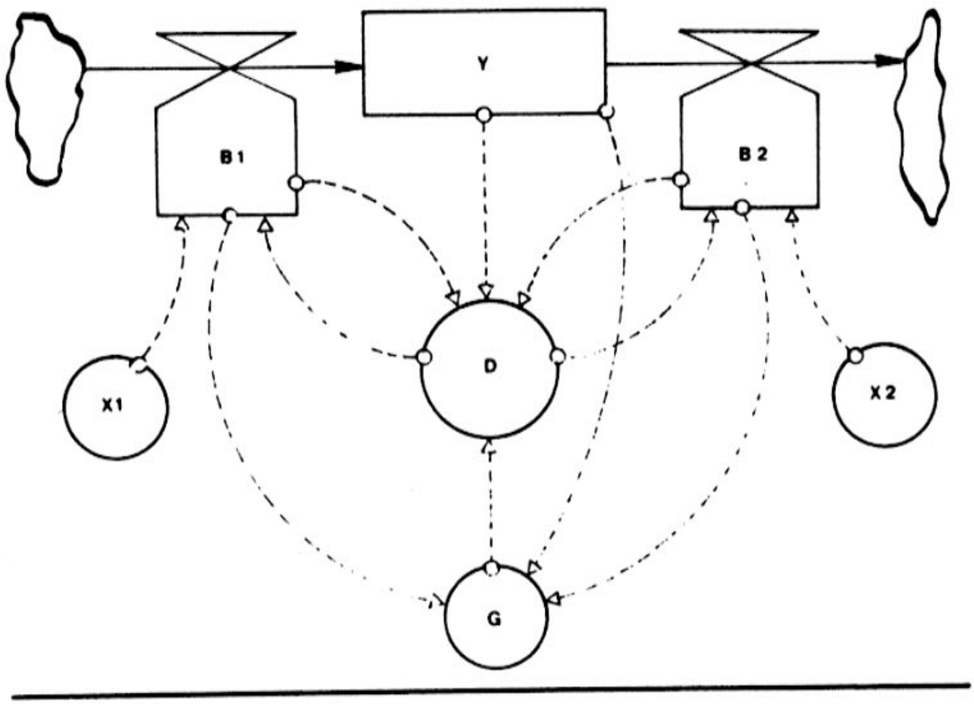

Figure 6.4: Adaptive control.

interpretable as governed by "stimulus-response" types of control.

Because theories using such control structures are so common, and because such structures are the bases for more complex ones, it is useful to spend a bit of time becoming comfortable with the kinds of over-time behavior that these control systems can produce.

In Figure 6.1, in the section above, we presented a diagram of a simple stimulus-response control system. In this example, the single dependent system state is incremented over time and decremented over time at certain rates. In the DYNAMO language, this can be expressed as:

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L    Y.K = Y.J+(DT)(RI.JK-RD.JK)
R    RI.KL = f1
R    RD.KL = f2
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where Y is the "level" of the state variable, and "RI and RD are arbitrary names used to refer to the "rate of increase" and "rate of decrease" in Y. The terms f1 and f2 are any logical or mathematical expressions involving any number of exogenous variables (that is, Y does not appear in f1 or f2, else the system would be "self-referencing").

With sufficient cleverness, any pattern of over-time behavior of Y can be produced by varying the expressions for f1 and f2. And, indeed, a very wide range of theories about the time path (or more accurately, the rate of change) of Y can be expressed with this simple model. The expressions for f1 and/or f2 might consist of pure white noise—expressing the idea that change in Y was produced by random action (a very useful baseline model in many cases). The expressions might consist of expressions of the familiar form: $f1 = a + b_1(X1) + b_2(X2) + b_3(X3) + NOISE()$. That is, the rate of increase and/or decrease is the result of the linear addition of the effects of a number of simultaneously operating exogeneous variables. The expressions might consist of equations of the increasingly familiar form: $f2 = ae^{b1(X1)+b2(X2)}$; that is, the log-linear or multiplicative interaction of several variables. Or the expressions could consist of sets of logical tests and hierarchically nested relations.

In order to get a good sense of how "dumb" systems behave over time, however, it is useful first to explore their response to simple stimuli. To do this we will perform three sets of simulation experiments. First we will subject our very simple integrating system (i.e., the one that we described in the DYNAMO equations above) to a variety of signals. This experiment is important in itself to reveal how the static-looking expressions produce imply dynamic behavior. The second and third experiments will look at the less common and obvious dynamics of simple integrating systems that have "delayed" effects: that is, time forms of relations that are not linear.[4]

Experiment: Simple Integration

Let us begin with the most obvious of all dynamic formulations. In our first experiment we have a dependent variable (Y) that is incremented (we could, of course, run these processes in reverse, decrementing the level) over time at rates (RI) that are functions of (a) a constant, (b) white noise, (c) normally distributed noise, (d) a steadily increasing stimulus (RAMP), (e) a change from one level of stimulus to another (STEP), and (f) a set of timed PULSEs. Simulations showing each of these stimuli, and the over-time level of the response state Y are shown in Figure 6.5.

In the first panel of the figure, the response variable (shown with the asterisk) is subjected to a constant input (the input signal is shown with the plus sign). It is hardly surprising, but nonetheless is quite important, that in "conserved" states the incoming signal continuously accumulates, generating a pattern of linear growth. Any slope can be produced by altering the sign and magnitude of the constant input. If, for example, the effect of the independent variable on the rate of change in Y were

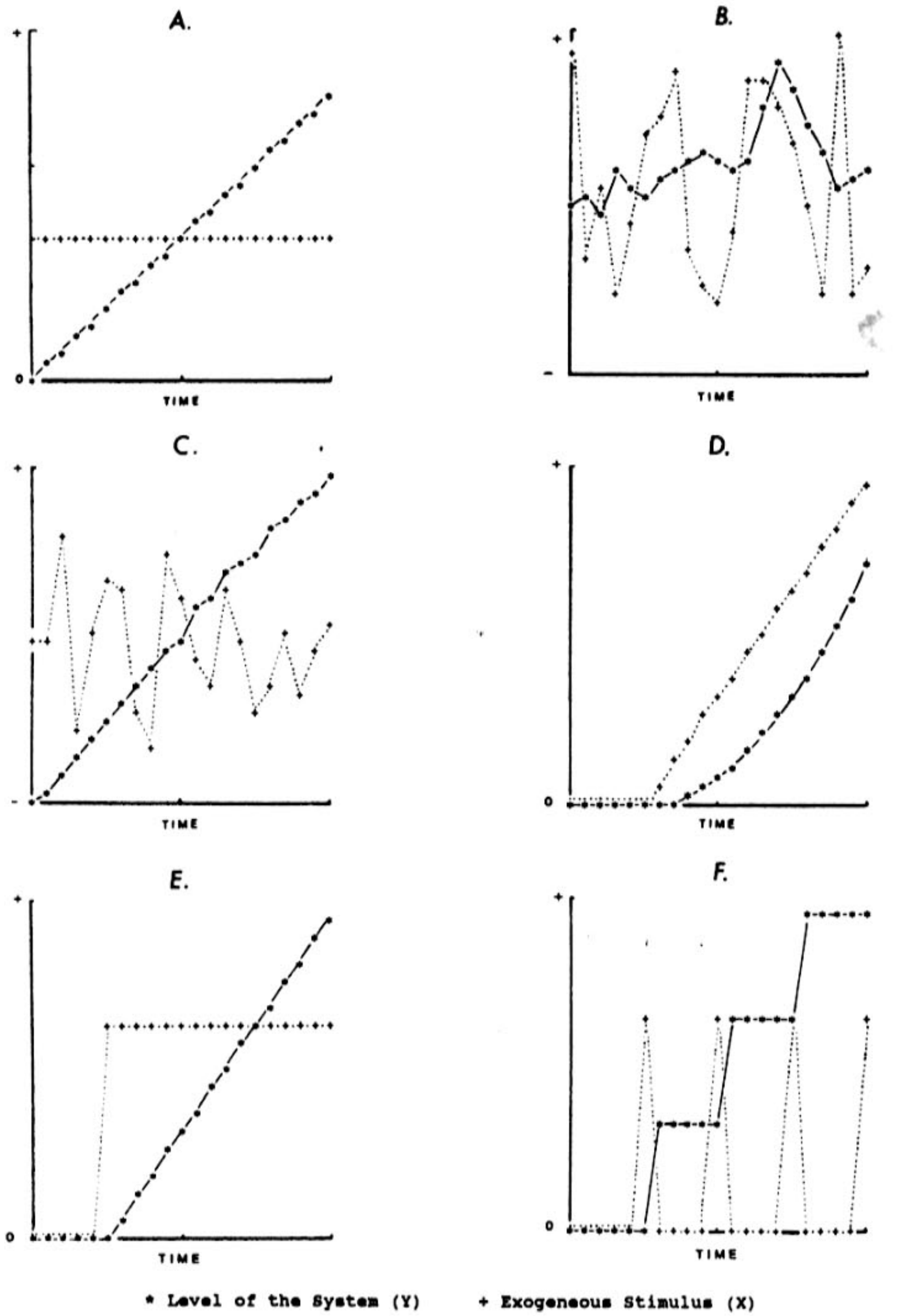


Figure 6.5: Stimulus-response experiments.

negative, the response of Y would be linear, but with negative slope with respect to time. Differing slopes (but always linear shapes) of the response could also be produced by the action of multiple constants on

Y. A process that was described by the following equation, for example, would produce an absolutely flat time response, despite the complex equation (so long as each X is a constant of unit value or the Xs change in exactly compensating fashions with respect to time):

$$Y.K = Y.J + DT(.5 + .3(X1) + .2(X2) - 1.0\,(X3))$$

It is worth noting at this point, as we shall again and again, that a given time path of response variable can be produced by a very wide variety of alternative underlying mechanisms. A pattern of constant change, for example, may reflect the action of one constant, a combination of many constants, compensating changes among multiple causes, or the action of a feedback control mechanism. The data do not speak for themselves. It is up to the theorist to offer convincing reasons for supposing that one underlying mechanism or another is producing a given response pattern.

In panel b of the figure white noise is used as the stimulus to our simple control system. The integration of white noise should, in the long run, have an expected value of zero. As the time trace shows, however, it is possible for a purely random process to display what appears to be consistent trends for some periods of time. This process is called "drift." The important point to note about the responses of simple integrating control systems to white noise is that integration dampens the "jagged" over-time behavior of the "independent variable" into a smoother-appearing response and that this response may display substantial short run orderliness, despite the purely random causal process.

In the third panel (c), our "dumb" control system has been subjected to a stimulus that is normally distributed with an expected value of a positive constant. The stimulus in panel c combines the constant trend of panel a with the "noise" of panel b. The response of the system is also the sum of the previous two patterns: linear trend in response to the constant part of the stimulus, and random variation around the trend as a result of the noise component. Where the rate of change in the stimulus is a constant, then, integration produces a linear trend in the response; where the stimulus is random, integration produces a dampened response with an expected value of zero.

When the independent or causal variables are themselves displaying trends (unlike the cases of noise or constant input), how does a simple integrating system respond? In panel d the stimulus is set to a constant of zero for a period of time and then increases at a constant rate (that is, the independent variable begins a linear upward trend). Since our response variable accumulates or integrates these increasingly large values of the stimulus, a pattern of exponential growth is produced. Many systems with more complex control structures (i.e., feedback) also produce exponential over-time behavior. The importance of the experiment in panel d is that it demonstrates that a simple system can also produce exponential responses when stimulus variables display trends. This fact again suggests that it may be dangerous to "reason backwards" from an observed behavior pattern to a hypothesis about the process that produced it.

In panel e of the figure another experiment with a trending independent variable is shown (a step function). For the first several time periods the stimulus is constant at zero, then shifts to a constant positive number. In both periods, the response is linear (because the stimulus is a constant), but the slope of the response changes when the stimulus takes on a positive value. Finally, in panel f we experiment with the "transient response" of our "dumb" control structure. The system is subjected to shocks (pulses) that occur at regular intervals. Each of these signals is absorbed by the response state, which changes in a stepwise fashion as it does so.

The over-time behavior of a single dependent state governed by a "dumb" or simple stimulus-response control structure is not difficult to anticipate with a few moments' thought. Despite this simplicity, there are several important basic lessons in this exercise. Where the causal effect of one variable (the stimulus) on the other is a constant, the response variable displays linear trend with respect to time. Constant causal pressures then produce trends, not absence of change in dependent states. Where causal variables are trending linearly, accumulating systems display exponential trending. Episodic "shocks" are accumulated as well by systems governed by such simple control structures. If the shocks are purely random, they may produce short-term "drift" in the level of the system; if they contain a "bias" (as in the case of panels c and f), trend, as well as drift, can be produced by seemingly random causal stimuli.

In a more general sense, it is most important to realize that systems governed by very simple control structures can produce quite complex responses if the stimuli to which they are subjected are complex. We have also only considered the simplest possible "ideal types" of stimulus-response systems. Often a single state may be affected by a large number of independent variables at the same time. The combined force of a number of constants, trends, noises, and shocks can produce extremely complex response patterns. These possible "realizations" of very simple "dumb" systems become even more complicated if we make more realistic assumptions about the time-shapes of the relationships between stimuli and responses.

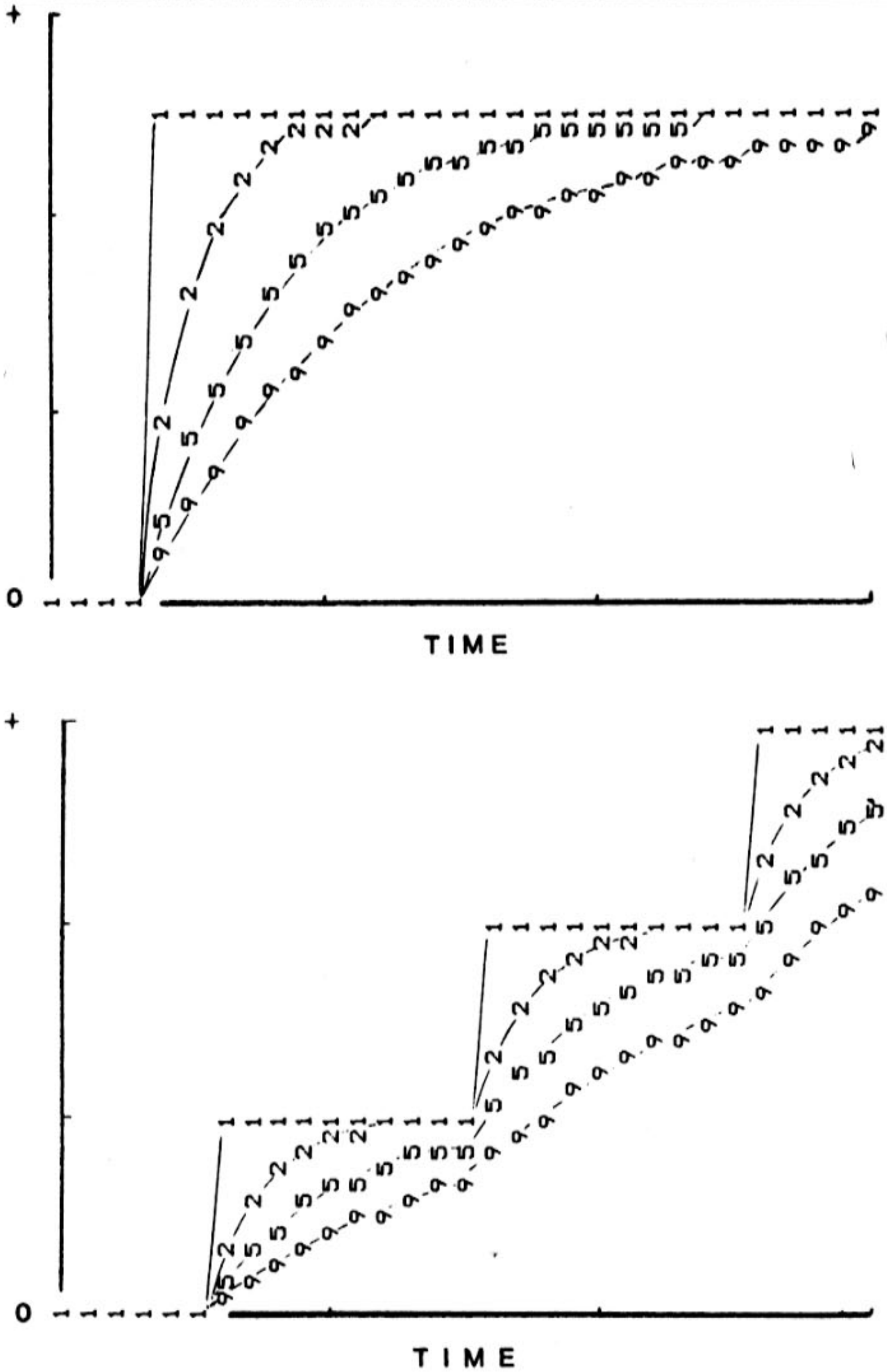
Experiment: Simple Integration with First-Order Delay

There are many cases in which it is unrealistic to assume that the response to a stimulus is instantaneous and constant. A "first-order" exponential delay assumes that the initial response to a stimulus is strong, but that the response continues to occur at exponentially declining rates thereafter. When a series of stimuli are received, first-order "exponential delays" are equivalent to weighting the most recent signal most heavily in formulating a response, but also using information about the previous signal (assigning it less weight than the current one) and the signal before that (again assigning less weight to it) and so on.[5]

First-order delays can occur in social systems in many ways. Suppose that the management of an organization orders the production of 100 widgets. Because of resistance and friction between workers and management, however, the production line will only produce 80% of the unfilled orders from management in each time period. If there are no new orders, 80 widgets will be produced in the first period after the order is given and 16 in the second period after the order is given (that is 80% or the remaining 20 widgets that were ordered but not yet delivered). By the beginning of the third time period after the order is given, 96 widgets have been produced and 80% of the remaining four are consequently done in the third period. The original order of 100 widgets will eventually be produced (actually not, as the process only approaches full realization, and never actually gets there), but may do so after a considerable time. The "friction," "inertia," and "resistance" of responses to stimuli in social systems can often be effectively modeled as exponential delays of various average lengths.

In the top panel of Figure 6.6 the transient response of our "dumb" system to a PULSE (that is, one time shock) is shown under different assumptions about the degree of friction and resistance (that is, the average length or half-life of the DELAY1 function). The figure shows the response of the system to first-order delays of 1, 2, 5, and 9 time periods. The responses shown are all of the same shape, but differ in how long they take to be fully realized. The delay of "average length" of two units reaches 50% of its final value at time point five—two time units after the shock (which occurred at time-point three); the delay of "average length" of five units reaches 50% of its final value after 5 time units, etc.

Real social systems, of course, do not sit still while each stimulus is translated with friction and delay into a response. Rather, continuous streams of stimuli are occurring. In the bottom panel of Figure 6.6 we show a very simple experiment to illustrate what happens when multiple



1 average delay one unit
2 average delay two units
5 average delay five units
9 average delay nine units

Figure 6.6: First-order delay.

stimuli are occurring in "dumb" systems with delay. In the experiments shown in the bottom panel, a set of pulses occur at time points 3, 13, and 23. Control structures with first-order exponential delays of average lengths of one, two, five, and nine time periods are shown responding to this stimulus.

There are two interesting aspects of the results in the bottom panel of the figure. The "delays" produce responses to the stimuli that are progressively "smoother" as the average length of the delay increases. This is a fundamental and important characteristic of all delays, with major implications for modeling the dynamics of social action: To the extent that relations among things operating over time involve resistance and friction, "dependent" variables tend to be seen as sluggish and smoothed reflections of the stimuli that generated them.

The second important aspect of the behavior of the simple stimulus-response mechanism in the bottom panel of the figure is somewhat more subtle. The delays of very short average length (that is, the curves one and two) succeed in "catching up" between the stimuli—which occur only every 10 time periods. The delays of greater average length (the curves five and nine) have not completely closed the gap between the original stimulus and their final response by the time that the new stimulus occurs. As a consequence, the responses of states with lengthy delays always lag behind the ongoing stimulus and never "catch up" (actually the short delays never catch up either, but the gaps are so small as to be, usually, of little importance). When the delays in a system are relatively long compared to the frequency of stimuli—and they usually are, as stimuli occur continuously—dynamic systems are never observed "in equilibrium." The status of the state space at any point in time in a system with friction and delay is a reflection of stimuli in past periods, as well as of immediately preceding stimuli. Where social action involves delay and friction, then, responses are not only "smoothed" reactions to stimuli, but are responses to past as well as to current stimuli.

Experiment: Simple Integration with Third-Order Delay

Simple "friction" resulting in the smoothing of responses to stimuli is very common in social systems. In many cases, however, the delay in responding to stimuli takes the form of a "higher order" function of time. The DYNAMO language provides as a convenient tool the third-order delay as a built-in function, and the time shape of this curve is sufficiently complex to capture a very interesting and important class of responses: those with "latency." In Figure 6.7 we show the results of the same sets of experiments that we discussed at some length in the

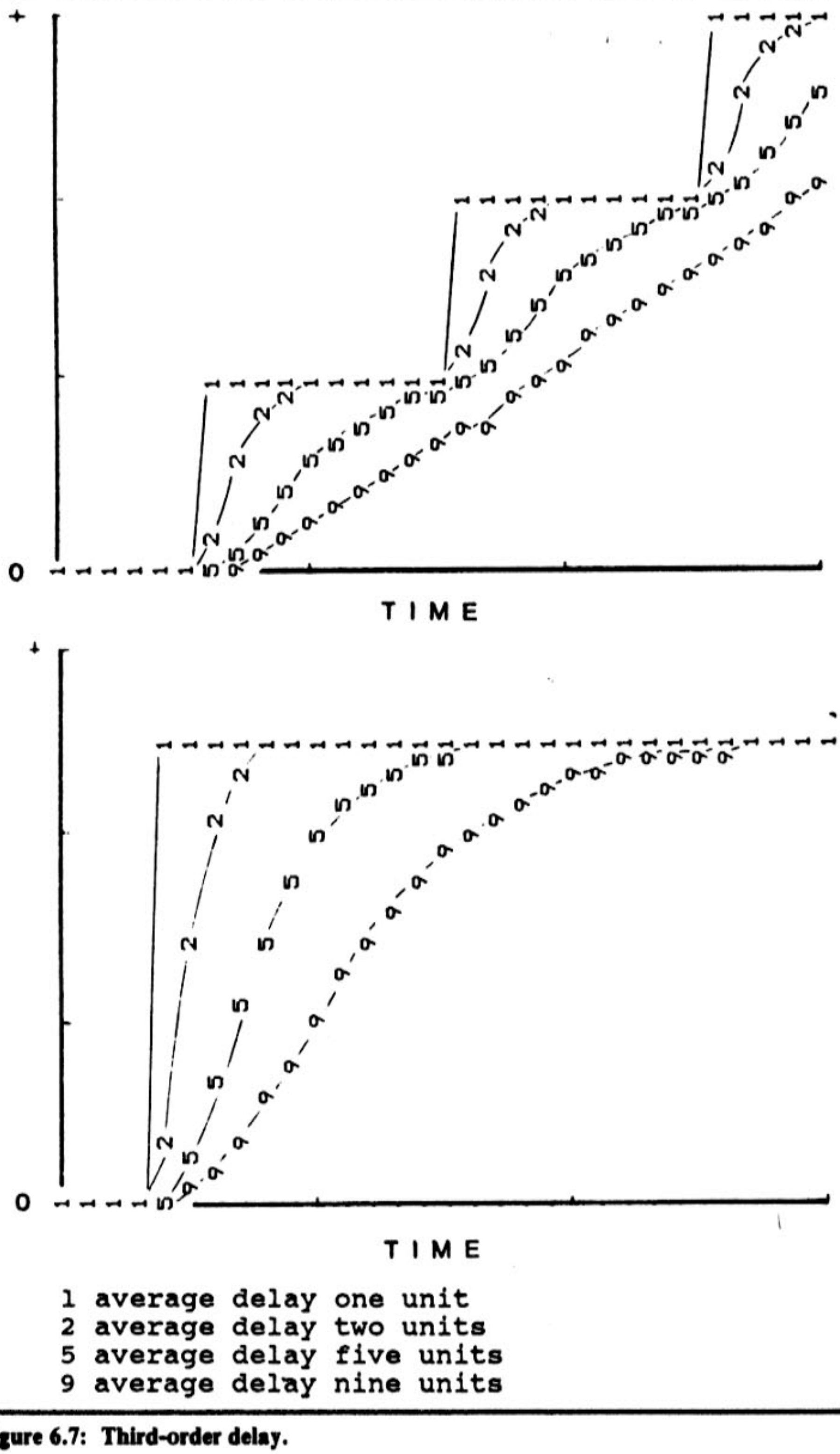


Figure 6.7: Third-order delay.

previous section, this time repeated with "third-order" delays (DYNAMO's functions DELAY3 or DLINF3).

Third-order delays, by their definition, produce an "S-shaped" pattern of response to a stimulus—as can be seen in the bottom panel of the figure. One can think about such delays as responses with a certain "latency." That is, it takes some time for any significant response to occur. Once response begins to occur, it accelerates up to the halfway point, then slows until the response is completed (again, the response is never really completed, but this rarely is of any importance). This kind of time-shape is more complex than the first-order delay, and may be more realistic for modeling the dynamics of many forms of social action in which the "resistance" or "inertia" is not constant, but is rather stronger at first and declines later.

The top panel of the figure repeats the experiment of subjecting our "dumb" control structure with delay to a series of timed shocks. As before, the important lessons are that delay tends to "smooth" response (albeit the "smoothing" is more complicated in higher-order delays) and that, in the presence of delays of substantial magnitude, the system never "catches up" in its responses to the string of incoming stimuli.

Summary: The Behavior of "Dumb" Control Structures

In this section we have examined some of the possible configurations and responses of the simplest of dynamic systems. The results themselves are somewhat complex, and it is probably helpful if we repeat some of the main points before turning to more complicated structures.

Systems with control structures that are of the simplest type, "stimulus-response," as opposed to the more complex "self-referencing," "smart," and "adaptive" types, are nonetheless capable of producing extremely complicated behavior patterns. The range of possible behavior of such systems is limited only by the complexity of the stimuli that it is subjected to and by the form of its response (i.e., whether the response involves simple integration or some nonlinear "delay" pattern of response).

We have examined the responsiveness of a simple system to a variety of abstract and ideal typical kinds of stimuli (constants, white and normal noise, pulses, steps, and ramps) that are the building blocks of the more complex and compound stimuli that occur in social systems. Among the most important results here are that the responses to constant stimuli are linear trends and that the responses to trending stimuli are exponential.

We have also taken a brief look at what happens when the time shape of responses to stimuli take somewhat more complex forms in "dumb systems." (The consequences are not the same in systems with more complex control structures.) Two types of "delays" (or "resistances" or "frictions") in responses were examined, corresponding to simple resistance and response with latency. The general lessons here are that such delays in response "dampen" and "smooth" the response of the system to stimuli, and that in the presence of such "delayed" responses systems never fully "catch up" in their responses to changes in their environments.

The Dynamics of Self-Referencing Systems

In the previous section we considered the behavior of systems that simply responded in a mechanical "stimulus-response" fashion to environmental changes. A large number of important phenomena can be be effectively represented by systems with such simple control structures, and virtually any pattern of observed trends over time can be reproduced by such models. Theories about the dynamics of social action, however, often suggest that actors or variables do not simply respond to external stimuli. Conceptions of the "control" systems governing the dynamics of action that allow actors to make reference to their own current status ("self-referencing"), as well as to external stimuli, are the next step up in the complexity of control structures.

Stimulus-response control structures take into account only changes in the environment and accumulate the past history of these events to generate the current status of the system. "Self-referencing" control structures take into account not only external events, but also the current status of the system in determining rates of change. That is, the current state of the system is one cause of change in the system. In the language of systems analysis, such control structures are characterized by "loops" of "feedback" and/or "feedforward," as is illustrated in the idealized diagram in Figure 6.2, shown earlier.

The dynamics of self-referencing systems, or systems with feedback, are quite different from those of the simpler stimulus-response type. We will spend a bit of time examining these dynamics in the abstract, just as we did with stimulus-response systems, because the "loops" in such systems are a basic building block of more complicated control structures. Once we have a feeling for the behavior of systems with simple "feedback" loops, the behavior of more complex "goal-seeking" and "adaptive" systems becomes quite easy to anticipate.

One way to understand why the dynamic behavior of self-referencing systems is inherently different from dumb systems is to examine the equations that describe the two types. The formal structure of the simplest dumb system can be stated as:

L $\quad$ Y.K = Y.J + (DT) (RI.JK)
R $\quad$ RI.KL = f(X)

That is, the level of the variable Y at a later time is equal to its level at the previous time plus the effects of some function of exogenous variables X. The basic form of a simple self-referencing system can be stated as:

L $\quad$ Y.K = Y.J + (DT) (RI.JK)
R $\quad$ RI.KL = f(X) + g(Y)

That is, the rate of change in the dependent variable is a consequence of both exogenous factors (X), and the variable itself (Y).

What kind of an effect the dependent variable has on itself over time (i.e., the g (Y) term), is up to the theorist to specify. In most models, this function is a simple constant. This is equivalent to hypothesizing that the rate of change is proportional to the level of the system. If the function is a negative number, increases in Y create decrements in the rate of change. This is what is known as "negative feedback." If the function is a positive constant, the rate of change in Y increases as Y increases, and "positive feedback" exists.

Let's suppose, for example, that we are interested in the dynamics of vocabulary development in individuals. One theorist might propose that the number of new words learned in each period of time is a function of the level of social interaction with adults (regarded as an exogenous X) and a positive function of the existing level of vocabulary. That is, the more vocabulary that exists, the more adult conversation is understood, resulting in more rapid learning of new words. This hypothesis is one of a positive feedback of the level of vocabulary on the rate of change in vocabulary development. Alternatively, one might hypothesize that the rate of change in vocabulary development is a function of interaction with adults, but a negative function of the existing level. That is, interaction gives rise to new vocabulary learning, but as learned vocabulary increases the number of unknown words declines and learning of new words slows. This theory proposes that there is negative feedback between the level of the state (number of words known) and the rate of change in vocabulary (new words learned per unit of time).

Systems governed by positive loops tend to display accelerating time trends. Since the current level of the system serves as a stimulus for further change, positive feedback tends to "amplify" whatever tendencies exist in the system. Systems governed by negative loops have the exact opposite tendency. As the level of the system becomes higher, the rate of change becomes more negative, creating a tendency to "dampen" the impacts of stimuli.

The behavior of real systems with feedback structures can, as with dumb systems, be very complex. If the time paths of the stimuli (exogenous variables) are complicated, and if there are numerous independent variables and feedback loops having impacts of the same dependent variable, the time path of the dependent variable can have any shape. The complicated behavior of real systems, however, is made up of combinations of several basic response patterns. We can get a better grasp of the behavior of feedback systems by looking at some of these "ideal typical" scenarios with simulation experiments.

Experiment: Positive Feedback

In a set of experiments, let's subject a single state system governed by positive feedback to several kinds of exogenous stimuli. In each of these cases, the system is set initially at 0, and the positive feedback loop operates to increment the rate of change by 10% of the current level of the system. The system is first subjected to a constant stimulus, then to a randomly varying pattern, to a trending independent variable, and lastly to episodic shocks (i.e., X is a STEP, NOISE, RAMP, and PULSE). The separate components of the rate of change are shown in three of the panels, with the impacts of the exogenous variable represented by +'s and the impacts of the positive feedback represented by the #'s.

In the first panel we see that the response of a positive feedback system to a constant input is exponential. The explosive growth of the system is generated by the effects of the feedback loop (the #), which creates increasing change as the level of the system increases. When the input stimulus is quite noisy, as it is in the experiment shown in the second panel of the figure, exponential growth also occurs, and for the same reason. The underlying process generating the pattern, however, is far from clear in this experiment—typical of data in which the signal-to-noise ratio is low (here the ratio is, on the average, about .2). In the third scenario, our system is subjected to a linearly trending independent variable (the +'s), and generates "super exponential" growth (that is, the rate of change itself increases at an increasing rate) again as a consequence of self-referencing. In the last experiment of the series, two

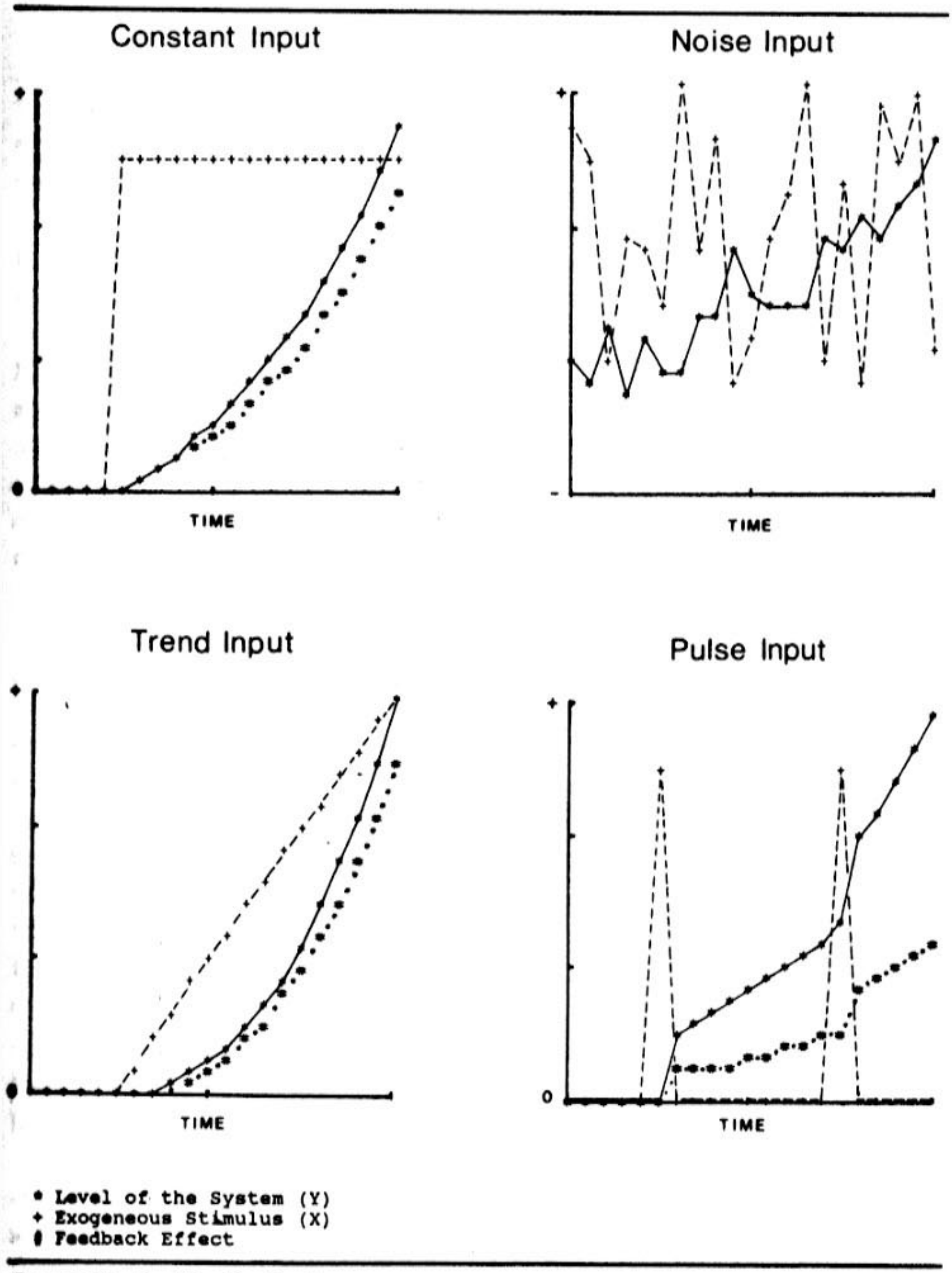


Figure 6.8: Positive feedback.

exogenous shocks occur, with no external stimuli between these events. The response of the system is again exponential, but the steepness of the exponential changes increases with each shock (because each shock increases the level of the system, hence increasing the power of the feedback).

Experiment: Negative Feedback

To get a feeling for the differences in the dynamic consequences of negative and positive feedback, we repeat the same set of experiments with a negative feedback loop. The result of this set of experiments are shown in Figure 6.9.

When a system is subjected to a constant exogenous stimulus without feedback, it responds with linear trend; when the system is governed by positive feedback, its response is accelerating growth; when it is governed by negative feedback, as in the first panel of Figure 6.9, it responds with decelerating growth. The impact of the exogenous variables in this case (the +'s) would create a linear trend in the level (*). However, as the level of the system increases the rate of change is reduced by the operation of the negative feedback (#), resulting in deceleration. In the presence of constant input then, systems with negative feedback control structures tend toward a steady state.

The second experiment with negative feedback control subjects the system to random stimuli. As with positive feedback in a noisy system, it is very difficult to perceive any pattern in the time-shape of the response variable here. In fact there is no trend, as the negative feedback acts to dampen the effects of the exogenous shocks. In the third figure the exogenous variable is trending linearly, and the system, being conservative, tends to respond exponentially. This response, however, is limited by the increasing negative feedback (#). Our last experiment shows the effects of shocks on systems governed by negative feedback. The complex pattern of response here is generated by the accumulation of rather large exogenous shocks (+) creating increasingly large negative feedbacks (#) that are self-dampening as the system tends to return to its original state. The general tendency of the system over time is upward because the magnitude of the shocks is far greater than the strength of the feedback mechanisms acting to limit their impacts.

Self-referencing or feedback systems can produce extremely complex-looking behavior. Their fundamental dynamic tendencies, however, are quite apparent from our discussion and experiments. If the rate of change of a system is a positive function of the level of the system (positive feedback), the control structure tends to create accelerating change that drives the system away from its original condition. If the rate of change in the system is a negative function of the level of the system (negative feedback), then the control structure tends to produce decelerating change that drives the system toward its original state.

These insights about the basic dynamics of self-referencing systems

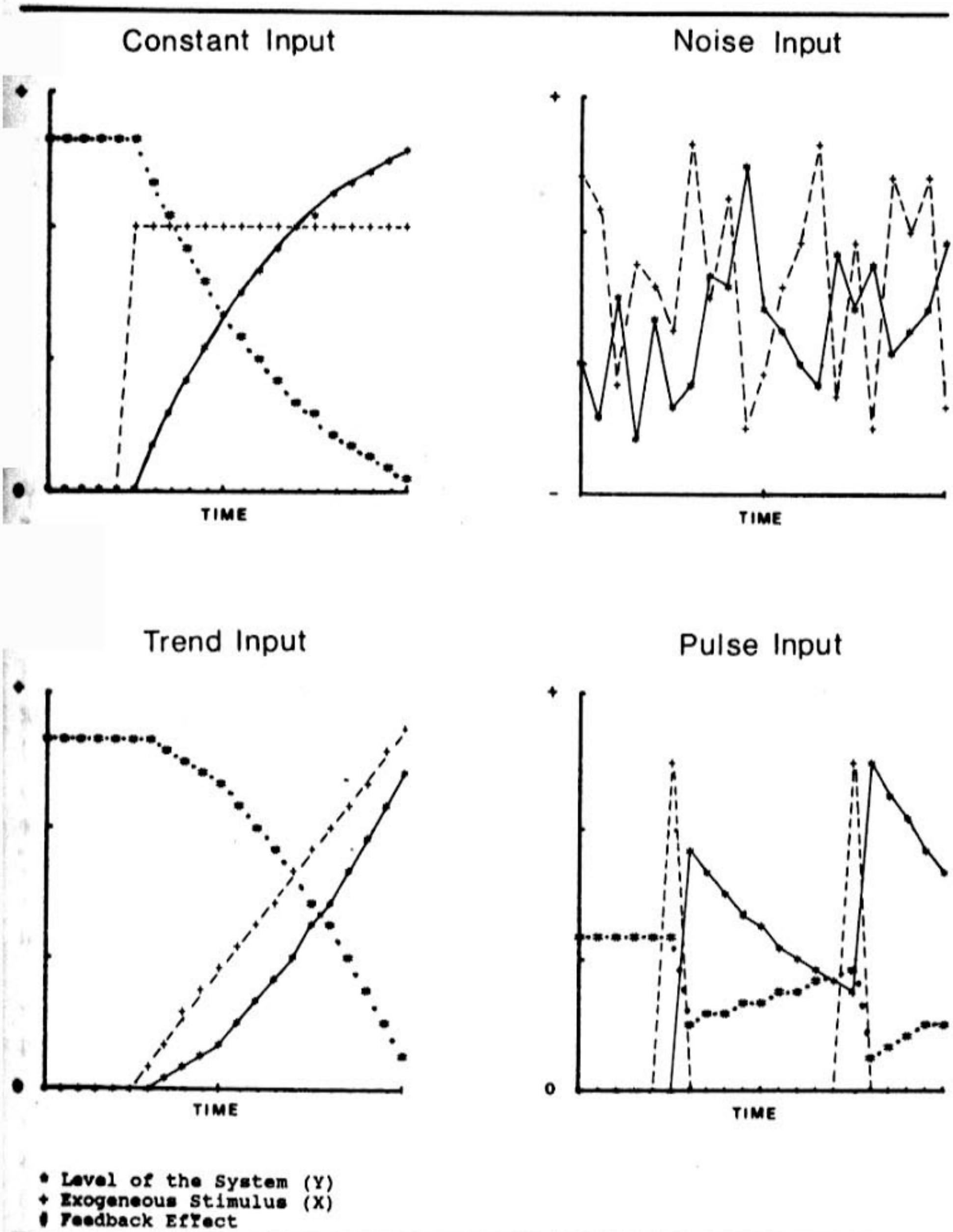


Figure 6.9: Negative feedback.

are quite familiar,[6] but this familiarity should not lead us to ignore their importance. The underlying dynamic tendencies of self-referencing systems are quite different from those of systems with "dumb" control structures that respond only to external stimuli. Unlike "dumb" systems, self-referencing systems can produce self-generating and self-limiting behavior and hence are frequently a more powerful analogy for theorizing about processes of social action and interaction than systems with less complex control structures.

Smart Systems: The Dynamics of Goal-Referencing Control

Many patterns of social action and interaction are regarded by theorists as being governed by processes that are more complex than stimulus-response and self-referencing feedback. It is often helpful to think of social actors as making reference to goals, as well as to exogenous factors and their own current status, in formulating acts.

The decision of an organization to change its formal structure, for example, is probably best thought of as an act formulated with reference to exogenous stimuli, the current state of the organizational structure, and some goal. Organizations, as "intendedly rational" actors, change their structure in an attempt to attain goals—greater profitability, better insulation from competition, conformity with the value preferences of important constituencies, or other factors. The streams of signifying acts performed by persons in face-to-face interaction can be thought of as the consequence of goal-referencing feedback as well. Individuals in such situations perceive the behavior of others (that is, makes reference to the environment), are aware of their own behavior, and have "goals" for the interaction. These goals may be instrumental, expressive, or both. The stream of acts is governed by the combination of information about the environment and the actor and by the goals.

Control systems that take goals into account, as well as information about the environment and current status of the system, could be called "smart," at least in comparison to stimulus-response and simple self-referencing systems. In terms of their formal structure, however, smart systems are simply feedback systems with a slightly more complex structure, as can be seen by comparing the diagrams of the prototype in Figure 6.3 with those in Figures 6.1 and 6.2. This similarity of formal structure is matched by a similarity of fundamental dynamic behavior of systems governed by simple self-referencing and goal-referencing control structures. Self-referencing systems tend to amplify (where the feedback is positive) or dampen (where the feedback is negative) stimuli received from the environment. Goal-referencing systems behave in the same fashion, but the effects of the feedback loop are proportional to the discrepancy between the current state of the system and some goal, rather than directly proportional to the current level of the system. Goal-referencing systems have a tendency to approach or diverge from certain goal levels, in contrast to the tendency of simple self-referencing systems to approach or diverge from their current levels.

To illustrate this behavior, let's construct a simple goal referencing system and examine its response to stimuli. Such a system is shown in the DYNAMO equations:

```
L    Y.K = Y.J+(DT)(RI.JK)
R    RI.KL = ENVIRON.K+FEEDBACK.K
A    ENVIRON.K = f(X)
A    FEEDBACK.K = PARM*DISCREP.K
A    DISCREP.K = Y.K-GOAL
C    GOAL = constant
```

The first statement specifies that the dependent variable (Y) changes at rates RI. The second statement says that RI has two component parts, one a consequence of ENVIRONment, and the other a consequence of FEEDBACK. The third statement defines the environmental impact on rates of change in Y as an arbitrary function (f) of some variable or variables X. The fourth statement specifies that the rate of change in Y is proportional (either positively or negatively, and with some intensity) to a "DISCREPancy." The meaning of this discrepancy is defined in the next statement as the simple difference between a GOAL (a "desired" level of Y) and the current status of Y. Then in the last statement the GOAL is set as a constant.

Experiment: Smart Feedback

To specify this theory into a particular model, we need to make some further assumptions. The magic number in this system is the quantity "PARM" that defines the effect of the discrepancy between goal and current status on future changes in status. For our simple example we will assume that PARM is negative. That is, our system contains negative feedback and attempts to close the gap between the goal and the current status of the system. For our simple example we will also assume that PARM is a number between zero and unity (in fact, we assume PARM = – .25). If PARM were zero, the discrepancy would have no effect on the rate of change; if PARM were unity, the discrepancy would be completely eliminated in each period of time. A value between zero and unity here is equivalent to assuming that the system responds to, but does not completely eliminate, the discrepancy in each period of time.

Some alternative sets of assumptions could also be made, though they do not seem to correspond readily to most kinds of dynamic systems that we ordinarily seek to understand. The feedback parameter could be set as a positive rather than a negative number. This positive feedback is equivalent to saying that the system seeks to diverge from the "goal" state. The feedback process could operate with an intensity of greater than unity as well. This alternative assumption would cause the system to "overshoot" or "overreact" to the discrepancy, creating either an oscillatory pattern around the goal (if the control process were a negative loop), or a pattern of "super-exponential" divergence from the goal state (if the loop were positive). Since these alternative scenarios are relatively rare in modeling real systems, we will bypass them and turn to examining the responsiveness of our "smart" system to constant, random, trending, and periodic environmental stimuli. The results are shown as Figure 6.10.

In the first panel of the figure we see a "smart" system striving to attain the goal of a level of 50 in the presence of a constant environmental stimulus of 5 units per unit of time. Since the system began at a level of zero, the initial discrepancy between the goal and the current status of the system is large. The feedback process (#) operates to increase the level of the system at rates that decrease as the discrepancy is narrowed. In the presence of the constant environmental stimulus (+) that begins at the third time point, however, the system "overshoots" its goal of 50 units. As this occurs, the effect of the feedback (#) becomes negative, attempting (unsuccessfully in this case, because the feedback has insufficient intensity relative to the continuing environmental pressure) to drive the level of the system back down to the goal level. As is fairly clear from the diagram, this particular process does approach a stable equilibrium, but the equilibrium level is not equal to the goal level.

In the second panel of the figure, our smart system is subjected to random stimuli from the environment. As before, the feedback process (#) initially operates strongly to raise the system from its initial level of 0 toward the goal state of 50. As the level approaches the goal, the discrepancy becomes less and the effect of the feedback approaches 0, except for its operation to smooth away the disruptive effects of the random shocks being received from the environment (+). In this case, since the effects of the environment have neither a positive nor a negative effect (on the average), the equilibrium level of the process is equal to the goal state, though the goal is never exactly attained.

In our third test of the behavior of this system the environment sends a strong upwardly trending stimulus beginning at the third time point.

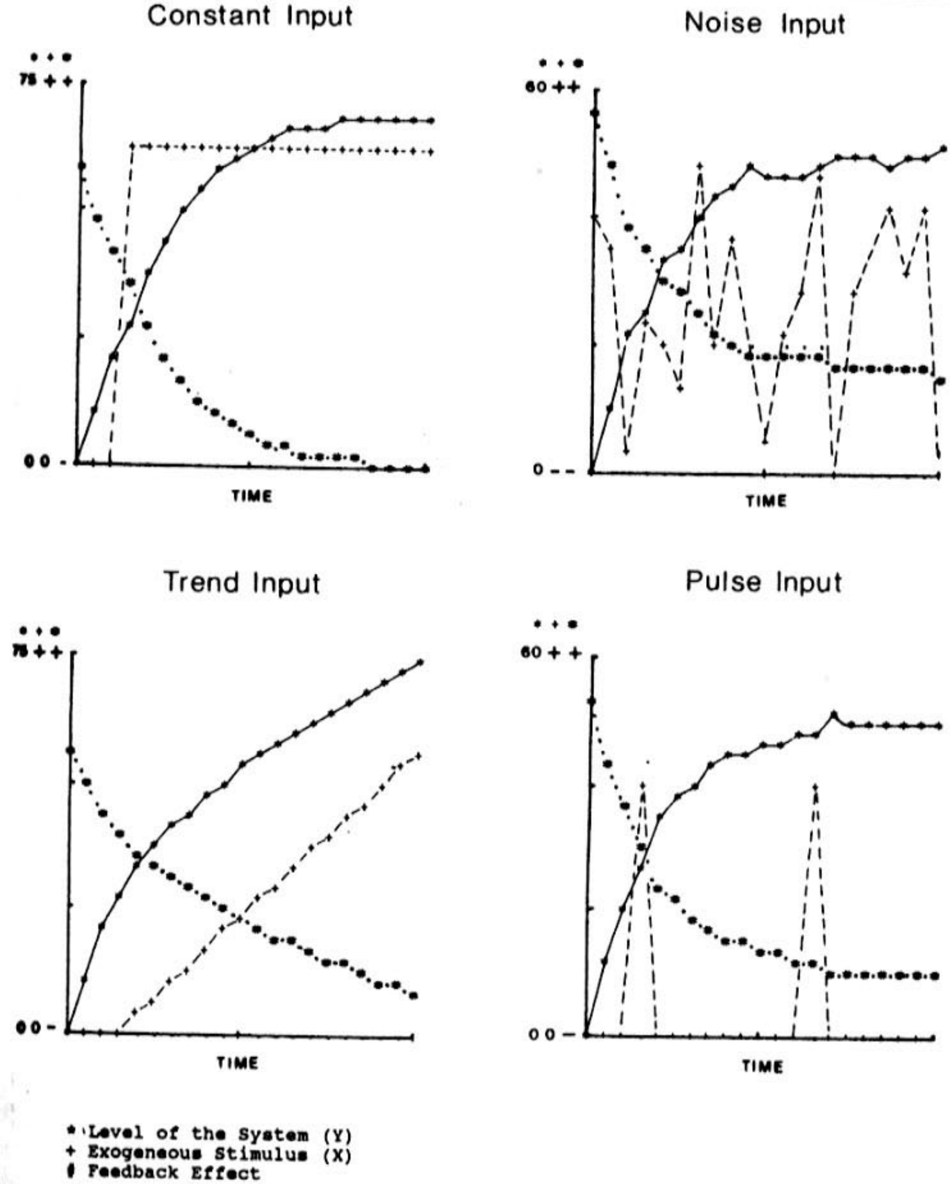


Figure 6.10: Goal-referencing control.

As in our first test, this environmental stimulus is too strong for the feedback process to fully control, and the level of the system (which reaches its goal of 50 by the ninth time point) continues to grow. The rate of increase in the system as a consequence of the steadily increasing environmental stimulus (+) is substantially reduced by the feedback process (#) and becomes increasingly negative as the system grows further and further away from the goal state. This particular process never reaches a steady state, despite the negative feedback loop, because the rate of increase in the environmental stimulus is greater than the intensity of the feedback process.

In the final experiment we have subjected the system to shocks (of a peak magnitude of 10 units) at the third and thirteenth time points. As in the second experiment with a series of random shocks, disruption of the goal-seeking behavior of the feedback loop (#) is only temporary, and the system approaches equilibrium at the goal level of 50 units. Although the figure is a bit too crude to demonstrate the point, the negative feedback loop exponentially smooths each of the disruptions.

The fundamental dynamic tendencies of systems with goal-referencing control systems are very similar to those of simple self-referencing systems. Indeed, both kinds of control structures are special cases of feedback systems, and produce similar-looking behavior in most cases. The notion that rates of change in variables may depend upon the discrepancy between the current state of the system and some goal state, however, is a powerful tool for thinking about the dynamics of social action. In some ways, however, systems that are "smart" in the sense of being goal referencing are still not smart enough to provide good analogs to many patterns of human social action and interaction.

The Dynamics of Goal-Setting Control Structures

Beyond goal-referencing control structures are still more complex ones in which the goals themselves are responsive to environmental and system status factors. Control systems of this level of complexity are sometimes termed "intelligent" or "adaptive" feedback systems. In building theories about human behavior, social scientists often have models of this complexity in mind. Such theories have normally been expressed only in everyday language, however, as their statistical and mathematical versions do not have desirable properties.[7]

A moment's thought suggests that "intelligent" or "adaptive" control is a very helpful imagery for describing many patterns of social action and interaction. Suppose, for example, that we have two actors playing a competitive game. Each actor may have the fixed goal of winning, but must formulate narrower strategic goals that change as a function of the unfolding interaction. At some points the actor may (if the rules of the game allow such complexities) attempt to maximize the accumulation of resources by making defensive moves; at other points the actor may attempt to attack. The strategic goals change over time as a consequence of the actor's own status, the behavior of the opponent, and the ways that these factors are related to the general goal of winning. More generally, many forms of human social action may be seen as governed by control structures that have several levels of goals that are more or less responsive to change over time originating from various sources.

In a formal systems analysis sense, goal-setting or adaptive control structures are simple elaborations of the goal-referencing structures that we have examined above. The difference between the structure of our prototypical goal-referencing system (Figure 6.3) and our prototypical goal-setting system (Figure 6.4) is straightforward. In both control structures the self-referencing or feedback effect is governed by a comparison of the existing state of the system and a desired or goal state. In the simpler goal-referencing system, the goals are regarded as fixed. In the goal-setting control structure, the goals are regarded as variables, and change over time as a consequence of other factors.

There are a number of interesting possibilities raised by making the goals of the system variable rather than fixed. The goals of the system may vary as a function of exogenous factors. For example, an adolescent male's desired (goal level) of "toughness" may change over time as a function of the expectations of the groups with whom he interacts. Of course, this process could be made even more complex by supposing that differential association is affected by toughness. The goals of the system may also change as a function of the same environmental influences that affect rates of change directly. For example, external threat to a society may have effects on internal cohesiveness both by directly affecting the rate of change in cohesion (as the public in general become frightened), but also by affecting the desired level of population morale and nationalism held by political elites, causing them to invoke public rituals to increase cohesiveness still further.

In addition to the possibility of making goals contingent on the environment, goals may also be directly contingent on the state of the system itself. In Figure 6.4, for example, we show goals as being affected by both the rates and the level of the system, as well as by environmental factors. Some goals may be contingent on the level of the process already attained. It might be hypothesized, for example, that the desired or goal level of occupational prestige attainment is a function of the level already attained: each person, regardless of his or her level of prestige, might be hypothesized to have a goal of 5% more prestige. Hence, as attainment rises (falls), the goal rises (falls). The goals of the system may also vary according to rates of change. If sales are decreasing, for example, goals for investment may be reduced by business management. In this case it is not the level of production or consumption that is having an effect on the goals for investment, but rather the rate of change.

The logically simple extension from goal-referencing systems to systems that set goals dynamically seems a small step, and in the abstract it is. However, the one additional "degree of freedom" is very consequential for both stating and analyzing the dynamics of social action. Systems, be they human or artificial, that change their goals as a consequence of contingencies arising from environments are a powerful analogy for understanding more complex patterns of social action and interaction that are only poorly approximated by systems with fixed goals. Many social science theories of dynamic processes utilize such imagery, but its implications have rarely been formalized.

Because of their flexibility and adaptability, we cannot present any single set of experiments to demonstrate the fundamental dynamic tendencies of models with adaptive feedback control. The answer to the question of how such systems *generally* behave is, quite properly, "it all depends." What it depends on, however, is not some hidden mystery. As simple extensions of goal-referencing feedback, the dynamics of adaptive models display tendencies either to equilibriation or to destabilization, depending on whether the feedback is positive or negative. In adaptive control models, however, the criterion that the system is attempting to reach or avoid through feedback keeps changing as a consequence of the current state of the system and exogenous factors. The shot pattern produced by the adaptive system depends on whether it is trying to hit or to miss the target, and on the fact that the target is moving.

Feedback Control and Delay

We argued earlier that social dynamics often involve complicated forms of relationships with respect to time, as well as among variables. In examining the behavior of systems governed by stimulus-response types of control, we explored several basic time-forms (DELAYs), and discovered that such delay can have the consequences of "smoothing" trends and preventing the full realization of the consequences of stimuli. We also suggested that the effects of delays in systems with more complex control structures were different. It's now time to talk a bit about this issue.

All systems that involve feedback loops (i.e., self-referencing, goal-referencing, and goal-setting systems) are particularly sensitive to the time shapes of relationships. In all such self-referencing systems, the rates of change depend on the current state of the system in ways that are increasingly intricate as the control structures become more complicated. If there is delay in the loop connecting the current level of the system to the rate of change, the feedback is operating with reference to a level that no longer, in fact, exists. As a result, the time trace of the system may be considerably different in the presence of delay than in the presence of instantaneous feedback, often overshooting or undershooting. Since feedback systems are self-referencing, distortions introduced by delays are themselves multiplied through the system, resulting in further disruption.

We have all had experiences with the effects of delay in systems controlled by feedback loops. Suppose that you are taking a shower, and you find that the water is not hot enough for your liking, so you turn the control knob to increase the flow of hot water. After what seems to be a reasonable interval, you notice no effect, so you turn the knob further. Suddenly the water is warm enough, and then too warm, so that you turn it down again. Again, nothing seems to happen, so you turn it down further. What has happened here is an overcompensation by the goal-referencing feedback structure (you), to a delayed response of the system (the water heater, pipes, valves, and all that). The main point here is that there has been an overcompensation as a result of delay in the system. We usually, of course, don't do as badly as just suggested. The lack of realism of this simple example, in fact, suggests a more complex model. Often the control structure is aware of the delays and hence either no overcompensation or a much-dampened compensation occurs.

Delays obviously occur in human-human, as well as human-machine interactions. Let's suppose that an individual is undergoing some stressful life event that is substantially reducing the individual's social performance (an example that we will treat in some detail in a later chapter). The individual is aware, with relatively little delay, of experiencing stress, and will seek to compensate. Our stressed person is also connected to a network of other persons who, upon perceiving that (s)he is undergoing stress, will attempt to be supportive. It takes far longer for members of the social network to become aware of our focal person's distress than it does for the person to become self-aware, however, and this can have interesting (and sometimes quite unfortunate) consequences. Where the stresses are relatively minor, and the individual is able to fully compensate for them without outside help, the delayed response of the network gives rise to a (sometimes annoying) helpfulness from the network after the crisis is already past. Where the crisis is so severe as to overwhelm the capacity of the focal individual to cope with it, help may come too late. In either case, the process of smooth interaction between person and environment and between person and social support network may be disrupted both by the crisis and by the delayed (and hence less than optimal) response to it. Such dynamics, most readers will agree, can be extremely consequential in human affairs.

To get a firmer grasp on the consequences of delay in feedback systems, let's construct an ideal-typical system and examine its responsiveness. We take as our starting point the goal-referencing negative feedback system we considered two sections ago, reproduced here.

```
L    Y.K = Y.J+(DT)(RI.JK)
R    RI.KL = ENVIRON.K+FEEDBACK.K
A    ENVIRON.K = f(X)
A    FEEDBACK.K = (PARM)(DISCREP.K)
A    DISCREP.K = Y.K-GOAL
C    GOAL = 50
C    PARM = - .75
```

One way in which delay occurs in human systems is that there is a slowness in perceiving the state of the system and changes in the state of the system. That is, humans are often slow to pick up the full magnitude of changes in their environment. We might model this phenomenon by modifying the equation describing the discrepancy in the above model to read:

```
A    DISCREP.K = DELAY1(Y.K,3)-GOAL
```

Delays might also be hypothesized to occur in responding to the state of the discrepancy, as well as in perceiving the state of the system. Let's suppose, for the purposes of illustration, that the system responds to the perceived discrepancy with latency (third order, or S-shaped delay), also having an average length of three time periods. Hence:

```
R    RI.KL = ENVIRON.K+DELAY3(FEEDBACK.K,3)
```

To get a sense for the effects of each delay and for the compounded effect of them both, we can design a series of simulation experiments. In the first experiment we create a "baseline" run by setting the system in equilibrium (that is, giving it a starting value equal to its goal value of 50 units). The system is a negative feedback one with an intensity of –.75 (PARM). After the third time unit we disrupt the system with an exogenous shock (the DYNAMO program for this set of experiments is appended). The results of this baseline are shown as the first panel in Figure 6.11.

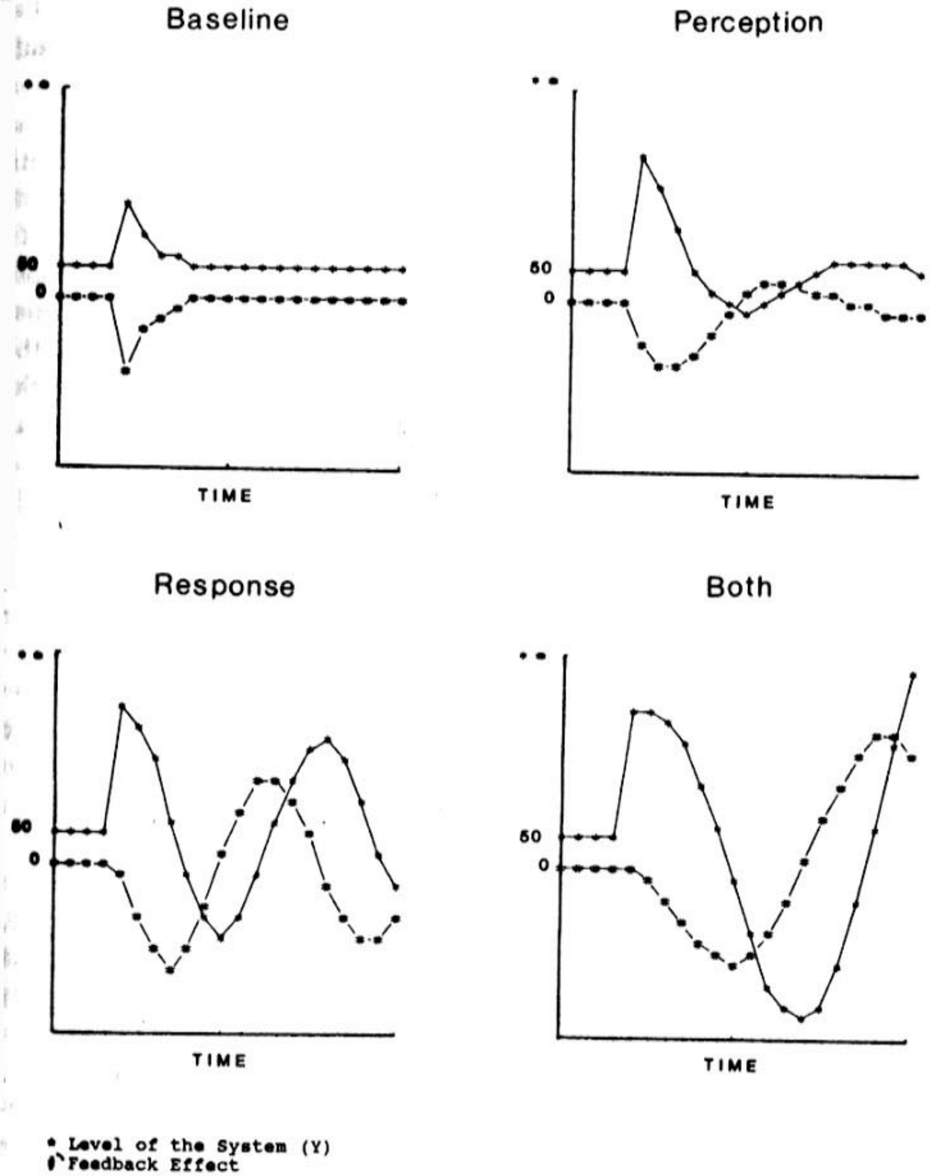


Figure 6.11: Feedback with delay.

The full value of the initial shock (which would have been to raise the system level (*) to 52.5 in a system without feedback) is dampened by the immediate negative feedback (#), so that it reaches a maximum of about 51.5. The negative feedback loop acts quickly to return the system to its initial level. After five time units have passed, the full effects of the initial shock have been almost completely removed, and the time-trace of the system level is essentially flat.

In the next panel of the figure we have added a delay of perception (of three time units average length), and repeated the experiment. The result is notably different from that of the same negative feedback system without delay. Because of the delay in perceiving the full extent of the shock, the initial negative feedback response is less in the system with delay, and, consequently the shock is more fully realized in the first time period (the system reaches about 52.25 at its maximum, as opposed to the 51.5 of the system without feedback). As the process continues, more interesting things occur. The control structure is always lagging behind the real status of the system (notice that the peaks and valleys of the feedback curve are two to three units later than the corresponding peaks in the system levels). As a result, the control structure takes the wrong corrective action, causing the system to overshoot its goal. In this case the system level not only returns to the goal state of 50, but actually drops below that level before recovering. Similarly, the feedback loop is initially negative (to compensate for the positive shock to the system), but assumes positive values (at about time points 10 to 15) to correct for its earlier overcompensation. A cycle of oscillating response is set off in this experiment as a direct result of delay in perception of the true state of the system. Note that the cycles of response show progressive dampening in this case. That is, the peaks and valleys become closer to the goal state the longer the system operates. While the system overcompensates, it does, eventually, approach equilibrium.

In the third panel of the figure we have repeated the experiment with only the delay of response but no delay of perception. Not surprisingly, the result is similar to that of the delay in perception. That is, oscillation and overcompensation are introduced to the system, and the cycles gradually dampen over time as the system approaches its goal state of 50.

The time trace of the response-delay experiment and the perception-delay experiments, however, are not identical. Both the initial response of the system to shock and the amplitude of the cycles (though not their period) are much greater in the response-delay experiment. Recall that the time shapes of the delay in perception and in response were specified to be different (that is, a first-order delay of perception and a third-order delay of response). Because the third-order delay responds more slowly at first than the first-order delay, the impact of the shock on the system is greater. Because this latency of response persists, the speed with which the system adjusts to its overcompensating mistakes is also slower, so cycles of overadjustment are more severe in the presence of this form of delay. The comparison of the second and third panels of the figure should suggest that the theorist's specification of the time shape of the relations among variables in dynamic systems is just as important as their choice about the form of the functional relations. Differing forms of time relations produce different time shapes in feedback systems, just as they do in stimulus-response systems.

Finally, let's see what happens when *both* delays of perception and delays of response operate simultaneously. These results are shown in the fourth panel of the figure. The consequences are striking, and important for thinking about human systems that often contain multiple sources of delay.

First, note that the system reaches a (slightly) higher level immediately after the initial shock in this experiment than in any of the others. The system is slow to perceive the full magnitude of the exogenous shock, as it was in the second panel; to this is added a slow response to the misperceived gap, as in the third panel. Consequently, the immediate response to the exogenous shock is additively dampened by the two delays.

Second, note that the period of the oscillations in the experiment with two delays (of average length of three each) is much greater (roughly double) than in the experiments with a single delay. Multiple delays in feedback loops interact multiplicatively to increase response times. From this fact follows the third important thing to notice about the results of the last experiment.

The system in the last panel of the figure is not approaching equilibrium over time. Note that the successive peaks and valleys of both the system level and the feedback process are further and further away from the goal level. As a direct consequence of the delay, a negative feedback system that would otherwise tend toward stable equilibrium now tends toward disequilibrium. In this case (though not generally for systems with multiple delays) the total delay is sufficient that the feedback loop tends to deepen each crisis, accentuating movements away from equilibrium.

Lest this seem a trivial and contrived example, it has been argued that federal monetary policy has, on occasion, suffered from the same type of dynamic. Efforts to slow inflation, because of lags in perceiving the rate of change in the economy and because of lags in implementing policy, may end up restricting money supply at the wrong time, leading to even more severe recessions than would have otherwise occurred.

The central points of this experiment are that the consequences of delay in feedback systems are fundamentally different from the consequences of delay in simple stimulus-response systems. Because action is self-referencing in feedback systems, misperception, latency, and other forms of lagged response tend to lead to distortions and overadjustments. This is because the effects of delays and distortions are multiplied through the system over time, just as all other signals are, by feedback loops. The consequences of delays for the dynamic tendencies of complex systems can in some cases be rather difficult to anticipate. If delays are of sufficient magnitude or of certain periods relative to the dynamic relations among variables, systems that would otherwise appear to tend toward equilibrium may not, and systems that may appear to have self-destructive tendencies may never realize them.

Conclusions

In this chapter we have examined the dynamics of a variety of abstract systems, ranging from very simple to slightly more complex. In particular, we have discussed a hierarchy of types of control structures of systems that can serve as an aid to thinking about, and building formal theories of social action.

The least complex systems considered here are those whose over-time behavior is due solely to responses to exogenous variables—what we have termed "stimulus-response" or "dumb" control structures. Conserved systems governed by stimulus-response control structures have distinctive dynamic tendencies that differ from those of systems governed by more elaborate control structures. Because of the operation of conservation, such systems respond to constant inputs with linear change, to trend input with exponential change, and to shock with stepwise change. "Delay" or nonlinearity in the time shapes of relationships in such systems result in varying degrees and forms of smoothed or dampened response to environmental changes. If the delays are of substantial magnitude, the system may never attain full realization of the impacts of environmental variables.

We also examined the dynamic behavior of systems governed by several more complex forms of control structures. The behavior of social actors may sometimes be more effectively captured if we regard the actors as self-referencing, goal-referencing, or even goal-setting, in addition to environment-referencing. The fundamental dynamic behavior of systems governed by structures of these types are fundamentally different from those of stimulus-response systems.

All more-complex control structures involve feedback. We have distinguished here between feedback that makes reference only to the current state of the system (self-referencing), feedback that makes reference to goal states as well as the current state of the system (goal-referencing), and feedback that modifies goals as well makes reference to them in controlling rates of change (goal-setting or adaptive systems).

The presence of feedback in the control structure of systems implies the multiplication and interaction of causal factors, as opposed to the simple addition of stimulus-response systems. That is, each change that occurs in a feedback system is also a cause of further change in the system.

Each loop (that is, feedback structure) can have a tendency to move the system toward a goal or away from a goal (the goal states themselves, of course, may be changing in the more complicated variants of feedback systems). The over-time behavior of feedback systems is fundamentally determined by the tendencies of these loops to move toward goal states (negative feedback), or to diverge from them (positive feedback). The behavior of a system governed by multiple feedbacks of both positive and negative characters as well as responses to environmental stimuli may be too complex to understand intuitively, but is decomposable into the interaction of the fundamental tendencies of the simple response and feedback response that make up the control structure.

Nonlinear causal relations and incomplete realizations—delays—also have different effects in systems governed by feedback than they do in stimulus-response systems. In feedback systems, delay in perception of change or delay in response to change can have nonintuitive effects. In negative (goal-seeking) systems, delay causes "overcorrection" and sets off cycles of oscillatory behavior. Usually such disruption slows the realization of movement toward equilibrium inherent in negative feedback loops; if the delay is sufficient in intensity, however, a tendency toward ever-deepening cycles can be generated.

We have, quite deliberately, kept the discussion of the dynamics of control structures at a very abstract level. It is quite important to understand the range of alternative types of control structures in the abstract because they are very useful "ideal types" that can be used by theorists in specifying the dynamics of patterns of social action of particular interest. It is quite important to understand the fundamental dynamic tendencies of these abstract systems to improve our understanding of the behavior of "real" systems, whether naturally occurring or artificial. As we shall see in the next chapter, interesting patterns of social action can be analyzed and theories about them built up from the application of these abstract tools with little difficulty.

Notes

1. The notion of "control" structures is central to all systems analysis and cybernetic thinking. The reader may be interested in examining some of the classic works in this tradition to get a sense of how

"systems" approaches use the notion of control as the basis for the classification of systems. See particularly Ashby (1958, 1962), Bayless (1966), Bellman (1961), Berrien (1968), Bertalanffy (1968), Cannon (1939), Foerster and Zopf (1962), Kremyanskiy (1960), Maruyama (1968), von Neumann (1951), Schank and Colby (1973), Schutzenberger (1954), Simon (1957, 1969, 1981), Sommerhoff (1969), and Weiner (1948).

2. There is no single consensual classification of types of control systems. The schema presented in this chapter is peculiar to the author, but is at least broadly consistent with the approaches of most writers in systems theory and cybernetics.

3. Theory and research on the development of single organizations and populations of organizations in management and sociology has advanced a number of interesting dynamic theories that emphasize relatively simple control structures. Some focus more on self-referencing growth, others more on exogeneous sources. For examples, see Anderson and Warkov (1961), Blau (1970), Cadwallader (1959), Campbell (1962, 1965), Cyert et al. (1971), Cyert and March (1963), Emery and Trist (1965), Haire (1959), Hummon (1971), Land (1975), and Simon (1947).

4. We have not provided the DYNAMO code for these simple experiments in appendicies (as we will do from time to time). The core of the models are as shown in the text.

5. The integrating, discrete, and continuous delay processes discussed here in terms of simulation methods are also dealt with statistically (Box-Jenkins, ARIMA, and Spectral models), and mathematically (stochastic processes and Fourier series). With regard to the latter, see Bartholomew (1973) and Doreian and Hummon (1976).

6. There are many excellent texts on the dynamics of feedback systems. Perhaps the most accessable to social scientists are those of Forrester (1968), Roberts et al. (1983), and Richardson and Pugh (1981).

7. Such models involve nonconstant coefficients, and are only now making their appearance in the statistical literatures in the various social sciences.

APPENDIX 6.1. Feedback and Delay Models

```
*            DELAY AND FEEDBACK EXAMPLES
NOTE
NOTE ALL FOUR SYSTEMS HAVE STRONG NEGATIVE FEEDBACK
NOTE SUCH THAT .75 OF THE DIFFERENCE BETWEEN THE CURRENT
NOTE STATE OF THE SYSTEMS AND THEIR GOAL STATES IS CLOSED
NOTE IN EACH TIME PERIOD. EACH MODEL IS INITIALIZED AT
NOTE EQUILIBRIUM AND THEN SHOCKED TO TEST TRANSIENT RESPONSE
NOTE
NOTE MODEL ONE IS SIMPLE NEGATIVE FEEDBACK
L            Y1.K=Y1.J+(DT)(RI1.JK)
N            Y1 = 50
R            RI1.KL = ENV.K+FEED1.K
A            FEED1.K = (-.75)(Y1.K-GOAL)
NOTE MODEL TWO HAS A FIRST ORDER DELAY OF 3 UNITS LENGTH
L            Y2.K = Y2.J+(DT)(RI2.JK)
N            Y2 = 50
R            RI2.KL = ENV.K+FEED2.K
A            FEED2.K = (-.75)(DELAY1((Y2.K-GOAL),3))
NOTE MODEL THREE HAS A THIRD-ORDER DELAY OF 3 UNITS LENGTH
L            Y3.K = Y3.J+(DT)(RI3.JK)
N            Y3 = 50
R            RI3.KL =ENV.K+FEED3.K
```

```
A        FEED3.K = DELAY3(((-.75)(Y3.K-GOAL)),3)
NOTE MODEL FOUR APPLIES A THIRD-ORDER DELAY OF 3 UNITS
NOTE LENGTH TO A SIGNAL THAT HAS A FIRST-ORDER DELAY OF 3
NOTE UNITS
L        Y4.K = Y4.J+(DT)(RI4.JK)
N        Y4 = 50
R        RI4.KL = ENV.K+FEED4.K
A        FEED4.K = DELAY3((-.75)(DELAY1((Y4.K-GOAL),3)),3)
NOTE THE ENVIRONMENTAL STIMULUS TO ALL FOUR MODELS IS
NOTE SET AS A PULSE OF MAGNITUDE 25 AT TIME 3
A        ENV.K = PULSE(25,3,50)
NOTE THE GOAL STATE FOR ALL FOUR MODELS IS SET TO BE EQUAL
NOTE TO THE INITIAL LEVEL OF 50 UNITS
C        GOAL = 50
NOTE OUTPUT SPECIFICATIONS
SPEC DT =.1/LENGTH =20/PRTPER = 1/PLTPER = 1
NOTE INTEGRATION INTERVAL IS SET TO 1/10 TIME UNIT.
NOTE SMALLER INTEGRATION INTERVALS ARE NECESSARY
NOTE TO ATTAIN ACCURACY IN SYSTEMS WITH DELAYS
NOTE THE SIMULATION IS TO RUN FOR 20 TIME UNITS
NOTE TABULAR AND PLOT OUTPUT IS TO BE PRODUCED FOR
NOTE EACH TIME POINT
PRINT Y1/Y2/Y3/Y4
NOTE PRINT VALUES FOR THE OUTPUT SERIES
PLOT Y1 = *(46,56)/FEED1 = #(-2,4)
NOTE PLOT Y1 USING THE * SYMBOL ON A Y AXIS WITH 46 AND 56
NOTE AS MINIMA AND MAXIMA. ON THE SAME PLOT, PLOT FEED1
NOTE WITH THE SYMBOL # WITH -2 AND 4 AS MINIMA AND MAXIMA
PLOT Y2 = *(46,56)/FEED2 = #(-2,4)
NOTE PRODUCE A SIMILAR PLOT FOR MODEL TWO
PLOT Y3 = *(46,56)/FEED3 = #(-2,4)
PLOT Y4 = *(46,56)/FEED4 = #(-2,4)
RUN
```