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HANDBOOK OF SYSTEMS ANALYSIS

VOLUME 1. OVERVIEW

CHAPTER 7. PREDICTING THE CONSEQUENCES: MODELS AND MODELING

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FOREWORD

The International Institute for Applied Systems Analysis is preparing a Handbook of Systems Analysis, which will appear in three volumes:

- Volume 1: Overview is aimed at a widely varied audience of producers and users of systems analysis studies.

- Volume 2: Methods is aimed at systems analysts and other members of systems analysis teams who need basic knowledge of methods in which they are not expert; this volume contains introductory overviews of such methods.

- Volume 3: Cases contains descriptions of actual systems analyses that illustrate the diversity of the contexts and methods of systems analysis.

Drafts of the material for Volume 1 are being widely circulated for comment and suggested improvement. This Working Paper is the current draft of Chapter 7. Correspondence is invited.

Volume 1 will consist of the following ten chapters:

1. The context, nature, and use of systems analysis
2. The genesis of applied systems analysis
3. Examples of applied systems analysis
4. The methods of applied systems analysis: An introduction and overview
5. Formulating problems for systems analysis
6. Objectives, constraints, and alternatives
7. Predicting the consequences: Models and modeling
8. Guidance for decision
9. Implementation
10. The practice of applied systems analysis

To these ten chapters will be added a glossary of systems analysis terms and a bibliography of basic works in the field.

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CHAPTER 7. PREDICTING THE CONSEQUENCES: MODELS AND MODELING

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1. INTRODUCTION

> Any model is a caricature of reality. A caricature achieves its effectiveness by leaving out all but the essential; the model achieves its utility by ignoring irrelevant detail. There is always some level of detail that an effective model will not seek to predict, just as there are aspects of realism that no forceful caricature would attempt to depict. Selective focus on the essentials is the key to good modeling. (Holling 1978)

Assume that the problem has been clearly defined, the objective specified, and a number of alternatives identified that seem worth further investigation. Before a decision is made, the decisionmaker ought to know, in so far as possible, what the consequences of his choice will be. To predict these consequences, one or more models are required, frequently much more elaborate than the models employed earlier to identify the alternatives or to define the limits of the inquiry. The purpose of this chapter is to show how models are developed, used, and refined to increase our confidence in what they tell us.

For the problems of sociotechnical systems that applied systems analysis addresses, the information required for decision is usually obtained by means of carefully constructed, explicit models, represented quantitatively (i.e., by using numbers and mathematical relations) and expressed at least partly by a computer program. These models are frequently the synthesis of a host of other models, simpler in varying degrees, many mental, implicit in the minds of the model builders, others explicit, variously expressed by words, diagrams, mathematical equations, random numbers, physical forms, or otherwise. There are, of course, still further models used by the analyst everywhere throughout the analytic process—in problem formulation to define the scope of what is to be included, in applying dominance or other schemes to screen the alternatives, in procedures to present the results, and, indeed, wherever the analyst has a decision to make.

Because modeling plays such an important role in applied systems analysis, the two are sometimes considered to be identical. Many studies do have one model—the one used to predict the consequences of a choice of alternatives—so dominant that the other models employed are seldom mentioned; the world modeling community offers examples (see Meadows, Richardson and Bruckman 1982). Other models are, nevertheless, present and used through the process, although most of them may be mental and never made explicit. The model (or the group of models considered as a single model) used to predict the consequences of the alternatives is usually spoken of as "*the model*" when systems analysis is discussed. These predictive models are the subject of this chapter; we do not, for instance, discuss the models a decisionmaker may employ to make use of the information the analysis provides.

This chapter begins with an explanation of what models are and why they are needed in systems analysis. It then discusses the four broad modeling techniques models most used in systems analysis. Next, to show how models are built and tested, it works through an example and expands the topic. It follows this with an explanation of the way these models are used to produce the necessary predictions. Finally, after discussing briefly social experimentation, model documentation, and model cost, it closes with a statement of what one can expect to get from models and modeling.

2. THE NEED FOR MODELS

A model is no more than a set of generalizations or assumptions about the world. It is a simplified conceptual or physical image of reality that may be used to investigate the behavior of a system or the result of action without altering the system or taking the action. The simple scrawl we might use to represent a road network in giving directions to a passing motorist is a model; it replaces the need to escort the motorist to his destination. Note that it is a simplification of the real world tailored to a specific purpose; it does not include information extraneous to the purpose in mind such as scenic highlights along the way, or where restaurants are located, or when parking is permitted. If the model purpose were different, say, because the motorist wanted to lunch along the way, then additional information would have to be included and the model changed.

Everyday decisions by individuals and the predictions on which they depend are most often based on judgment derived from an implicit model that exists only in the mind. Such a judgmental or mental model is made up of the assumptions and intuitions the holder has about the issue with which he is concerned. Most decisions, even some of considerable significance to others as well as to the decisionmaker himself, are based largely on implicit or mental models. Nevertheless, as the importance of the decision increases, the originally implicit model tends to be made explicit before the decision is taken, as when someone lists the pros and cons of an action he is about to take and assigns weights. At other times, an implicit model is not only made explicit but supplemented by other explicit models such as diagrams, graphs, tables, and/or mathematical formulae. Formal studies of even relatively simple issues, however, demand that the models be as explicit as possible so that others can follow the reasoning and approve what is done.

Why are elaborate models required in applied systems analysis? Why not, for instance, try out each alternative on a full scale for a time sufficiently long to determine what would happen? There may be exceptions, but in every case I can imagine, this would be too expensive, or too dangerous, or otherwise impractical; consider, for example, the Oosterschelde example of Chapter 3. A small-scale experiment with a segment of the real world is sometimes a possible, even a desirable, way to predict what might happen, but even this would not avoid sophisticated mathematical models, for they would be needed to design the experiment and to analyze the data.

It is generally agreed among psychologists and philosophers that the human mind operates entirely through models. Mental models have many advantages. They can contain rich stores of information, they can handle incommensurable factors, and they can balance conflicting values (Meadows, Richardson, and Bruckmann 1981), but they have biases and gaps that may be completely unknown to the holder and undiscovered by anyone else. They cannot, moreover, handle problems that demand an extremely precise answer or require knowledge from too many disciplines.

Meadows and Robinson (1982) list five reasons why promoters of the computer as a forecasting tool claim that mathematical models should be superior to the best mental models:

1. *Rigor*. The assumptions in computer models must be specified explicitly, completely, and precisely; no ambiguities are possible. Every variable must be defined, and assumptions must be mutually consistent. Computer modelers often mention that the discipline required to formulate a mathematical model is helpful in organizing and clarifying their own mental models, even before any computer analysis takes place.

2. *Comprehensiveness*. A computer model can manipulate more information than the human mind and can keep track of many more interrelationships at one time. It can combine observations from many mental models into a more comprehensive picture than could ever be contained in a single human head.

3. *Logic.* If programmed correctly, the computer can process even a very complicated set of assumptions to draw logical, error-free conclusions. The human mind is quite likely to make errors in logic, especially if the logical chain is complex. Different people may agree completely about a set of assumptions and still disagree about the conclusion to be drawn from them. A computer model should always reach the same conclusion from a single set of assumptions.

4. *Accessibility.* Because all the assumptions must be explicit, precise, and unambiguous in order to communicate them to the computer, critics can examine, assess, and alter computer models, whereas mental models are virtually unexaminable and uncriticizable.

5. *Testability.* Computer models can easily test a wide variety of different conditions and policies, providing a form of social experimentation that is much less costly and time-consuming than tests within the real social system.

Computer models have not had either the acceptance or the success that many of their advocates feel they should have. Even though a model of this type may be an appropriate tool for most problems to which systems analysis is applied, they are, as Meadows and Robinson go on to say "... more often made than used, more often criticized than praised." Judgment, by committees and individual experts, largely based on individual mental models, is still widely used for tasks that systems analysts would like to take over. Judgment, moreover, by committee and individuals, can be improved through the use of structured discussion, a form of modeling as yet little employed in applied systems analysis (see, however, Holling 1978 and Checkland 1981).

As said earlier and in Chapter 4, models have many roles in systems analysis. In this chapter we are interested in models as devices, processes, or procedures to predict, or to at least provide insight concerning, the consequences that result from the choice of an alternative.

3. MODELING TECHNIQUES

Models differ in many aspects—in degree of abstraction or complexity, in how time or chance events are handled, and in many other ways—and may be classified accordingly. Specht (1968) separates models into five categories: verbal, people, people and computers, computers, and analytical. Greenberger et al.(1976) distinguish four classes: schematic, physical, symbolic, and role playing. The simple road map mentioned in the previous section is a schematic model; a wooden airfoil in a wind tunnel would be a physical model. The models used for predicting the consequences, the so-called systems analysis models, while they make use of mental, schematic, and sometimes (but rarely) physical modeling, depend for the most part on four basic modeling techniques: analytic, simulation, gaming, and judgmental. A given model may employ more than one of these techniques. The common man-machine model—the people and computer model of Specht's classification—employs simulation, gaming, and judgmental models, for instance.

The modeling techniques most used for applied systems analysis are quantitative (for instance, represented by mathematical equations or a coded set of instructions for a computer). Often they are the only modeling techniques considered for "the model." These models resemble those used in the physical sciences, consisting of a set of logical relations from which one obtains the outcome by solving the equations in closed mathematical form or by or statistical analysis. For such a model to be strictly quantitative, it would have to represent the situation and the activity under investigation so faithfully that a decision could be based solely on the results obtained from the model. For some questions, such models may exist, but not when social and political factors are as prevalent as they are in the applications of applied systems analysis; in such cases, the model results must always be tempered with judgment—i.e., modified by the decisionmaker's and/or the analyst's mental models. Nevertheless, the adjective quantitative is applied to any model where most of the relations are represented analytically or on a computer. Quantitative models are of two types: analytic models and simulations, although not all analytic models and simulations are quantitative.

Many issues have major aspects that cannot be expressed satisfactorily by quantitative means. Frequently these are aspects that depend for understanding on the social sciences where, because of the nature of their subject matter, few models with the predictive quality comparable to the models found in the physical sciences or even in economics have been developed. Without such building blocks, the predictive models for systems analysis must depend on a more direct use of judgment and intuition and less on quantitative relations. To achieve this dependence, human participants, usually experts or especially qualified people, are brought into the model structure. Gaming and group judgment are two ways to bring human participants into systems analysis models.

I will now discuss the four modeling techniques in separate sections, the latter two in greater detail than the former. For more information on analytic models and simulations see—in addition to Volume 2 of this *Handbook*—Greenberger et al. 1976, Chapters 3 and 4, for a good introductory treatment of this type of modeling. In addition, Moder and Elmaghraby (1978) and Drake, Keeney and Morse (1972) cover more sophisticated methods and give numerous applications. Meadows and Robinson (1982) compare nine studies that make use of systems dynamic, econometric, input-output, and optimization models in various combinations and provide useful insights on the effectiveness of computer modeling.

Analytic Models. In an analytic model mathematical statements are used to represent the relations that hold between the variables of interest. The use of mathematics as a surrogate for reality has a long and successful tradition in physics and engineering and more recently in operations research. An analytic model is particularly desirable because the outcome for a full set of alternatives can often be predicted by a closed mathematical form (as by the square root law of the Fire Deployment example of Chapter 3) or graphically (as from Figure 3.1 for the blood-supply example). Problems of flows in networks, queueing, search, inventory control, and others can often be modeled analytically. Numerical analysis and a computer may be needed to aid in finding a solution, but it is a use of the computer different from that in simulation.

Most systems analysis models are descriptive. That is, they predict the values of a set of consequences for a particular alternative under a specified set of conditions. Ranking the alternatives is done externally to the model. Sometimes, when the alternatives are similar and differ only in a set of parameter values, it is possible to design a "prescriptive" model, which ranks the alternatives on a performance scale. The user then does not have to compare the alternatives to select the one he prefers; he merely has to agree on the scale. The model contains an optimization procedure (linear programming, for instance) that indicates the set of parameter values that yields the best value of the performance measure (say, the minimum monetary cost to set up a system). The selection is best, however, in an overall sense only to the extent that the one-dimensional scale on which the model measures performance incorporates and weighs properly all the factors that the decisionmaker has in mind when he seeks a best solution. Nevertheless, prescriptive models are the most sought after models.

Simulation. Although every model is a simulation, in operations research and systems analysis parlance the term simulation is often used in a special sense: simulation is the process of representing item by item and step by step the essential features of whatever it is we are interested in and then predicting what is likely to happen by operating with the model case by case, i.e., by estimating the results of a proposed action from a series of pseudo experiments (pseudo because they are performed on the model rather than in the real world). The series of experiments is needed to take account of the effects of chance on the system (simulation, in systems analysis, is seldom used in a deterministic situation, i.e., one where the effects of change can be assumed negligible), for each individual experiment with the model may produce a different outcome. After a large number of experiments, what is likely to happen can then be determined by statistical analysis of the set of outcomes.

More often than not, the simulation is a computer simulation in which the representation is carried out numerically on a digital computer, using computer-generated random numbers, frequently without employing any formal analytic techniques. A great advantage of this type of simulation is that a digital computer, using random numbers, can represent with precision processes for which satisfactory analytic approximations do not exist. For example, traffic flow, an intricate process, can be expressed in terms of simple events, such as a car turning left at an intersection or a vehicle parking, and simple rules, such as when attempting to turn left the car waits until oncoming traffic has gone by, or a vehicle attempting to park forces the following cars to stop. Typical of many real systems, traffic flow is subject to chance elements; thus by selecting random numbers from the appropriate distributions, the computer determines, say, whether a given car turns left and for how many oncoming cars it has to wait. The computation is carried out at high speed with relations that indicate the manner in which real activities might take place in real time. A large measure of realism can thus be attained. In fact, the analyst has to guard against attempting to provide a one-to-one representation of the real-world process rather than abstracting just the features essential to his problem.

Simulation with a high-speed digital computer is an extremely powerful technique. A system that is not well enough understood for mathematical relations between variables to be set up may often be modeled as a simulation and the relations discovered. While analytic models are cheaper to use in both time and money, simulation is often chosen because it is easier to set up and not costly at the model-building stage. As Bowen (1978a) remarks: "... In principle, ... a simulation is the least desirable of models. It has low insight, since it does not provide explanation of the observed outcomes, and it may involve an undesirably long, confusing, and expensive analysis phase. Nevertheless, it may be a correct choice as a model, if only because no other choice is open."

Gaming. Gaming or operational gaming (recently called interactive simulation by some who feel gaming is not a suitable term for a serious research effort) is a form of simulation modeling in which analysts, expert consultants, and sometimes decisionmakers simulate the behavior of major elements in the model. A human "player" may, for instance, simulate the actions of a plant manager or of a political party or the changes that take place in a sector of the economy. The players may be assisted by computer simulations and analytic models or even play against such models.

Gaming originated with the military. Military staffs found that map exercises in which opposing teams acted out the moves that might be made by opposing armies were useful for examining the feasibility of war plans and the adequacy of logistics. Since the activities of the participants in such an encounter bore considerable resemblance to playing a game, the activity came to be called gaming. Gaming is now used also to study future weapons and potential conflict between nations. In business its use is widespread, particularly for training. Although gaming is little used to study public problems, it can be argued that some form of gaming is needed if human judgment is to be introduced into models to investigate such problems (Bowen, 1978b).

To illustrate, a game to investigate policy options to counter organized crime might be set up as below (Quade, 1975b). Three teams would be used:

1. A player team, Blue, to simulate in some sense a National Council on Organized Crime plus local authorities;

2. A player team, Black, that simulates the activities of organized crime in city X;

3. A control or umpire team, Green, to structure the game, provide a startup situation, rule on moves, etc.

The game would start from an initial situation (prepared by Green) with a move by Black—e.g., various actions involving gambling, loansharking, dishonest businesses, and the like. This would be followed by

Blue's move involving mainly actions by the local authorities. The results would then be evaluated by the control team, taking into account both the local moves and the legislative and operational components of an overall strategy to combat organized crime previously formulated by Blue in its role as a National Council: the activity of preparing this latter being probably the most important aspect of the game.

After the results are communicated (in part) to the player teams, another move follows. The control team determines the number of moves, the timing, updates the scenario, and provides information about such factors as the state of the economy and the political situation. Conclusions are drawn at the end based on the synthetic experience of all concerned.

Gaming can be used to tackle many problems for which no satisfactory quantitative model can be constructed. The players can use their intuition and judgment to take into account such hard-to-measure factors such as courage, cooperation, commitment, and morale. A realistic environment and intelligent opponent can force the players in a two-sided game to consider aspects of the issue that might be overlooked were they working in isolation without teammates and without an intelligent opposition searching for flaws in every move. Gaming works well as an educational device and for improving communication among players of different disciplines. Its predictive quality, however, is questionable for it so clearly depends on the intuitive insights provided by the participants (Quade 1975a, pp 199-212). For additional discussion, see Helmer (1978).

Difficulties sometimes arise with analytic models and computer simulations when the system being modeled contains one or more decisionmakers whose decisions influence the model outcome importantly. If these decisionmakers follow some simple rules—for example, if they maximize their net benefits—then it may be possible to describe their behavior by mathmatical models. Demand functions, which express how much of a commodity a consumer will buy at various prices, are one version of such models. The decisionmaker, however, may be something like a legislative body, a political party, a protest group, a particular individual, or even inanimate, say a sector of the economy that in our present state of knowledge we do not know how to model satisfactorily. Another approach is then needed.

One such is to insert individual "players" into the model to represent these internal decisionmakers. These players are then supposed to act like their real-life counterparts would act or, in some circumstances, to optimize with an assigned goal in mind (Helmer 1966). In other words, if we know of the existence, position, and action possibilities of these decisionmakers whose intervention may affect the choice of alternatvie, we may try to imitate their behavior by appropriately chosen actors. We expect these actors to behave, in the model, in a way that corresponds to what the actual decisionmakers would do, or should do, in real-world situations, with all the ambiguity and uncertainty there present. Incidently, this is a reason for the growing importance— for systems analysis— of the psychological and sociological theory of value and choice. We are unable to model—and thus predict—the consequences of a course of action unless we understand the laws of behavior of the group that will be affected by it.

If all of the dependencies, except for human decisionmaking, are programmed into a computer, the whole model becomes an interactivve model, or man-machine model, where human decisions interact with input and output data from the computer program. Models of this type are frequently called "role-playing" models and are usually classed as a form of gaming.

Judgmental models. In addition to the judgment and intuition of individuals applied through their implicit mental models, the multidisciplinary nature of applied systems analysis usually makes reliance on the judgment of several people indispensible. A committee or panel exercising its judgment as a group is a firmly established and much used substitute for explicit modeling to provide advice or predictions. It is one, however, that is open to a number of objections, based on the well known deficiencies of committee deliberations that affect the quality of the end product (Helmer 1978, 1966). There are, however, a number of ways to structure group discussion that will improve the focus of its judgment. These devices include scenario writing, Delphi, cross-impact analysis, and various team and workshop approaches. They are models (at least in an extended sense) for they play the same role in applied systems analysis as simulation, mathematical modeling, or gaming. The team-workshop approaches, such as Lasswell's decision seminar (Brewer 1972, Brewer and Shubik 1979), the one used by Holling and his colleagues (1978) to investigate environmental management problems, and the scheme used by Checkland (1981) for business problems, employ many of the other modeling techniques, such as simulation and cross-impact analysis, during their sessions. Except for a remark about individual judgment I will confine the discussion to Delphi and scenario writing.

The judgment of an individual is sometimes used as a direct link in an otherwise analytical model to model processes that would otherwise be difficult or costly to handle. For instance, there are models for finding efficient vehicle routes and schedules through a network of city streets, in which the selection of routes by a traffic expert, based on his experience and justified by heuristic arguments, is combined with the formal mathematical techniques of graph theory to avoid the computational difficulties that would be required were graph theory to be used alone. In IIASA's Energy Program, individual judgmental models were used to link together the various (sub)models where each model evaluated only a particular aspect of the problem (Energy Systems Program Group 1981, p.28).

Delphi. Delphi is an iterative procedure for eliciting and refining the opinions of a group of people by means of a series of individual interrogations. Originally the interrogation was by written questionnaire, but more recently on-line computer consoles are used to speed up the process. Ideally for systems analysis purposes, the group should consist of subject-matter experts and especially knowledgeable individuals, possibly including some of the responsible decisionmakers. The idea is to improve on the committee process for arriving at a prediction or recommendation by subjecting the views of the individual participants to each other's criticism in ways to avoid the psychological drawbacks associated with face-to-face confrontation. To this end, anonymity, to the extent that the responses to a question when supplied to the participants are not attributed to the responders, is usually preserved during the exercise and sometimes even when it is over.

Discussion is replaced by exchanging information under the control of a steering group. In each round of questions after the first, information about the outcome of the previous round is fed back to the participants (without letting them know, however, which opinion was contributed by which particular participant). As Helmer (1978), one of the developers of the technique, describes it: "... Some of the questions directed to the participating experts may, for instance, inquire into the reasons for previously expressed opinions; and a collection of such reasons may then be presented to each respondent in the group, together with an invitation to reconsider and possibly revise his earlier estimate or, conversely, to state counterarguments explaining why the reasons presented are found unconvincing. This inquiry into the reasons for stated opinions and the subsequent feedback of the reasons adduced by others constitutes the elements of what may be thought of as an anonymous debate which serves to stimulate the experts into considering pertinent factors they might through inadvertence have overlooked, and to give due weight to considerations they may at first have been inclined to dismiss as unimportant." As the communication channel is controlled, "noise" —material judged irrelevant or redundant—can be reduced.

Four rounds are usually adequate: a second giving reasons for deviations from the first-round median; followed by a third with new estimates in the light of the reasons for deviation on the second with counterarguments; followed by a fourth estimate in the light of the counterarguments. The median of the fourth round is then used to represent a consensus. (If the result sought is not expressed numerically, it can usually be rephrased to permit quantitative evaluation.)

Although the group opinion tends to converge with iteration (as measured by the interquartile range, say), the normal outcome is a spread of opinion. Using the median to represent the group response reduces pressure for conformity and insures that the opinion of every member plays some role in determining the final outcome.

Delphi can be employed whenever expert judgment is required. For this reason, it is often used in conjunction with gaming. Its purpose is to estimate the answers to questions for which there is no "hard" model way to find the answer. There is some experimental evidence that Delphi results are usually more accurate than those obtained from a committee, particularly for numerical estimates such as forecasts as to when an event will happen or the future value of some index; the evidence, however, is not adequate enough to convince all analysts. Thus Delphi is not a substitute for an analytic model or simulation unless one feels so little confidence in the validity of the models he can construct that he would be willing to depend on committee judgment instead (see also Linstone and Turoff 1975).

Scenario writing. Before alternative actions can be designed, compared, or evaluated, the conditions under which they are to take place must be known or forecast. In applied systems analysis, a *scenario* is the set of conditions and characteristics that define the situation or environment under which a system or policy is assumed to perform. It is a description of the essential features (in the sense that they affect the actions under investigation) of the hypothetical context or contingency in which the action is to take place. *Scenario writing* is preparing a logical sequence of hypothetical (but credible) events that leads from the present to the scenario.

As a form of model building, scenario writing is clearly an art. There is not much that can be formalized or codified about how to do it well. Olaf Helmer (1966, p10) describes it as follows: "... Scenario-writing involves a constructive use of the imagination. It aims at describing some aspects of the future, but, instead of building up a picture of unrestrained fiction or even of constructing a utopian invention that the author considers highly desirable, an operations-analytical scenario starts with the present state of the world and shows how, step by step, a future state might evolve in a plausible fashion out of the present one. Thus, though the purpose of such a scenario is not to predict the future, it nevertheless sets out to demonstrate the possibility of a certain future state of affairs by exhibiting a reasonable chain of events that might lead to it."

A scenario can be generated from a simulation or through the sequence of plays in an operational game, but, most commonly, it is developed from the mental models of one or a few individuals. Scenario writing is not only the most frequently used means of deciding on the future contingencies in which alternatives are to be compared, but it is also a useful device for beginning the construction of a more analytic model. For further information, see Brown (1968), DeWeerd (1973), and Chapter 9. The central purpose of the IIASA energy study described in Chapter 3 was to look at the energy supply and demand balance for the next fifty years of a world that is notably heterogeneous, at least as we view it today. Not the least of the highly variable factors is the present per capita energy consumption, which in one major world region (North America) is over 40 times what it is in another (south and southeast Asia and sub-Sahara Africa excluding South Africa), thus implying the need for much more economic growth in the latter region than in the former. The approach the energy analysis team took was to write scenarios, from this point of view (Energy Systems Program Group 1981, volume 1):

> In writing scenarios, we were in no sense attempting to make predictions. Rather, we viewed scenario writing as a way to organize our thinking about available information. Specifically we insisted rigorously on two criteria—internal consistency and global comprehensiveness...

The purpose of the scenarios is to detail realistically the engineering and economic consequences that might follow from two sets of reasonable assumptions [embodied in the high and low scenarios]. The results should be interpreted carefully. The numbers are meant to provide insights and to help in meeting the intellectual challenge of grasping the dominant characteristics, trends, possibilities, and constraints on global and regional energy considerations. They are not predictions, and should serve only as guidelines for determining what is feasible over the coming five decades, assuming there are no social and political constraints.

Table 3.6 and Figure 3.10 give some of the central results emerging from the analyses based on the scenarios. We have commented earlier on a number of important lessons emerging from the analysis based on the scenarios—the continuing importance of liquid fuels and the need for introducing coal liquefaction in a major way by the end of the fifty-year period. Another lesson is worth mentioning here: The fundamental balance of the scenarios could not have been achieved without major energy conservation efforts, particularly among the developed economies.

4 MODEL BUILDING.

Even in well established scientific fields model building is not a cut-and-dried process but a highly creative activity.

Developing a simple model. Before listing some general precepts, consider, as an illustration of model building, the development of the square-root law used in the fire department deployment example of Chapter 3. In its simplest form, this model is expressed by the equation

$$E(D_1) = k_1\sqrt{A / N},$$

where $E(D_1)$ is the expected distance between points in the region at which fires occur and the closest available engine company, k_1 is a constant, A is the area of the region, and N is the number of firehouses that have engines available to respond.

The analysts, Kolesar and Blum (1973), had a feeling that, since area is proportional to distance squared, there might be a relation of the same sort between average travel distance in a region and the area of the region. With this in mind, they set out to investigate the possibility for a square city whose streets form a rectangular grid with a single firehouse located at the center (Fig. 7.1). Within this city, fires were assumed to occur at random, with equal probability and severity everywhere.

The derivation of the model in this case, as described in Walker, Chaiken, and Ignall (1979, pp. 181-182), is as follows:

> We would like to determine the expected response distance for this city's fire company. We begin by answering the question "What is the chance that the fire company will have to travel less than s miles?" for any distance s that lies between 0 and $\sqrt{A/2}$. To answer the question, consider a square that is $s\sqrt{2}$ on a side, which is centered inside the original one and is oriented the same way. Every point inside this square is no further than s from the firehouse, while every point outside it is further than s from the firehouse. [Because the fire company in traveling must follow the streets which are parallel to the axes; all points on the boundary are thus the same distance from the firehouse.] The chance that the company will have to travel less than s miles is, then, the probability that an alarm occurs within the smaller square. This probability is the same as the ratio of the area of the small square to the area of the city. That is
>
> $$P(\textit{response distance} \le s) = [s\sqrt{2}]^2 / A.$$
>
> The probability density of response distance, $f(s)$, can then be obtained by differentiation: $f(s) = 4s/A$. So the expected response distance is given by:

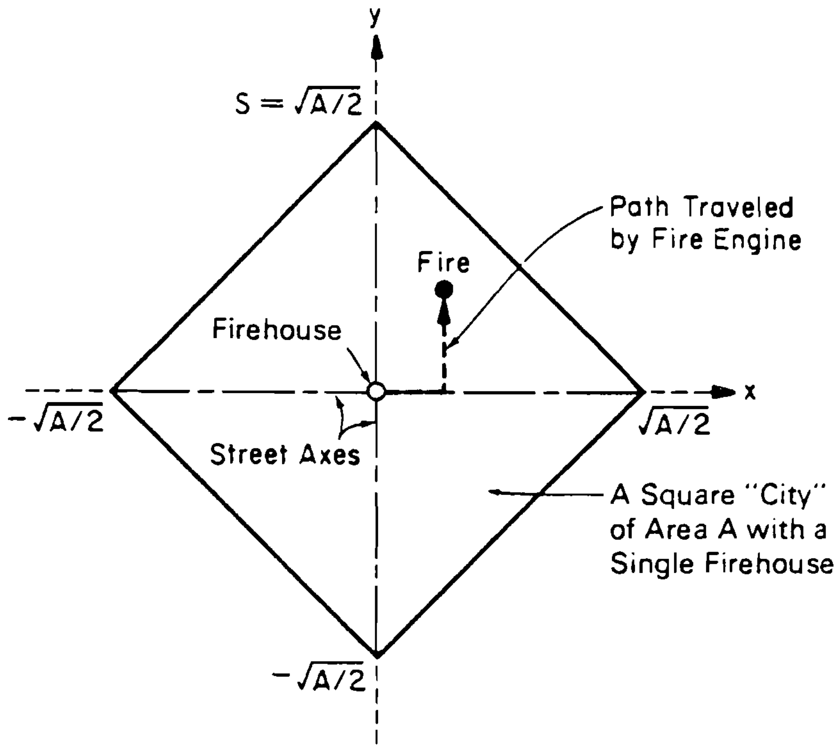

Figure 7.1. An idealized city with one firehouse.

Source: Walker, Chaiken, and Ignall 1979.

$$E(D_1) = \int_0^{\sqrt{A/2}} s f(s) ds = \int_0^{\sqrt{A/2}} [4s^2 / A] ds = \cdots$$
$$= (\sqrt{2}/3)\sqrt{A}.$$

Hence, in the case of a single company ($N=1$) in a square city, the square-root law holds with $k_1 = \frac{\sqrt{2}}{3} = 0.4714$.

The model was then extended; first to a square city made up of smaller square cities, then through stages to more general configurations. In order to simplify the mathematical analysis required for these extensions, the analysts made a number of assumptions:

> Alarms are distributed randomly but with uniform probability density throughout the region of interest
>
> Firehouses are spread either in a regular pattern or randomly throughout the region of interest
>
> Boundary effects are insignificant
>
> Units are always available to respond
>
> Fire companies travel either on a straight line between two points or on a dense rectangular grid of streets.
>
> In the real world, of course, none of these assumptions is strictly true. Complications that are not consistent with this simple model abound: a city is of finite size and irregular shape: the distribution of units is not homogeneous: several companies (in varying numbers) are dispatched to each alarm: in the event of a very serious fire, companies from other regions may be relocated into the depleted area: and responding units must follow actual street patterns that are often irregular, observe one-way streets, and route themselves around obstacles such as parks and rivers... (Walker, Chaiken, and Ignall 1979, p. 185).

Notwithstanding such complications, the square root model provides estimates useful for the purpose for which the model was intended—to estimate the average travel distance in a reasonably large region over an extended period of time. Before this statement could be made with confidence, however, the model had to be extensively tested. The mathematical derivations lent an air of plausibility to it, but, as these were based on simplifying assumptions that were not true in the real world, checks were needed. The testing involved the use of alternative models, historical data, and simulation (Kolesar and Blum 1973).

General remarks. In applied systems analysis, a model builder is likely to find himself working in an area where the relations between the variables important to his problem are very imprecisely known and the data for improving them, while often abundant, must be turned into useful information. His first step is to select certain elements as being relevant (and to set aside for the present all others) and to make the relations between them explicit. To do so, he uses established models from the disciplines involved where such models are known and conjectures the other relations using judgmental models based on his own intuition and that of experts he consults. The choice of techniques should follow from the nature of the problem, not the other way around, for, if the choice of analytic approach or modeling style comes first, the problem may have to be altered or even redefined to suit it.

At every stage, the process is full of pitfalls (Majone and Quade, 1980). For instance, during data analysis: "This transformation of data into information involves three basic judgments, which all present the risk of serious pitfalls. The first is that the advantages achieved through data reduction compensate for the probable loss of information; generally speaking, the existence of sufficient statistics, i.e., of summaries of the data which contain exactly the same amount of information as the original sample, is the exception rather than the rule. The second is a judgment of the goodness of fit of the model to the original data. The third is that this particular model, among the infinitely many possible ones, is the significant one for the problem under examination. All the operations and judgments involved in data reduction, transformation, and testing are, of course, craft operations." (Majone, 1980)

To build a model means that most aspects of the real world must be aggregated or simplified.

Simplifications are of many types. One is to omit factors because they are judged to be irrelevant to the outcome. One does not, however, omit factors because data or theory do not exist; one simply models them as best he can (see Forrester, as quoted in section 3.4). Sometimes factors are omitted because the analyst finds them too difficult to quantify. If that is the case, however, they must be handled in some other way; preferably by changing the model to a type that will accommodate factors that are unquantified. Other simplifications are to assume that variables are constants and that complicated relationships are linear. [There is always a preference for linear models because well known techniques exist for solving many such models.] Another is to assume that the average value of a function of a variable is equal to the function of the average value of that variable.

Aggregation such as treating areas as points or all members of a class as being of one "average" type or replacing stochastic processes by deterministic rules are common aggregations that result in simplification.

Simplifications are introduced for analytical or computational convenience (for instance, the assumptions used in deriving the square root model of the preceding section) or sometimes to avoid the cost of gathering the data that would be required were the more realistic assumptions to be used. It is, of course, the purpose of the model that tells us what to include and what to leave out. Detail that later turns out to be unneeded may be included at the start for it may take investigation by the analyst to find out what can be omitted or aggregated. Compromises are always necessary; sometimes detail that the sponsor thinks should be important is included merely to retain his confidence.

It should be clearly stated what has been assumed in the way of simplification and *why*, and, in so far as possible, the sort of uncertainty that the assumption is likely to introduce in the model output.

Improving a model. The *ad hoc* and tentative model that represents the analyst's first cut is improved as new information and insight become available. To do this, the analyst works with his model, trying it out for cases in which the results he would like it to produce are known or can be conjectured from other models. He heeds the judgment of people experienced in the subject matter who feel they can recognize when the model results "seem reasonable." He checks his model against historical data. If it can be made to fit, this does not prove the revised model to be true, for by manipulating a few parameters this can usually be achieved (Bush and Mosteller 1966). But, if the data are extensive and the adjustments slight, it tends to increase his confidence in the model.

Verification. A model is said to be *verified* if it does what the model builder intended it to do. For a computer model, this means that the equations are correct and have been properly programmed. Typically, an attempt is made to verify such a model by setting some of the data input to extreme values, say zero, or by holding some of the input variables constant to determine whether the output changes in anticipated ways as the other inputs change. Using such trivial or degenerate cases, however, is not an adequate check. Better is to check the output against results provided by previously verified models or by testing with sample data that corresponds to known output. As models become more elaborate, verification can become extremely difficult (Meadows and Robinson 1982).

Validation Validation is the process of determining that the outputs of a model conform to reality. No model can be validated in an absolute sense. As Holling (1978) and his coworkers express it: "In fact, it is the central tenet of modern scientific method that hypotheses, including models, can never be proved right; they can only be proved wrong (Popper, 1959). This is why the frequent claims of—and demands for—valid models in ecological management, impact assessment, and policy design are so unsound. Provisional acceptance of any model implies not certainty, but rather a sufficient *degree of belief* to justify further action. In practice, the problem is one of model invalidation—of setting the model at risk so as to suggest the limits of its credibility." [Emphasis in the original.]

More recent writers hold absolute invalidation impossible also (Toulmin 1974; Majone 1980). Nevertheless, one has little confidence in a model that appears invalid; for a good description of how invalidation is attempted, see Holling (1978).

In a practical sense, models are valid only in so far as they are accepted by the primary decisionmaker and their output judged useful by him in reaching a decision. To increase our confidence in a model to the stage at which we are willing for it to be used as a laboratory world to test the consequences of alternative policies, we subject it to a range of tests and comparisons designed to reveal where it fails. When such tests of the model have been completed, the model will not have been proved valid and not all the uncertainties will have been eliminated; the user will, however, have an understanding of the extent and limits of the model's predictive capabilities.

The more susceptible to invalidation a model is, the less confidence we have in it. Often there is empirical evidence that can be used to calibrate the model until it will predict results that are consonant with other existing data. Curve fitting is an example of such calibration. This calibration does not, however, insure that the model is a good predicter of the future, although it contributes to our confidence.

5. PREDICTING THE CONSEQUENCES

The consequences that result from implementation depend both on the nature of the alternative and on the context or environment in which it is implemented. The common practice in systems analysis is, first, to generate by scenario writing, by qualitative forecasting methods, or by some other means one or more possible future contexts and then, for each such context of interest, or for a representative set of such contexts, to determine the consequences that follow from selecting and implementing of each alternative.

By the context—called also the environment, state of the world, state of nature, or scenario—we mean the aspects of the world existing at the time the alternative is implemented that influence what its consequences will turn out to be. Thus, in the Oosterschelde example of section 3.4, to predict the impacts of the three alternatives—for instance, the change in attendance at the sea beaches—a context had to be forecasted (called a scenario there) which specified the growth of population, the recreational investment policy, the state of the economy, and so on during the time the alternatives were being implemented.

Establishing the context. The implementation of alternatives takes place in the future. Hence prediction is necessary to specify each possible context. More often than not, prediction is by mental model and amounts to no more than a judgment that the future will be like the present. Occasionally, only a few factors are significant and various mathematical forecasting models can be used to define the context.

In forecasting, we make the essential assumption that the future is partially determined by the past, on which data can be made available. This assumption implies these important questions related to the data needed for a reliable forecast:

(i) How far into the past should the record reach?

(ii) How broad should the observations be, i.e., how many different phenomena must be observed to forecast one selected phenomenon?

(iii) To what extent can we trade the length of record for number of observations, or weigh scanty new data against abundant old?

(iv) How far ahead can we infer from the data available?

One should not overestimate the power and possibilities of forecasting techniques based on statistical data and formal models. For one thing, the data may not be rich enough to provide the necessary length and broadness of the record. Secondly, the phenomena in the past were observed (measured) with errors.

Thirdly, there are phenomena to be forecast in some systems analyses that are related to phenomena in the past that are either not measurable or missing from the statistics. For these reasons alone, in making long-term forecasts of changes in technology due to inventions or forecasts of changes in societal and political attitudes, expert judgment may do as well as any computer model we have today.

There certainly are many other cases where expert-based, judgmental forecasting may be appropriate, because human experience and intuition may—implicitly and even unconsciously—make use of correlations and associations that cannot readily be formalized. The most frequent use of Delphi has been for forecasting and parameter estimation.

Whatever the forecasting techniques, the ability to determine the future in terms of reasonable probabilistic confidence is limited. There are many cases in analysis where the future that we must consider is more distant than any explicit model-based forecast of the external conditions can reach with confidence (as in the energy study described in section 3.5). In these cases, the analyst tends to predict the future environment by *scenarios*, i.e., hypothesized chains of events. He is still able to say: if the external events follow scenario No. 1, the results of the action will be ..., but he cannot say much about the probabilities.

For questions where there is a considerable interval of time between the decision and full implementation, say the time between the decision to design a new supersonic transport and the time it is put into commercial operation, predicting the future can be so uncertain that it becomes desirable to compare alternatives in several different contexts or contingencies (also sometimes called alternative futures) that might come about. A common method for preparing these contingencies is also scenario writing. Those that are selected for use in comparing the alternatives are chosen as representative of the full set of possibilities. How this should be done is not at all clear. Among those selected would be the one considered to be the most likely; others would be selected because they might affect the ordering of the alternatives. In military analyses, for instance, a "pessimistic" contingency, one in which the enemy is assumed to be best prepared to counter the alternatives, would certainly be included as well as an "optimistic" contingency, say one in which it was assumed that enemy intelligence had not anticipated certain of the alternatives under investigation. Calculation of the consequences for several contingencies may then give an idea of the range of uncertainty to be expected. The energy study summarized in section 3.4 centered most of its attention on two scenarios looking 50 years into the future: a high scenario and a low scenario, the former assuming a higher economic growth throughout the world and the latter assuming a lower worldwide economic growth (and Table 3.6 and Figure 3.10 give results that emerged from these two scenarios). However, to explore the appropriate sensitivities, the analysis team also looked at three other scenarios: one involved a nuclear moratorium, one involved a significantly enhanced nuclear energy capability worldwide, and the third assumed that the 2030 energy demand and use would be only about double what it is today (or a third less than that in the low scenario, a result that keeps the world's per capita energy consumption constant over the next 50 years). Important insights emerged from all three cases.

A few summary remarks are appropriate here:

a) As the probabilities of the scenarios are not known, nothing can be said about the *expected* outcome of the action.

b) It is important to consider several scenarios, and to choose them in a systematic way. One of these should be the scenario that seems most likely to come about, but comparisons based on others may present special insights. Thus, for example, we also want to consider, among others, scenarios that are structured so as to present circumstances unfavorable to achieving the objective, but which we feel are still likely,

c) An alternative that is very sensitive to small changes in the scenario assumptions should possibly be rejected, or redesigned with the purpose of decreasing the sensitivity, even though it may rank high for certain favorable circumstances.

d) Scenarios that represent positions being widely and/or influentially held, even if they are at extremes, may be important to be explored. For example, the three energy study scenarios just cited clearly respond to the interests of the communities wishing to (i) ban nuclear energy altogether, (ii) place principal reliance on it in the world's energy future, and (iii) reduce greatly the world's consumption of energy, respectively—and the findings shed important light on the potential consequences of these extreme positions.

Establishing the consequences. Given a context, a model or set of models is then used to predict the consequences of each alternative. This same model set may also serve for the other contexts and all alternatives unless the alternatives are radically different. If they are, another model or set of models may have to be constructed. For example, unless the alternatives are of essentially the same type, differing only in parameter values, they may generate consequences of different types and hence may require different models. Thus, in a benefit-cost comparison to determine whether public money would be spent for flood control, a new hospital, or an urban park several models would be required to determine the benefits of each alternative.

One of the major difficulties in systems analysis is that the rankings of the alternatives may not be the same in all contingencies. Further models, those of decision theory, are sometimes used in such cases (Schlaifer 1969). That is, one argues that certain of the contingencies are more likely to occur than others and hence probabilities can be assigned to them subjectively. An approach that would be appropriate were the probabilities known can then be used (White and Bowen 1975).

In spite of the many difficulties with large computer models (these difficulties are well treated in Meadows and Robinson 1982), many analysts try to design an elaborate computer model that will predict the full spectrum of impacts. A better approach, at least in my view, is to use a collection of smaller-scale models that can be linked together (Goeller 1973, 1977; Paxson 1971) by means of various logical connections (which are in themselves models). These smaller models can be set up on-line on a large computer and, during presentations by telephone connection through a portable terminal used to answer questions from the decisionmaker regarding changes in the impacts that follow from changes in the contingencies and other assumptions.

Sensitivity analysis. To analyze a model's sensitivity, the analyst changes some assumption, parameter value, or structural specification within the limits of uncertainty and then determines the new outcome to discover the extent to which it differs from that of the standard—or base-line—case. In fact, this process is usually repeated for several new values—often high and low estimates—that represent reasonable variations of the item of interest. If the changes in the outcomes are sufficient to suggest modifying the decision or policy that was preferred on the basis of the base-line results, then the model is said to be sensitive to the factor involved. To detect possible covariations, it is sometimes necessary to change two or more factors simultaneously. "Within the limits of uncertainty" is, of course, a subjective judgment; other authors say "realistic" changes (Holling 1978). Models that are not sensitive are more credible in the sense that their outcomes do not depend so critically on questionable assumptions.

When the assumptions about the context, environment, or scenario are changed, rather than those related to the systems model, and the resulting changes in the results examined, the process is often called a "contingency" analysis.

In the usual form of sensitivity testing, just one parameter is varied at a time. This is seldom good enough (Holling 1978, p. 103); it is almost always necessary to test for interactive variation by changing more than one factor at once, as mentioned above. However, this approach can easily generate so many cases that running them all becomes prohibitively time-consuming. Another way to test for sensitivity to a number of parameters simultaneously is to use a Monte Carlo sampling process (Emerson 1969). This can be done by selecting values of the uncertain parameters randomly from their frequency distributions for each one of a series of trials. The model result is then determined for each set of parameters. If this is done enough times, we can get an idea of what is required in the way of parameter changes to alter the outcome.

Sensitivity analysis must of necessity be undertaken in close communication with the decisionmaker, since it takes his judgment to decide when a modification in his decision is called for. The analyst needs his guidance also in deciding where to check for sensitivity.

What sensitivity testing does is help to make explicit the types and degrees of uncertainty that exist in the model outcome and to identify the dominant and controlling parameters. There is a misconception about sensitivity analysis (Bowen 1978a) that sometimes occurs; namely, that it can compensate for the simplification that occurs in a model when expected values replace stochastic processes.

Sensitivity testing is a powerful way to tackle uncertainty but, if the model is elaborate, it can cost a lot in computer time. The claim made earlier in section 2 that computer models can be easily tested is true in theory but, in practice, the expense and the time required tend to rule out extensive testing (Meadows and Robinson 1982).

6. SOCIAL EXPERIMENTATION

One way to determine the consequences of an alternative or proposed program may be to perform an experiment, that is, actually implement what one proposes to do under controlled conditions and observe the consequences that follow. When an experiment can be used and is properly designed and executed, the consequences can be inferred with greater confidence than from any other method. Unfortunately, it is often a completely impractical approach (for example, in the flood control example of Chapter 3), or it cannot be properly controlled (Nagel and Neef 1979, p. 180ff, give some examples), or it may be too expensive. For a discussion of when to conduct a social experiment, how to manage one, and some practical advice, see Volume 2.

7. DOCUMENTATION AND COST

One of the important hallmarks of professionalism in applied systems analysis is that, as a study proceeds, the analysts document their work: assumptions, data, parameter estimates and why they are chosen, model structure and details, steps in the analysis, computer code and changes thereto, results, sensitivity tests, and so on and so on. Thus, at the completion of the work the analysis team has the basis for preparing a complete and conscientious documentation of their work that will be understandable to someone technically trained but not a member of the project team (House and McLeod 1977, pp. 76-87; Meadows and Robinson 1982). House and Mcleod suggest standards and formats for such documentation.

In the flurry of activity that brings the study to a conclusion and presents its findings to the client, there is a temptation to slight the final preparation of the documentation—or to forgo it altogether. There are compelling reasons for the analysts not to yield to this temptation:

- If the study's findings are adopted by the client and implementation takes place, new questions will arise that will need further analysis, which must not be delayed while the analysts—either the original ones or new ones brought in for the implementation phase—try to puzzle out what was done originally in the face of incomplete or inchoate documentation of the original analysis.

- After a major study is completed, it is not unusual for new analysts to test the results in various ways—an important step in the process of gaining confidence in the analysis results. If analysts other than the original ones cannot understand the documentation, this confidence is seriously undermined right at the start.

- In general, clear and complete documentation buttresses confidence in the applied systems analysis; its absence carries with it inevitably the opposite effect.

Beyond these rather practical reasons, there is the overriding one stated at the beginning of this section: clear documentation of a study's processes, as well as its results—is a hallmark of professionalism in applied systems analysis.

The costs of building and using a large simulation model or of an operational game can be significant. Some idea of what these costs might be are given by Shubik and Brewer (1972).

8. WHAT DO MODELS GIVE US?

In many clearly defined situations, particularly where repetitive operations are involved, models can be designed to give predictions in which great confidence can be placed. The statistical models used in the blood-supply study and the deployment models used in the Wilmington fire study of Chapter 3 are examples. In contrast, the safety models for the Oosterschelde study yield predictions that are far less firm; there the analysts had nothing but fragmentary data from which to estimate at what water level a dike would fail or how much damage would result from a particular set of dike failures. On account of such uncertain elements, the models used were challengeable, but until the basic data are improved, so are any other models that might be used.

The predictive models for the sociotechnical problems of applied systems analysis are not like the scientific models of, say, mathmatical physics. They have not yet been shown to be the appropriate models for identifiable classes of real situations. They must be freshly devised—or at least modified—for each particular application. They can not always be expected to give good results when the contingencies with which they are associated are changeable (Boothroyd 1978). The world is just too complex, unpredictable, and disordered for our models of large-scale problems with social impacts to do much more than provide useful insights. As Charles Hitch (1957) said of applied systems analysis twenty-five years ago (he called it operations research):

> ...operations research is the art of sub-optimizing, i.e., of solving some lower-level problems, and ... difficulties increase and our special

> competence diminishes by an order of magnitude with every level of decision making we attempt to ascend. The sort of simple explicit model which operations researchers are so proficient in using can certainly reflect most of the significant factors influencing traffic control on the George Washington Bridge, but the proportion of the relevant reality which we can represent by any such model or models in studying, say, a major foreign-policy decision, appears to be almost trivial.

Our computer capabilities have increased by a factor of at least a hundred since then and we can do better, but not a great deal better.

Models for ecological management, impact assessment, social policy design, and for many other issues to which systems analysis is applied have turned out to give predictions in which our confidence is low. Yet these are important concerns that must be investigated and the policymaker's choice is limited; either he must base his predictions and actions on the explicit models developed by analysts assisted by using expert judgment or on judgment alone.

What then do we get from our models if their predictions are so tentative? At the very least we get insight into the consequences of our alternatives, information that may enable us to intuit improvement in the model and to design a better alternative. Indeed, the process of building the model may often be more valuable than the results we get from the model itself. "Experts create models, but models also create experts" (Greenberger et al, 1976). Almost everyone agrees that the people involved in modeling learn a great deal about the problem. This is one of the reasons why many modelers so often push for gaming, for it offers a chance to involve the actual policymakers.

We should not look on systems analysis models as mere "black boxes" that produce predictions when properly stimulated. So narrow a view ignores an important process: in using and building models, analysts learn about the problem. An explicit model of any kind introduces structure and terminology to a problem and provides a means for breaking a complicated decision into smaller tasks that can be handled one at a time. It also serves as an effective means of communication, enabling the participants in a study to make their judgments within a defined context and in proper relation to the judgments of others. Moreover, through feedback–the results of computation in a mathematical model or the criticism of an expert's judgment, for instance–the model can help the analysts and the experts on whom they depend to revise their earlier judgments and thus arrive at a clearer understanding of their subject matter and of the problem.

These secondary characteristics of a model–separating tasks and providing a systematic, efficient, and explicit way to focus judgment and intuition–are crucially important, for they provide a way of conjecturing what the major consequences may be when adequate quantitative methods are not available.

In connection with the San Diego Clean Air Project (Goeller et al. 1973), Bruce Goeller developed a number of modeling premises that should be considered by every analyst (as quoted by House and McLeod 1977):

> The first, and most basic, premise holds that it is impossible for a comprehensive model to realistically internalize the policymaking process, that is, to individually weigh and trade off the numerous factors involved in making a policy decision and to select the preferred alternatives. Past attempts to do so were not considered credible to either the researcher or the policymaker.
>
> To overcome this deficiency, the policy analyst is viewed as a person who constructs and maintains a toolkit of models and analytical techniques that can be brought to bear on specific policy issues; the specific mix of these tools is variable and determined by the specific problem...
>
> The second premise is that the methodological approach of policy analysis models should often differ from that of planning (implementation analysis) models because their purposes differ. *Policy analysis*, in our view, is primarily concerned with deciding *what* to do; that is, what are preferred. Implementation analysis is concerned with deciding

how to do something; that is, what actions by what institutions will bring a particular preferred policy into being. Since they must evaluate many possible policies in terms of many possible impacts, policy analysis models should strive for flexibility, inexpensive operation (both in terms of computer and human costs), and relatively fast response; moreover, they should allow policies to be described at a relatively gross and conceptual level. Implementation analysis models, in contrast, can, and generally do, operate at a considerably more detailed and concrete level, since they will be used to evaluate only a few alternatives...

The third premise is that a policy model's primary purpose is to improve decision making rather than to improve forecasting per se. For example, a relatively crude model that can clearly demonstrate that alternative *A* performs better than alternative *B* under both favorable and unfavorable assumptions will probably lead to a better decision than a complex model that can perform only a highly detailed expected value extrapolation. Policy models generally need the capability easily to perform various kinds of sensitivity analyses, not only on the policies themselves, but on the basic technical and scenario assumptions as well...

The fourth premise is that our *Tinker Toy* approach to a comprehensive model (where a kit of tools exists that may be used in different combinations) is better suited to many kinds of policy problems than the *monolithic* model approach. With the Tinker Toy approach, the component models, which relate to different parts of the problem, may be used separately to analyze a particular part of the problem in many different ways, with a minimum of data inertia or housekeeping problems, thereby increasing the anayst's understanding of that part of the problem and his ability to design effective policies for it. When the component models are used in combination, the output data set from one model is generally part of the input data set of a subsequent model. Although the analyst could submit a combination of models as one computer run, he often gains advantages from making separate serial runs. This enables him to see various intermediate results, to check the output data from one model for reasonableness and, if necessary, to modify them before they are input to the next step. He can adaptively intervene in the interaction process between the models to reflect the effect of factors that the models do not explicitly treat or to heuristically increase the efficiency of search or convergence (Paxson 1971)...

The fifth premise is that the design of a comprehensive policy model should be decision-maker-oriented from the start. Initially, the model should be considered as a black box (toolkit!) and the question should be what knobs, representing policy variables (and the scenario), and what dials, representing impacts, should be put on the front of the box to make it useful to the decision makers. Only after this exercise should attention be given to designing the algorithmic contents of the box.

The sixth premise is that there might be synergistic complementaries from developing comprehensive policy models, using the Tinker Toy approach in a region that already has a fairly well-developed system of planning models. First, and most obvious, the planning models could be used as part of the detailed implementation planning process after the preferred policy is chosen. Second, they could be used as a pump-primer for the policy analysis methodology: By generating detailed forecasts of numerous regional characteristics (population and land use by small areas, etc.) in machine-readable form, planning models provide a voluminous but internally consistent and systematic data base that may be aggregated, incorporated, and used in various ways by the policy models. This approach can be particularly effective for studying the near-term effects of near-term policies since it is common to treat land use and other slowly varying regional quantities as exogenous in such studies. In this context, we use the planning methodology to provide a detailed forecast of the region in the near term assuming that the "do nothing" or "existing trends" policies prevail, and then use the policy model to predict the impacts of changes in policy. We call this a perturbation approach.

The final premise is that the practicality and usefulness of a particular policy model for other (related) policy problems is strongly determined by the concreteness of the original policy problem for which it was developed.

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