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Complexity and Analyzability: Understanding Dynamics by Simulation

At a number of places in the preceding chapters the term "complexity" has been used to refer to social phenomena and to the theories that we would construct about them. Patterns of social action and interaction that involve change over time are inherently more "complex" than patterns that do not change, or are considered at only a single point in time. The theories that are used to understand and make generalizations about dynamic patterns consequently tend to be more "complex" than theories of systems in equilibrium or theories that describe patterns of covariation across systems at a single point in time.

The complexity of phenomena, and the complexity of the theories that we create to understand the phenomena, have consequences for how we can go about understanding the full implications of our efforts at theorizing. Some theories are fully comprehensible by logical deduction (using either "common sense" or more formal means.[1] Many others (particularly when stated in mathematical forms such as linear differential equations or structural equations) can be quite fully understood by direct solution.[2] Many of the theories that are constructed to describe the dynamics of social action and interaction, however, are too "complex" to be understood by these means. One of the main reasons for formalization of theories about dynamics utilizing semimathematical languages is to enable us to apply an alternative tool for analyzing and understanding our theories-simulation.

In this chapter we will first take a somewhat more rigorous look at the notion of the "complexity" of a theory and examine why this raises problems of analyzability. We will then look at how simulation methods can be used to analyze and make deductions from complex theories. This discussion has two parts. First we will briefly examine the logic of

"understanding by simulating," then we will discuss strategic approaches to simulation analysis.

Complexity and Analyzability

The term "complexity" has a rather clear meaning within systems analysis.[3] Now that we are in command of the basic systems language of "state spaces," "connectivity," and various functional and time relations among states, we can provide a definition that is sufficient for our purposes. A system may be said to be more complex than another if it contains more elements in its state space than the other; it may be said to be more complex if the states in its state space may take on more values than the other (e.g., continuous state systems are more "complex" than discrete state systems); it may be said to be more complex than another if the elements in its state space are more extensively interconnected than those of the other; and, a system is more complex to the order of the functional forms connecting the states to one another (i.e., a relationship described by a complex polynomial is more "complex" than one described by a simple linear equation). Finally, a system is more complex than another if the time-shapes of the relations among the states are of higher order (e.g., a system connected by relationships involving third-order delays is more "complex" than one involving simple continuous integration).

The logic behind all of the dimensions that lead to increased "complexity" in the definition above is this: A system is complex to the degree that we must have more information in order to be certain about (that is, to make accurate predictions about) its behavior. Simple systems are capable of only a limited variety of possible behaviors; hence it is rather easy to predict their response to any given stimulus. More complex systems are far less "analyzable" because they are capable of producing a larger variety of responses to stimuli. This range of possible behaviors is frequently termed the "degrees of freedom" of the system, analogously to the statistical use of the term: Less information is necessary to make accurate predictions about the dynamics of simple systems than complex ones.

Formal theories about social action and interaction can be regarded as systems (in this case, systems composed of symbols and relations among symbols) of varying complexity, just as can the social phenomena they mimic. Theories are simpler if they have smaller state spaces (fewer concepts), are conceptualized qualitatively rather than quantitatively, have relatively few "laws" governing the connections among concepts

(e.g., a "causal chain" is "simpler" than a "path model"). Theories are simpler if they posit relations among terms that are easily characterized (e.g., "if-then" or $Y = a + bX$) rather than more difficult to describe (e.g., "if X is a and not b, then Y is c, or $\ln(Y) = \sin(X)$). And theories are simpler if they describe relations that occur over time in simple fashions (e.g., statements about covariation at a time point are "simpler" than statements about the effects of prior changes in one variable on subsequent changes in another).

We need no special intellectual tools to comprehend the meaning of, and make deductions from, simple theories. Syllogisms with only a few terms or single linear equations are "obvious" in their meanings and implications.[4] Slightly more complex theories are still amenable to direct analysis if we can learn to use certain tools. Quite complex lines of qualitative relations can be parsed using the rules of formal logic; most linear and some nonlinear simultaneous equation multivariate models can be directly solved with calculus and persistence.

Truly complex theories, however, often exceed our capacity to comprehend them. The effects of changing one variable may be almost impossible to trace if that variable is interconnected in complicated and dynamic ways with large numbers of others that are themselves connected. In many cases the available mathematical and logical tools are simply insufficient to give determinant answers to questions about the consequences of changes in variables and the overall behavioral tendencies of the theory under various conditions.

Because theories about dynamics must specify relations in time, as well in functional form, they tend toward complexity. It is in circumstances of this kind of complexity that simulation methods are often used in the physical and social sciences to understand and work out the implications of theories.

Understanding by Experimentation:
The Logic of Simulation

A "simulation" is usually defined as a construct that has the appearance or form, but not the substance of some real object.[5] In a certain sense, all theories about social action and interaction are simulations—theories are artifacts designed to mimic (albeit in highly selected and abstracted ways) characteristics of real social action.

Both social and physical scientists routinely employ simulations in the study of complex dynamic relations.[6] Meteorologists create artifacts (usually computerized models) designed to mimic the interactions of

temperature, pressure, humidity, and other factors over space and time. Ecologists describe the rise and fall of populations of various species in changing environments over time. Political scientists create models that mimic swings in voter sentiment; economists seek to mimic trends in investment, consumption, interest rates, and the like. In all of these cases it is the simulation (the theory or model) itself that is the focus of attention. In a certain sense, the scientists are studying the simulation as a way of attempting to understand the reality that it (supposedly) represents.

It is misleading to think of "simulation analysis" as a single thing. In fact, there are three distinctive and separate activities that are all often called "simulation": making projections, validating theories, and analyzing theories. When the economist makes a prediction about the course of interest rates over the next quarter by projecting forward from current values of a dynamic model of the economy, (s)he is "simulating." This type of use of dynamic theory involves the application of a theory that has already been constructed and validated, and is not our focus in this volume. When political scientists create a dynamic theory of trends in voter sentiment, substitute known values and parameters from a real case, and make "postdictions" about election outcomes they are "simulating."[7] In this case the object of the exercise is to assess the validity of the theory that gave rise to the simulation model. This use of simulation for validating models is also outside our interest in this volume.[8]

The third use of simulation, and probably the least well-understood use, is for analyzing and constructing theories themselves. This is the application of simulation method that most concerns us here. Social science theories that involve extremely large state spaces with complex functional and time connectivity among the elements can rapidly exceed the capacity of the analyst to comprehend the implications of the theory. This is particularly true for theories involving dynamics where nonlinear and feedback relations exist. To explicate such theories, explore their implications, and make deductions from them, simulation methods are often the only available alternative. The use of simulation methods for this purpose is different from the questions of application and validation of the theory. In this application, simulation is used to answer such questions as: Does a pattern of small group interaction embodied in the formal theory have tendencies toward equilibrium, or not (or more properly, for what ranges of values of state space elements and relations among them does the theory display equilibriating behavior)? Which political parties have the largest impact on the overall behavior pattern of coalition formation in a model of legislative dynamics? Which

exchanges among the business firms in a model of a local economy are the most critical ones in producing the over-time behavioral tendencies of the model?

Where the purpose of the application of simulation methods is to understand the theory itself, the logic of the inquiry is a familiar one. We are attempting to build an understanding of an artifact by experimentally subjecting it to known stimuli and observing the consequences. With carefully designed programs of experimentation it is often possible to obtain quite sound "approximate solutions" to the behavioral tendencies of even the most complex and nonlinear of theoretical systems.

In thinking about very simple theories such as $Y_{t+1} = bX_t$, we can "simulate" the dynamics without any special aids. That is, we can ask and answer without difficulty such questions about the dynamics of this theory as: How does Y behave over time if X is a constant? What is the responsiveness of Y to changes in X? Under what circumstances does Y reach a steady state? In asking and answering these questions, we are simulating the theory. That is, we are subjecting the theory (in this case a simple linear equation with a lag of one time unit) to a series of mental experiments. We "plug in" values for X (e.g., X is a constant, X varies randomly, and so on) and calculate the implications for the time track of Y. We can also, of course, "understand" the implications of this theory by direct solution of the mathematics: A steady state in Y is attained, according to this theory, only where X is a constant, the response of Y to X (at lag of one time unit) is precisely B, and the value of Y at any time point can be calculated if we know the value of X at the prior time point.

If our theory was somewhat more complex, involving, say, a system of several simultaneous linear differential equations, the implications would be more difficult to work out in one's head and we might have to resort to some calculations. We might proceed by altering the values of each of the variables one at a time and observing the consequences for other variables. A small system of simultaneous linear differential equations can also be "understood" by direct solution: The equilibria of such equation systems can be directly calculated (if they exist), and the values of partial derivatives are informative about the questions of the relative importance of variables. Despite the different technology, we are still striving to understand our theory and work out its implications by simulating it, just as we were when all the necessary calculations could be done in one's head.

When the theory that we are trying to get a grasp on is still more complex, as when there are multiple actors with multiple states coupled together in nonlinear fashion, we can use simulation methods to understand its implications. As in the simpler cases above, the logic is

straightforward. We systematically vary the values of state space elements and the relations among them and observe the consequences for the behavior of the model over time. In complicated models, of course, we may never be able to achieve a full comprehension of the system's behavior because the variety of possible system states and relations becomes very large very quickly. We can, however, derive approximate solutions.

Simulation, then, is simply a method of understanding by experimenting with an artifact. Theories about the dynamics of social action and interaction are "artifacts," and one method for understanding them is to experiment with them or simulate them. "Complex" theories, particularly ones involving statements about relations that operate over time, can often be understood only by such experimentation, since they exceed our capacity to comprehend their meanings by "common sense" or direct solution.

By their very complexity, however, theories about the continuous-time continuous-state dynamics of social action also suggest an infinite range of possible "experiments." What does one really need to know in order to "understand" a theory of this type? And how can we design "critical experiments" with our theories to reach this understanding?

Simulation Strategies for Analyzing Complex Theories

Social science theories formulated as continuous-state continuous-time dynamic models can very easily become so complex that the optimal strategy for working with them is computer-assisted simulation. Indeed, one major reason for the formalization of such theories into "semimathematical" languages is to allow computers to do the tedious and mechanical calculations necessary to understand the full implications of our theoretical models. The mechanics of using computers to perform simulation experiments are, for our purposes, rather uninteresting. What is of interest for our purposes is the question What should we ask the computer to calculate? That is, what questions do we want to ask in order to analyze our theory and how can we design the necessary critical experiments (in this case, the "experiments" being simulations of the model on the computer)?

One kind of question that we might want to explore by simulation consists of "what if . . . " speculations. What if, for example, there were no middle-aged people at a certain point in time in the simple population model we discussed in Chapter Two? What would the time-trace for total population size look like under this circumstance, as opposed to a

circumstance in which the middle-aged population was initially set at some "normal" level? What if half of the male population were destroyed by a war at a certain point in time; what would the long run consequences be?

These kinds of experiments to explore the implications of theories about dynamics can be very informative. Indeed, one can test a theory and sometimes make reasonable decisions about competing specifications for it on the basis of such experiments. We might, for example, have in mind two alternative specifications of how actors in competition with one other respond to one another's behavior. While holding everything else constant, we can explore the over-time behavior of the interaction between the competing parties under the alternative specifications of how the process works (that is, examining some of the consequences of specifying a different form of relations among state space elements). Let us suppose that our experiment with the first specification of how actors interact yields a pattern of exponential escalation of conflict between the actors, while our second specification yields a pattern of a waning exponential decline in conflict levels. We have not, by this experiment assessed the empirical validity of either of the theories; we have, however, learned that one or the other is a better specification of what we really meant to say about this aspect of our theory.

"What if . . ." kinds of experiments with theories can be very valuable and can be used to make informed decisions about alternative specification of the theory. Such experiments, however, tend to be rather unsystematic. It is also important to subject any dynamic theory to systematic experimentation. In addition to examining specific "realizations" of the theory to explore specific questions, there are three kinds of "general" questions that should be explored: equilibrium tendencies, sensitivity, and transient response. Each of these general questions can be addressed by particular programs of experimentation with the theory.

Equilibrium

One of the most important things to explore about a theory is the type of behavior over time that it implies. There are two different but closely related questions here: questions of the equilibrium behavior (that is, loosely, the "long-run" tendencies) and questions about the transient response, (loosely, the "short-run" behavioral tendencies).

There has been an unfortunate tendency in the social sciences for theorists to confuse the notion of the "equilibrium behavior" of systems

with assertions that (a) social systems do indeed have stable equilibria, (b) that observed social patterns, particularly ones that don't seem to be changing very much at the moment, are "in equilibrium," and (c) that such equilibria represent "desirable" adaptations."[9] Each of these assertions may or may not be true with regard to a particular pattern of social action. Examining the equilibrium behavior of a theory of social dynamics does not imply the acceptance of any of these assertions.

Exploring the equilibrium tendencies of a system is equivalent to asking what the time traces and final levels of the elements of the state space are under a particular set of fixed (and unchanging) initial conditions. For example, we might wish to know what the final level for the size of the total population is, given a particular age structure, fertility pattern and mortality pattern. If births exceed deaths, of course, population does not reach a "stable equilibrium." We are asking a particular kind of "what if . . . " question in equilibrium analysis: What if the initial status of the state space were fixed, the parameters of the model held constant (that is, the relations among the elements of the state space), and no external or exogenous shocks occurred.

For any particular specification of the levels of the elements of the state space and relations among the elements, we are usually interested in two things about the "equilibrium tendencies": whether the system does, in fact, approach a steady state (that is, a condition where the levels of the variables do not change with respect to time); and what the "time-traces" of the variables look like over time (that is, do they approach their limits, if any, linearly, by some monotonic function, or do they oscillate or behave in some unstable fashion). Where models do reach a stable equilibrium, we may also be interested in the actual level of the state variables at equilibrium as well. Where models do not reach a stable equilibrium, we may with to assess these levels at some fixed point of time.

The methodology for determining "equilibrium" results by means of computer aided simulation is obvious and simple. The initial values of the state space element are set at the desired levels, all sources of "exogenous" shock or change in the model are eliminated, and the results of the operation of the model are calculated for as long a period of time as is necessary. That is, the model is simulated until the values of the state space elements stop changing at some desired level of accuracy, or until the failure to attain a steady state becomes obvious.

Usually we are interested in still more general questions than whether stable equilibrium is attained, at what level, and by what time path for a particular set of initial conditions. The really interesting questions about the equilibrium tendencies of a theory are not limited to a particular

"realization," but rather are the following: Under what conditions is stability attained? Under what conditions are the time paths of variables "smooth"? Many fairly simple models, and particularly models with linear relations among state space elements have "general equilibria." That is, they display very much the same time-traces and final conditions of stability regardless of the particular levels of the variables at the initial time point. Models with nonlinear connections and feedbacks, however, do not always produce the same kinds of over-time behavior when they begin at different initial levels.

To answer these more general questions, the theorist must design and execute a set of experiments with his or her model. In principle, each element of the state space must be systematically varied through its entire range while holding all other variables constant, then while varying each other variable in a systematic fashion, then each pair of other variables, etc. In each case, the model is run to its stable result (or to a fixed time point, if it does not display stability). In principle, if all of the resulting information could be comprehended, a general solution about the equilibrium limits of the theory would be obtained. That is, we would know under what conditions the theory predicted what kinds of stable or unstable realizations.

In practice, such a program of systematic experimentation is usually both impractical and unnecessary. For models of any complexity, the number of alternative sets of initial conditions is ridiculously large. It is not worth the time and trouble to generate all of the possible results and it is doubtful that we could summarize them in any meaningful way if we could generate them. A better strategy is to think first, and design a more intelligent program of experimentation. There are several useful guidelines. (1) Most variables vary in fairly narrow ranges, and we probably have little interest in the implications of the theory for conditions that are not likely to ever be observed. (2) If we consider that variables in the state space tend to covary, many of the possible combinations of initial conditions can also be regarded as less useful, even if they fall within the plausible ranges for each variable. (3) While the overall behavior of the model may be quite complex and nonobvious, portions of the model may be very simple and straightforward. There is no need to go excessive lengths to explore obvious relationships (but be careful, not all that appears obvious in complex models, is). (4) Finally, we can restrict our attention still further by focusing on variables that are more central to the theory. Elements of the state space that are more closely coupled with more other elements of the space are likely to be more consequential in determining the equilibrium behavior of the system; elements of the state space that are connected to only a small

number of other elements are likely to be less consequential.

By thinking first, then, the exploration of the equilibrium conditions of a theory can be considerably simplified. By focusing on the most "central" (in the network sense of the term) elements of the state space, by bypassing obvious relationships, and by limiting the ranges of initial conditions considered, a pretty good picture of the general long-run behavior implications of the theory can be had. This solution to the problem of assessing the equilibrium tendencies of complex models generates decidedly "approximate" solutions and understandings. In complex theories, however, approximate understanding of the implications of the theory may well be all that is possible. In many circumstances, particularly in the early phases of constructing and examining alternative theories of social dynamics, approximate understanding of the equilibrium bounds of the theory is all that is necessary.

Sensitivity

Exploration of the conditions under which a theory implies stability or continuing change in the long run is a special case of "sensitivity" analysis. More generally, "sensitivity" analysis is an attempt to assess which variables or relationships are the most consequential for determining the over-time behavior of the system. Returning very briefly to our simple population model in the earlier chapters we might ask whether adding an additional young person to the population or adding an additional old person to the population has greater consequences for the total size of the population in the future (the answer, fairly obviously, is that adding a young person does, because of the implications for the birth rate). Alternatively, we might wish to compare alternative assumptions about the parameters of the system. For example, we might want to know whether a 5% increase in birth rate or a 5% decrease in the death rate has greater implications for the size of the population in the future. In each case we are asking which variable is "more important," or how "sensitive" the over-time behavior of the system is to change in particular quantities or relationships.

As in seeking to understand the long-run or equilibrium implications of our theory, sensitivity analysis calls for an intelligently planned set of simulation experiments. Again, in principle each variable or relationship or interest should be systematically varied throughout its range while holding all the other variables and relationships in the system constant at each of their possible levels. The consequences of each change in the variable or parameter of interest for all other system states at some future time point could thus be systematically assessed. Again in

practice such an exercise is, if not impossible, usually wholly unnecessary.

The same principles of design hold for a set of experiments with the sensitivities of variables and parameters as hold with exploration of questions about equilibrium. Variables and relationships that are most "central" to the theory deserve more attention than those that are less connected. There is little point in exploring the sensitivity of the model to implausible levels of states or implausible combinations of state levels. Many relationships may be quite simple, even if the theory as a whole is not, and hence need less attention. Variables that have very limited interactions with others in their consequences, for example, are much easier to understand than those involved in complex feedback relations (a corollary of the centrality principle).

Good judgment is necessary in deciding how much effort should be devoted to assessing the sensitivity of the whole theory to change in particular variables and relationships. Usually a good sense of the "relative importance" of variables can be had by examining the connectivity of a theory, and confirmed by relatively simple simulation experiments. Once key relationships or variables have been located, more detailed experiments can be conducted by varying the variable or relationship in question systematically across its useful range at selected levels of other variables.

As in the case of the analysis of the equilibrium bounds and behavior of the theory, the analysis of sensitivity by simulation experiments generates "approximate solutions." Such solutions may be the only possible ones for very complex theories. In most cases the approximations to understanding of sensitivity by simulation are "good enough" for purposes of developing theories and for comparing alternative theories.

Transient Response

Equilibrium analysis and sensitivity analysis of a system are efforts to answer the general questions: What are the long-run behavioral tendencies of the dynamics specified in the theory? and Which variables and relationships are the most consequential for determining the over-time behavior of the system? The answers to these basic questions tell us a good deal about the general plausibility of a theory of social dynamics. In both equilibrium and sensitivity analysis, however, our attention tends to focus on the "long-run" or "final" consequences of the network of assumptions that is the theory. While these are very important things to understand about the theory, we may also be interested in the

behavior of system in the "short-run," and in the analysis of immediate rather than ultimate consequences of changes in variables.

Transient response analysis examines what happens when the system is subjected to stimuli. Its primary purpose is to trace the cycle of consequences resulting from a change in one part of a complexly connected system, and thereby to gain an understanding of the forces underlying the behavior of real systems in which many stimuli are constantly "shocking" the system.

The nature of the experiments that are conducted to examine the transient responsiveness of models follow from this intent. First the model is allowed to run to its steady state for some particular set of initial conditions; if no such steady state exists, some "baseline" realization of the system is used as the starting point instead. At this point the variable or parameter of interest is subjected to a stimulus with known characteristics (usually a PULSE, or a STEP, in DYNAMO terminology), and the pattern of change in the other variables in the system is traced as the response occurs along the pathways connecting the variables of the system.

Returning one last time to the simple population model of the earlier chapters, we might conduct a transient response analysis in the following way. First, to establish a baseline a certain set of initial conditions of the state variables and a certain set of initial conditions and a certain set of parameters (i.e., birth rates, death rates, etc.) could be specified, and the particular realization of the model calculated. The population model is one that does not attain a steady state across plausible levels of most variables, so transient response analysis is done on a "baseline" realization. Next, we might "schedule" a "war" to increase the death rate tenfold for a one-year period after some period of time, and rerun the model, making no other changes. We could then compare the results of the two realizations to attempt to understand the time shape of the system's response to changes in the death rate. In the population model this kind of transient shock reduces total population at all future points in time and creates oscillations in the time path of the model as well.

The analysis of transient response is an important step in understanding most dynamic theories. Where elements in the state-space have complex over-time relations (delay and feedback), transient response testing provides the major device for understanding the process of change implied by the specification. Sometimes the theorist will find unanticipated consequences of their assumptions in exploring transient responses. In designing a program to assess the transient response characteristics implied by his or her theory, the analyst must again use

good judgment and the principles of design that have been discussed with regard to equilibrium and sensitivity analysis. The range of alternative experiments that could be done to understand the processes of change in any dynamic theory of even moderate complexity is very great. Again, however, good judgment and careful experimental design can often yield very good "approximations" to understanding with relatively little effort.

Conclusions

Theories of the kinds of dynamics of interest to social scientists can rapidly become complex enough to require special aids and tools for their understanding, as well as for their construction. In this chapter we have examined how complexity in dynamic theories arises, and examined one strategy—simulation—for understanding and analyzing complex theory.

Complexity in theories arises from the number of elements of the state space, the range of values that can be taken by state space elements, the degree of connectivity of the state space, and nonlinearity in the functional and time-shapes of relations among state space elements. Many, though by no means all, theories of the continuous state continuous time dynamics in the social sciences are of sufficient complexity that they exceed our capacities to understand their full implications "intuitively" or by means of general (e.g., mathematical or logical deductive) solutions.

Simulation of realizations of such theories can often provide approximate solutions that are sufficient for our purposes. One major reason for the formalization of theories about dynamics is to enable the use of computers to calculate the results of large numbers of simulation "experiments" with theories.

In addition to experiments with theories that explore particular realizations (i.e., particular sets of values of variables and forms of relationships among them), strategies of "research on theory" can be designed to create approximate general understandings of complex theories. Most particularly, programs of systematic simulation experiments can be designed to understand the "equilibrium," "sensitivity," and "transient response" implications of theories. Fully determinant answers to questions about long-run and short-run behavior implied by the theory, and about the relative importance of particular assumptions are not possible with simulation methods. In most cases, however, careful and thorough application of principles of experimental design

can yield a program of experimentation that provides information sufficient to our needs.

Notes

1. On methods for the formal analysis of theoretical systems by the application of logical rules, see particularly Dubin (1969), Hage (1972), Hearn (1958), Reynolds (1971), Stinchcombe (1968), and Willer (1967).

2. For some exemplary discussions of direct solution methods for analysis in social science applications, see Abelson (1967), Blau (1970), Blalock (1969), Caplow (1968), Cohen (1962), Coleman (1964a, 1964b, 1966, 1972, 1973), Davis (1967, 1972), Fararo (1972), Hamblin et al. (1973), Hummon (1971), Kassarda (1974), Kemeny and Snell (1962), Land (1970, 1975), Leik and Meeker (1975), Rapoport (1960, 1966); and Rapoport and Chammah (1965). Some outstanding examples of the approach in other kinds of systems analysis can be found in Braun (1975), Hall (1962), Luenberger (1979), and Takacs (1962).

3. There are a large number of excellent works in both the "general systems" tradition and in the disciplinary social sciences that devote extensive discussion to the meaning and implications of systems complexity. My list of favorites includes Ashby (1952, 1958), Baumgartner et al. (1976), Burns et al. (1985), Boulding (1970), Brunner and Brewer (1971), the essays in Foerster and Zopf (eds., 1962), Perrow (1984), Kochen and Deutsch (1980), Lange (1965), Mesarovic and Macko (1969), Pattee (1973), Schank and Colby (eds., 1973), Simon (1965, 1981), Sommerhoff (1969), Weaver (1948), and Weiner (1948).

4. Actually, this must not be entirely true. A fair amount of training is necessary for the proper application of even "simple" deduction or for comprehending the "simple" linear equation.

5. Perhaps the most interesting discussion of the nature of simulation models are contained in the essays of Abelson (1968) and Simon (1969, 1981).

6. For discussions of the application of simulation methods in various social science disciplines, see particularly Abelson (1968), Alker and Brunner (1969), Bloomfield and Padelford (1959), Brody (1963), Coe (1964), Cohen and Cyert (1965), Cole et al. (1973), the essays in Dutton and Starbuck (1971), Federico and Figliozzi (1981), Guetzkow et al. (eds., 1972), Guetzkow and Valdez (eds., 1981), Laponce and Smoker (eds., 1972), Levin (1962), Malone (1975), Marshall (1967), McPhee et al. (1971), Meier et al. (1969), Orcutt et al. (1961), Patten (1971), and Schmidt and Taylor (1970).

7. For an excellent example of this type of validation exercise in political science, see Brunner and Brewer (1971).

8. The topic of empirical validation of dynamic theories by simulation methods is widely discussed in a number of disciplines, ranging from applied statistics to management and economics. The interested reader can get an introduction to this literature by looking at Chorafas (1965), Coleman (1964), Deutsch et al. (1977), Dutton and Starbuck (1971), Emshoff and Sisson (1970), Federico and Figliozzi (1981), Hermann (1967), Martin (1968), Mihram (1972), Mize and Cox (1968), and Naylor et al. (1965).

9. The debate in sociology has been particularly bitter as "systems" approaches have been confounded with politically conservative policy positions and structural-functional theorizing. The debate sheds a good deal more heat than light, but for the interested reader a good introduction is provided by the essays in Demerath and Peterson (eds., 1967) and an article by van den Berghe (1963).

Part II

The Dynamics of Simple Systems

If we applied the definition of "complexity" that we developed in the previous chapter to the formal theories of social dynamics that have most concerned social scientists, we would classify these models as quite "simple." Most dynamic theorizing in the social sciences focus on the behavior of systems with relatively few states, low connectedness, and relatively simple functional and time relations. Perhaps the largest group of processes that have received attention involve only a single "dependent" state. Many others involve chains of a few states that are coupled together in very simple ways, very few involve extensive feedback or other complexities in their relationships among variables over time.

Simple systems, we must hasten to point out, are not trivial. Indeed, the "simple" systems that we will examine here have dynamics that are of extreme importance. The dynamics of growth, diffusion, contagion, population movement, and mobility are all quite effectively modeled (at least in "baseline" form) as consequences of quite simple dynamic systems. These dynamic processes are central to our understanding of economic, political, and socio-cultural phenomena. Simple models are widely applied with great profit in all of the disciplinary social sciences.

One goal of the chapters in this section is to reexamine these processes (all of which are treated extensively in the statistical and mathematical literatures as well) within the framework of dynamic "systems" developed in the previous section. These exercises will clarify the nature of the systems approach and its formal language, improve our understanding of some of the most common dynamic theories in the social sciences by translation into this language, and suggest ways in which a wide array of theoretical problems might be attacked as "simple systems."

There are two other reasons for spending a good bit of time with "simple" systems, in addition to the central role that such systems have as theories in themselves. Both of these reasons have to do with how we can go about constructing and understanding theories of systems of greater complexity.

"Simple" systems are the component parts of complex ones. To construct theories of complex social dynamics, or to analyze theories of

high complexity, it is necessary to have a firm grasp on the behavior of their component parts. To choose a simple example, one cannot understand the dynamics of the transmission of a message in a social network without having a grasp of how the individuals composing the network receive, process, and send information. The dynamic behavior of the network (a more complex "system" composed of "subsystems"— the actors plus the relations among them) is not reducible to the characteristics of the individuals in the system; but the behavior of the network is not intelligible without understanding the characteristics of the individual actors. All of the elements of even the most complex systems are, in themselves, quite simple, and we will examine these elements in the chapters in this section. Understanding the dynamics of these simple systems is a necessary, but not sufficient, condition for constructing and understanding theories about the dynamics of more complex systems.

In addition to being "building blocks" for more complex models, we can make a good deal of theoretical progress by tinkering with simple models and making them "slightly" more complex. Using the language of system dynamics and the method of analysis by simulation, we need not be as restrictive in our assumptions about the dynamics of simple systems as we would be if we were using statistical or mathematical models.

Statistically formulated statements of theories most often assume that the populations they describe are homogeneous (i.e., all individuals in a given population are equally probable to be subjected to a stimulus in a period of time and all individuals have the same probability distribution of responses to stimuli). It is sometimes useful to elaborate such models by creating multiple populations. In models of movements between occupational statuses, for example, one early approach to dealing with the poor fit of simple Markov processes was to divide the population into "movers" and "stayers." We will take a look at how relaxing homogeneity assumptions can provide greater insights in simple dynamic processes.

Theories of the dynamics of simple systems have also often assumed that the functional relations among variables are linear (or log-linear, in some cases), and that the processes are time homogeneous (i.e., they involve smooth integration, rather than lag and delay). Such assumptions are necessary for the successful application of statistical and mathematical methods to the verification and analysis of the theory, but are not necessary if the "approximate" solutions available by simulation are sufficient. We will also consider some of the ways that more relaxed assumptions about the forms of relations among variables and over time can lead to greater insights about the dynamics of simple processes.

Baselines

Before we make our theories about the dynamics of "simple" systems "slightly" more complex by adding nonlinearity, more complex time relations, or population heterogeneity, the "baseline" models should be thoroughly understood. In many cases, the highly simplified "baseline" models of diffusion, growth, and other similar processes do remarkably well in accounting for the essence of the dynamics, and additional complexity may not be worth the effort.[1] Even if increasing the complexity of such theories does contribute to improving our understanding, we must compare them to simpler baselines to determine "how much" better the more complex theory is. Thus even if the intent of the theorist is, ultimately, to create a complex model, it is best to start simple.

Increasing Complexity of "Simple" Systems

The simplest of all continuous time, continuous state models is quite easy to envision. It involves a single state, a single rate, and a simple signal, as in Figure II.1.

This model says that the level of Y accumulates from a source at the rate B. The speed of this process is governed by a random process. What makes this model so "simple" is that it involves only a single "level," and the process describing the rate of change in this level (i.e., the "rate") is a single and simple signal (random "white noise," in this case). The behavioral possibilities of the model in Figure II.1 are not very interesting. We will, however, spend a few minutes with it later because of its importance as a "baseline."

In increasing the complexity of this model to the point where it can usefully represent social dynamics, we can move in either of two directions. In practice, we usually move in both, but is useful to keep a conceptual distinction: (1) the number of states and flows among them can be increased, or (2) the complexity of the control structures governing these flows can be increased. That is, in different terms, we can consider either "more variables" or "more complex relationships" among them.

Consider the modification of Figure II.1 shown in Figure II.2.

In Figure II.2, the theory has become more complex by the addition of more independent variables and more complex relations between the independent variables and the single material state (Y). Roughly translated, the theory in Figure II.2 could be stated as follows. The level
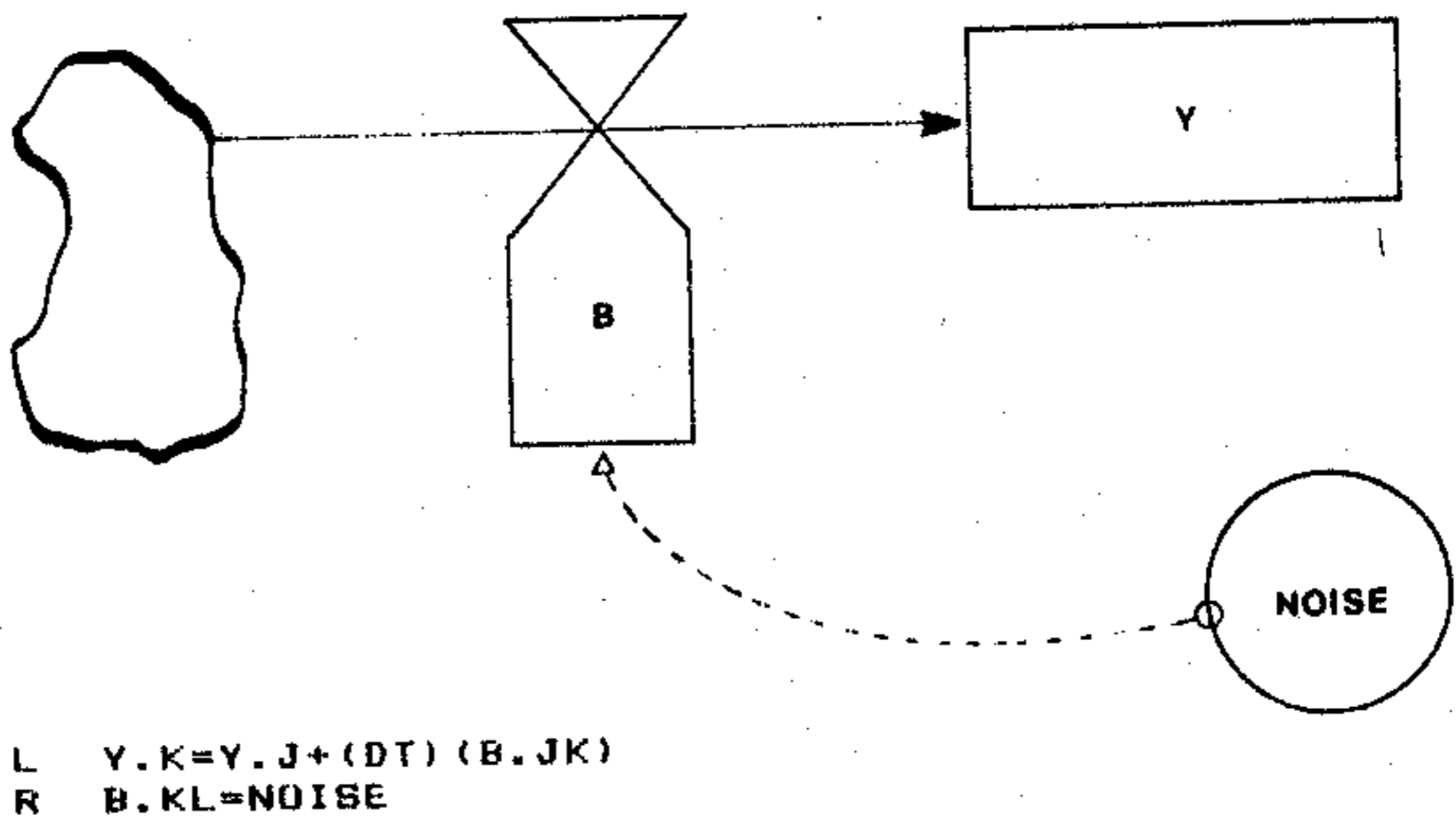
```
L    Y.K=Y.J+(DT)(B.JK)
R    B.KL=NOISE
```

Figure II.1:   Simple baseline model.

of Y changes over time at rates (B) proportional to the discrepancy (D) between a goal (G) and the current state of the system (Y). However, the response involves delay of an average duration of one period and having the shape of a third-order exponential (DELAY3,1). The discrepancy between the goal and the current state of the system might be calculated as a simple difference (D = G - Y). Goals, however, might be set as a function of a level of motivation (MM) and the current level of the system (Y), in some complex way. For example, the goal at any point in time is some fraction (determined by MM) of the current status of the system.

In this case, the "control" system displays considerable complexity. Indeed, the control structure could be said to represent a structure that is "self-referencing" and "goal directed"—that is, the rate of change in Y depends on the level of Y, and the action taken (B) is a function of a comparison of the current state of the system to some goal, and the goal is itself variable according to the state of the system.

This kind of elaboration of a simple system is of considerable importance in the study of human behavior. While many dynamic processes may be modeled with quite "simple" or "dumb" control structures, other forms of social behavior may require that we regard the control systems as being "smarter." Smarter control structures make reference to the self, are aware of the physical and informational environments, and formulate action strategies in very complex ways. As we proceed through the development of models in this section, one way
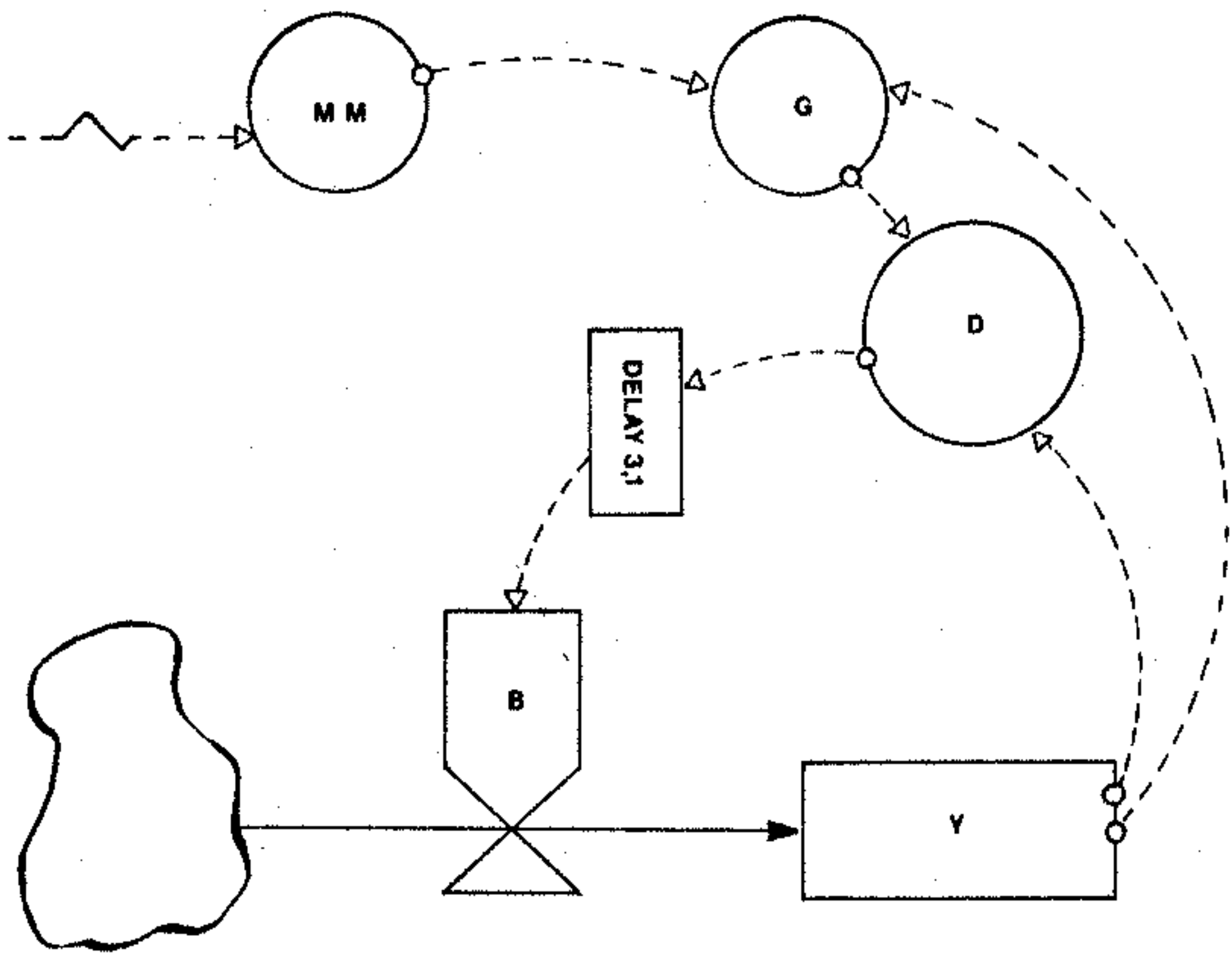
```
L   Y.K=Y.J+(DT)(B.JK)
R   B.KL=DELAY3(D.K,1)
A   D.K=Y.K-G.K
A   G.K=MM.K*Y.K
A   MM.K=. . .
```
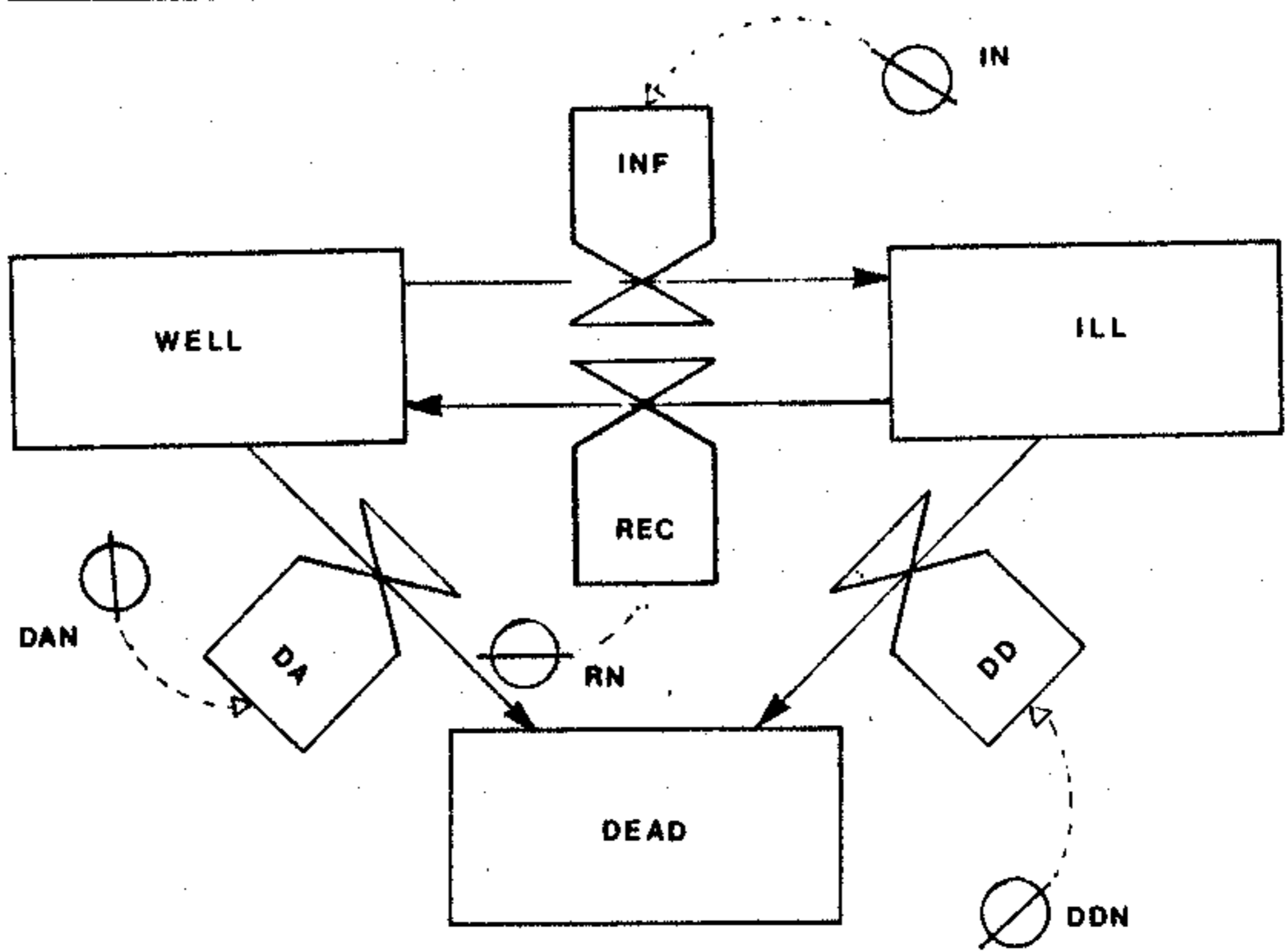
Figure II.2:   More elaborate control.

in which we will elaborate "simple" dynamics is to make them "smarter."

The elaboration of our simple baseline that is shown as Figure II.3 represents another direction of movement toward greater complexity.

This model has three "dependent" variables (the number of persons who are WELL, the number who are ILL, and the number who are DEAD). Transitions occur back and forth between WELL and ILL at rates governed by constants (the INFection rate and the RECovery rate); transitions occur between WELL and DEAD at a constant rate (DA, DAN) and between ILL and DEAD at constant rates (DD, DDN). Models of this type, that describe movements of "things" among multiple "statuses" are common in all of the social sciences—differing only in the definitions of "things" and definitions of "statuses."

The theory in Figure II.3 is more complex than the one in Figure II.1 primarily because it includes more elements in its state space. The

```
L    ILL.K=ILL.J+(DT)(INF.JK-REC.JK-DD.JK)
L    WELL.K=WELL.J+(DT)(REC.JK-INF.JK-DA.JK)
L    DEAD.K=DEAD.J+(DT)(DA.JK+DD.JK)
R    INF.KL=IN
C    IN=.  .  .
R    REC.KL=RN
C    RN=.  .  .
R    DA.KL=DAN
C    DAN=.  .  .
R    DD.KL=DDN
C    DDN=.  .  .
```

Figure II.3:   More elaborate state space.

connections among the states remain quite simple (indeed, unrealistically so). While maintaining quite simple forms of relationships among the elements of the state space, the state space is expanded to include multiple simultaneous equations or processes.

Outline of Part II

In the four chapters that follow, we have two major goals. First, we will become comfortable with the basic "building blocks" of more complex systems, and develop an understanding of their dynamic behavior. Second, we will examine some of the most widely used

"simple" dynamic systems models in the social sciences using the DYNAMO language and simulation methods. As we do both of these things, we will be developing skills in systems thinking, translation from everyday to formal language, and a sense of how simulation experiments can be used to enrich the insights of "theoretical research" on the wide range of social science problems that can be characterized as "simple" systems.

The first two chapters (6 and 7) deal with systems that are relatively simple in terms of their state spaces, but increasingly complex in their "rates" or control systems. We will first discuss the basic ideas of "dumb" and "smart" control structures, and the related ideas of "feedforward" and "feedback." We will look at the construction of simple systems with increasingly complex control structures, and examine their typical dynamic behaviors. After these basic principles are in hand, we will illustrate the utility of such simple models by developing a theories of growth, decline, diffusion, and contagion.

The following two chapters (8 and 9) concern elaboration of models with relatively simple control structures into more complex systems by the addition of states. We will first discuss the architecture of "chains," and look at the wide applicability of such models for subject matter of interest to social scientists. To illustrate the dynamics of "chain" models, we will then develop models of three kinds of processes of great interest and generality: age structures of populations, models of vacancy chains and models of multistate mobility and transition processes.

Note

1. The role of "baseline" models in theory building is extensively discussed in an article and rejoinder by Mayhew (1984), and a sympathetic critique by Turner and Hanneman (1984).