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NETWORKS AS AN AID IN TRANSPORTATION AND CONTINGENCY PLANNING

by

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ABSTRACT

As a mainstay of transportation analysis, network modeling is an alluring methodology around which to build decision aids for contingency planning. And yet, because contingencies in transportation are so diverse, any single methodological approach is best suited only for certain of these decisions. By summarizing varied uses of network optimization and current capabilities of network-planning computer systems, this paper identifies the strengths and weaknesses of network analysis in supporting various planning and control issues that arise in contingency planning. It also proposes a framework for designing decision aids that combine sensitivity analysis, scenario planning, and simulation methods with the enormous computational capabilities of network optimization. Illustrations of network analysis are given in the context of vehicle fleet planning, equilibrium analysis of urban traffic flow, and energy distribution systems.

INTRODUCTION

All decision makers must deal with contingencies (uncertain events). They must plan for them; they must respond to them.

In designing their street network, could urban planners in Houston have foreseen and planned for a population growth of almost 70% in the last twenty years? How could transit authorities in the Northeast have anticipated and planned for the blizzard of 1978? How might shippers and carriers best respond to diesel prices that have escalated by some 200% in the last five years? And, how might any distribution manager respond to events like the oil embargo of 1973-74?

These contingencies are typical of those that arise in transportation planning. Moreover, each is complicated by system effects. That is, events in one location, or affecting only one part of a large and complex system, can have rippling effects and provoke derivative, and sometimes substantially amplified, events elsewhere in the system. Any problem setting endowed with network structure, as in each of the previous examples, is susceptible to this cascading of consequences. Because the network induces dependencies between its components, its analysis often requires an overall network perspective. This observation is widely accepted and indeed has stimulated the development of powerful network analyses that are capable of optimizing large and complex networks. And yet, these network capabilities have had but limited impact on contingency planning. This limited use is in part explainable: certain contingency planning issues can be resolved adequately without the need to consider detailed network structure. A more aggregate perspective may be sufficient. In other instances, though, contingency planning is inexorably tied to underlying network structure. In these instances, network analysis not only might be an attractive aid to planning, but might be required for planning to be effective at all.

This paper aims to identify when and how network optimization might be used fruitfully in conjunction with scenario planning or simulation methods to deal with contingencies. It first summarizes a variety of uses of network models as well as current computational capabilities of network computer planning systems. It then discusses network analysis in a broad context of managerial problem solving, pointing to contexts in which network models might be used to greatest advantage. Finally, it describes a conceptual approach for using network optimization models for contingency planning.

Our discussion is tailored for nonspecialists. Hopefully, an accessible account of these ideas might introduce nonspecialists to network modeling and in the process stimulate them to consider this methodology as a practical and powerful decision aid.

For concreteness, we have cast our discussion in the context of transportation planning, interpreted broadly, including distribution planning, logistics, and pipeline transport. Most of the material is also valid in a variety of other settings, such as communication planning and computer networking.

1. NETWORK MODELS

The term network typically elicits images of interconnected roadways or railbeds, of interconnected electrical components, and of other physical facilities. And indeed, many networks that arise in transportation and other contexts are of this variety. And yet, networks arise in other ways as well. For instance, *route maps* often combine several physical legs of a trip and/or several modes of transit into a single link representing a route joining two geographical locations. Moreover, routes need not be restricted to fixed physical facilities. Airways and waterways, for example, often are only minimally limited by their physical environment.

Another type of network is a *schedule map*. These networks link geographical locations via roadways, railbeds, airways or waterways, or via composite routes while introducing a time dimension into the network representation. These networks, therefore, not only capture spatial sequencing of trips, i.e., their *routing*, but also their temporal sequencing, i.e., their *scheduling*.

How might each of these different types of networks be used in transportation planning? How might each type be used in contingency planning? This section addresses the first of these questions by briefly reviewing several illustrations of various network applications and by summarizing current capabilities in solving network models.

A COOK'S TOUR OF NETWORK APPLICATIONS

The Sioux Falls street network (LeBlanc [1973]) shown in Figure 1 is typical of the street networks used in transportation analysis. The nodes in this network represent intersections in the physical street network as well as centroids of population. The links correspond to thouroughfares and major roadways. In this example, as in most studies, the network model does not represent the full detail of the physical street network. It subsumes many secondary streets and many intersections so that the network becomes as simple as possible for the study at hand; at the same time, the model captures the essential characteristics that are required for the analysis to be performed. Although the data aggregation used in constructing this network is inevitable and remains essentially an art for most applications, several recent studies have suggested that "good" aggregations, while only approximating the underlying physical network, might be adequate for most planning purposes (Bovy and Jansen [1981], Geoffrion [1976], Hearn and Kuhn [1977], Zipkin and Rainer [1981]).

There are numerous of ways to use models like the Sioux Falls network in practice. For example, suppose that we knew the demand patterns for auto travel (as trip tables or as demand relationships that depend upon prevailing network conditions) between origin and destination pairs, and that we also knew how delay on the links depends upon the flow in the network. Could we then predict the flow pattern during the peak morning and evening rush hours? Presumably as users begin to make trips on any route in the network, the delay on that route becomes more pronounced and some users either shift to new routes or

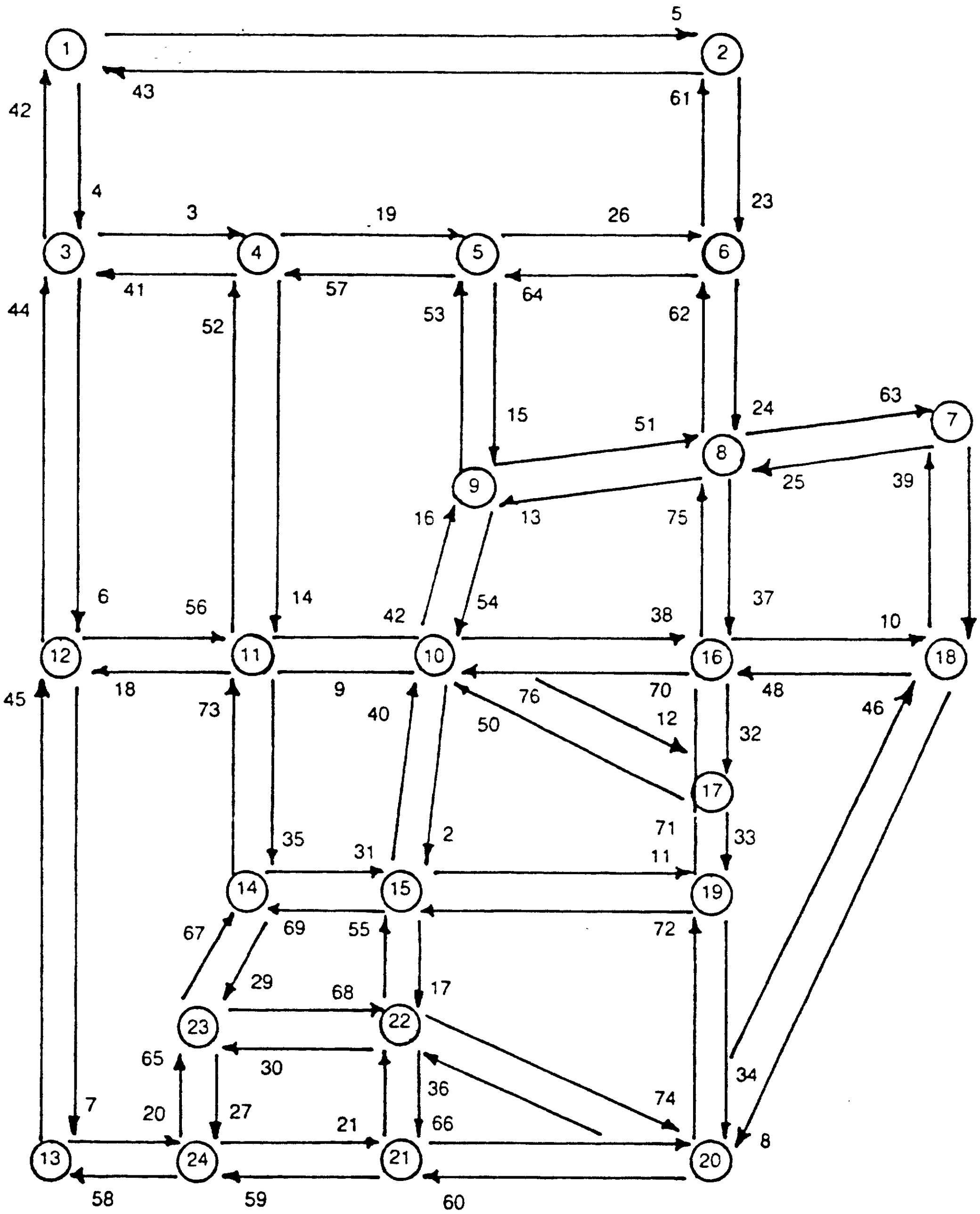

Fig. 1. Sioux Falls Street Network

decide against making a trip. But then, in either case, this route would become less congested, possibly while other routes become more heavily traveled and congested, and hence the route becomes a more attractive alternative for travel. Attracting more users would again, however, add to the route's congestion and stimulate users to seek other route choices. Would this on-again, off-again attractiveness of this route as compared with other alternatives ever equilibriate so that no user has any incentive to change route choice? Since users are making similar assessments of all routes, and might be considering other modes of transit as well, they will simultaneously be making choice decisions for many routes and will be facing a delicate balancing act (an equilibrium assessment) among their various alternatives for travel. With this behavioral assumption that users simultaneously choose minimum delay (or cost) routes, this *urban traffic equilibrium* model becomes a descriptive tool for replicating prevailing flow patterns. Its success is measured by the fact that it has become one of the staples of urban transportation analysis. For example, an equilibrium model is now an essential component of the U.S. Urban Mass Transit Authority's [1976] basic planning system.

This equilibrium model has a variety of uses in policy analysis (Florian [1976]). Suppose, for example, that we change the underlying network topology by altering one-way street assignments, by establishing priority bus lanes, or by changing bus or subway fares (and hence affecting the demand for trips by autos). What would be the resulting changes in flow patterns and loading on the street network? Presuming that the equilibrium model retains its descriptive power as these changes in the underlying problem setting are made, the model then becomes an attractive predictive tool for answering such questions.

Physical networks like the Sioux Falls street map are used in many other ways as well. For example, shippers use them to plan the distribution of retail goods to outlets throughout cities. They'd like to assign delivery points to their fleet of trucks and would also like to find the lowest cost routing sequence for each truck that is consistent with priority requirements, time-windows imposed upon deliveries, and similar restrictions. With gasoline prices increasing by some 240% in the last ten years and labor costs increasing as well, these *vehicle routing and scheduling* issues have begun to attract increasing attention by practitioners and researchers alike (Bodin, Golden, Assad and Ball [1981]).

The Sioux Falls network, which has analogs in most other modes of transportation, is useful in modeling transportation infrastructures directly. Alternately, we could represent the infrastructure by modeling routes rather than physical distribution channels. As an example, consider plant loading and distribution planning for an automobile manufacturer. Figures 2 and 3 illustrate a version of this planning problem for Chrysler Corporation (Shapiro [1979]). In this application, Chrysler is deciding on the best assignment of six carlines to three locations -- Hamtramck, St. Louis, and Newark, Delaware -- to meet demand for each carline at each of 550 customer zones. The links in the network shown in Figure 3 do not correspond to physical transport facilities. Rather, they represent composite routes by rail and/or truck from the plants to the customer zones. Moreover, the per unit cost on the link corresponding to each plant-customer zone-carline combination includes not only the transportation costs to the customer zones, but also the inbound transportation cost to the plants and the production costs at the plants. The problem is to choose the production level by carline at each plant and to assign customer zones to the plants in order to minimize overall costs. That is, we must determine the minimum cost flow pattern on the links of the network in order to satisfy the demand requirements at the customer location nodes. Figure 2 shows the geographical division of customer zones by plants for one of the carlines.

Many applications enrich this model by adding regional distribution centers that would function as intermediaries for serving the final customers. We might then want to solve the *production and distribution system planning* problem as before, or might wish to consider the best design of the distribution system in terms of the sizing and location of distribution centers. Models of this type have been applied with great success in practice. For example, a distribution design system based upon these network concepts developed by Hunt-Wesson Foods has accrued savings estimated in the low seven figures (Geoffrion and Graves [1974], Geoffrion [1978]).

In addition, route planning and loading models such as the Chrysler application can be combined with local routing decisions that are made after goods have reached their regional or local distribution centers (this is the vehicle routing problem discussed earlier). Studies of this nature can have impressive payoffs. As but one illustration, in 1976-77 the Cahill May Roberts

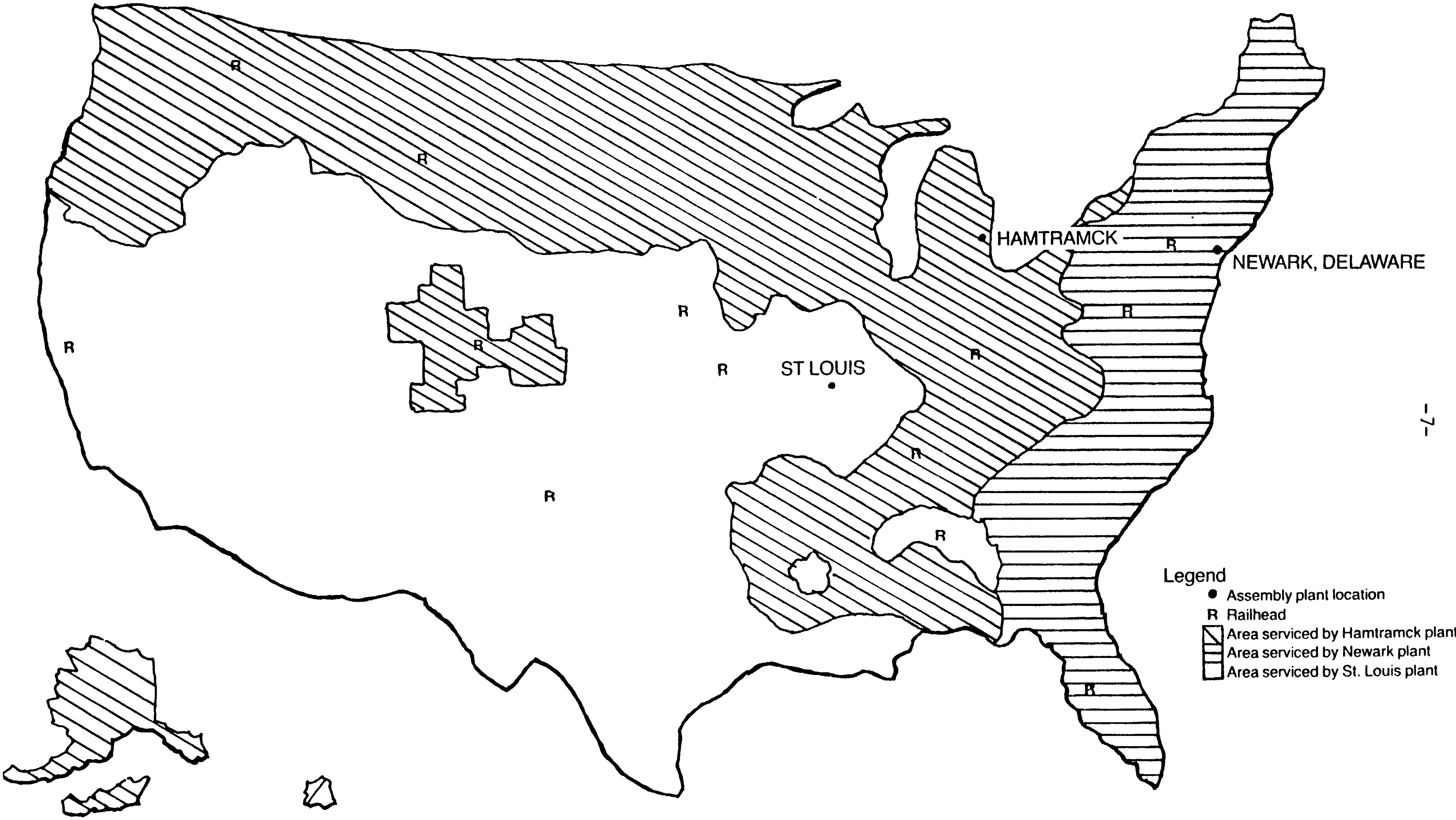

Fig. 2. Regional Assignments For A Model Type In Chrysler Plant Loading

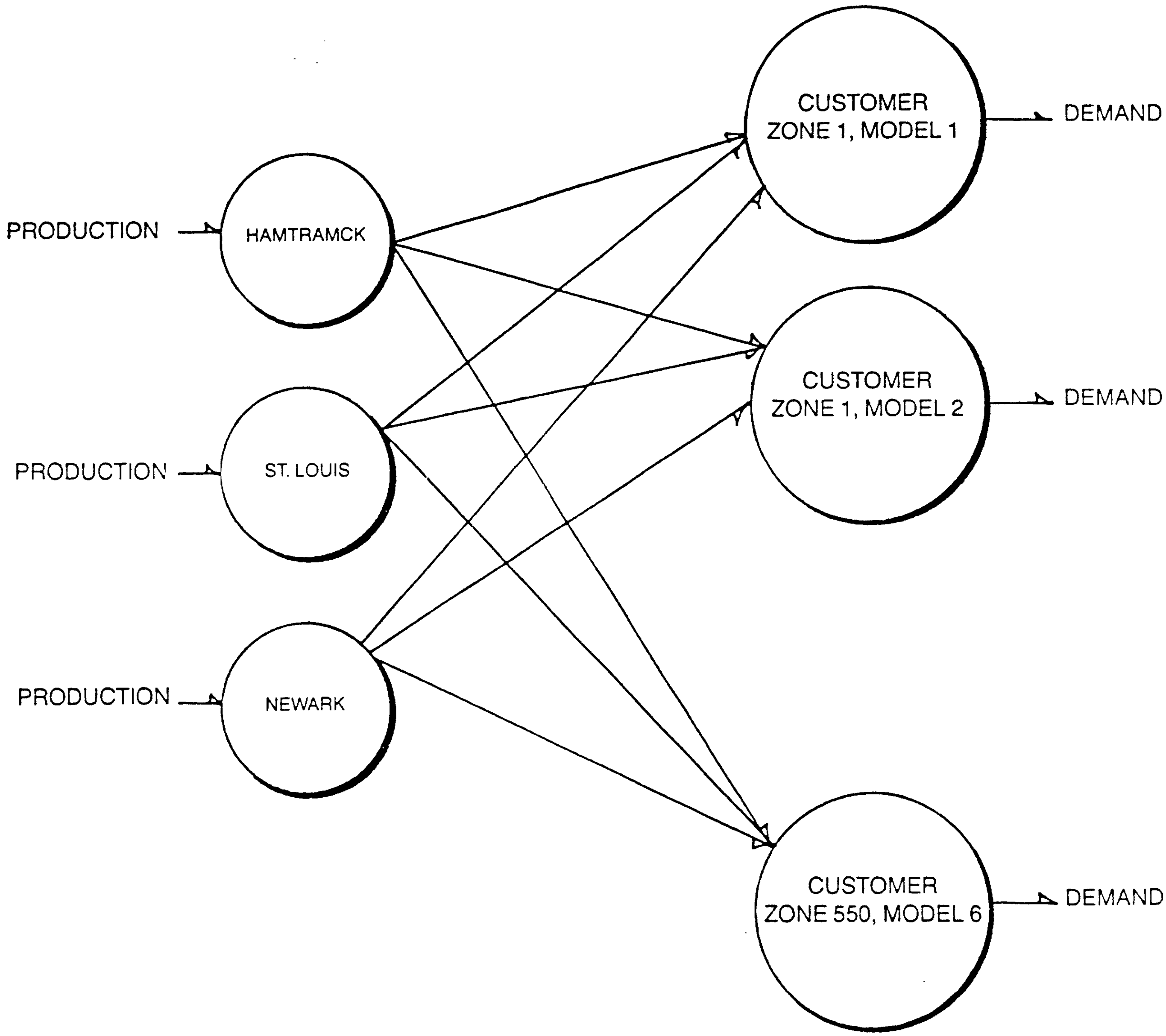

Fig. 3. Network For Chrysler Plant Loading

Company used a network study to reduce its transport costs to city depots by 20% and its local delivery costs by 23.3%; moreover, it increased customer service levels by 60% as well (Harrison [1969])!

Figure 4 illustrates another type of distribution network, one that arises in energy planning. Here Alaska and Texas function as sources for natural gas serving demand generated in the Eastern, mid-Western and Western regions of the United States. If each of these production and consumption points were to operate in isolation, the prices in each location would adjust to insure equilibrium of supply and demand. With transshipments between locations as possibilities, though, supply and demand need not equilibriate at each location. Instead, natural gas will flow from production to consumption regions until the "market clears" and the network itself achieves an equilibrium. That is, if a producer ships between two regions, then the price at the origin plus the distribution cost must equal the price at the destination. (If the destination price were insufficient to cover wellhead price plus distribution cost, the producer would be induced to sell at the wellhead rather than ship the goods. If the destination price were to exceed wellhead price plus distribution cost, the producer would ship more at a profit until the added availability of natural gas at the consumption point drove down the price to its equilibrium value.)

This *spatial equilibrium model* of network flow has applications in a variety of problem settings. For instance, it lies at the core of the Project Independence Evaluation System developed by the Federal Energy Administration [1976]. It also has been applied to agricultural markets (Schmitz and Bawden [1973], Hall, Heady, Stocker and Sposito [1975]) and to water resource allocation (Flinn and Guise [1970]). Moreover, the model has several similarities with the urban transit equilibrium model discussed earlier. Indeed, the two models can be viewed as specialization of a common, and more general, equilibrium model (Magnanti [1980]).

Figure 5 illustrates yet another type of network -- a *space-time scheduling* network encountered in airline fleet planning (Simpson [1969]). The network at the top of this figure represents a geographical map linking three airports. In order to assign its vehicle fleet to possible service

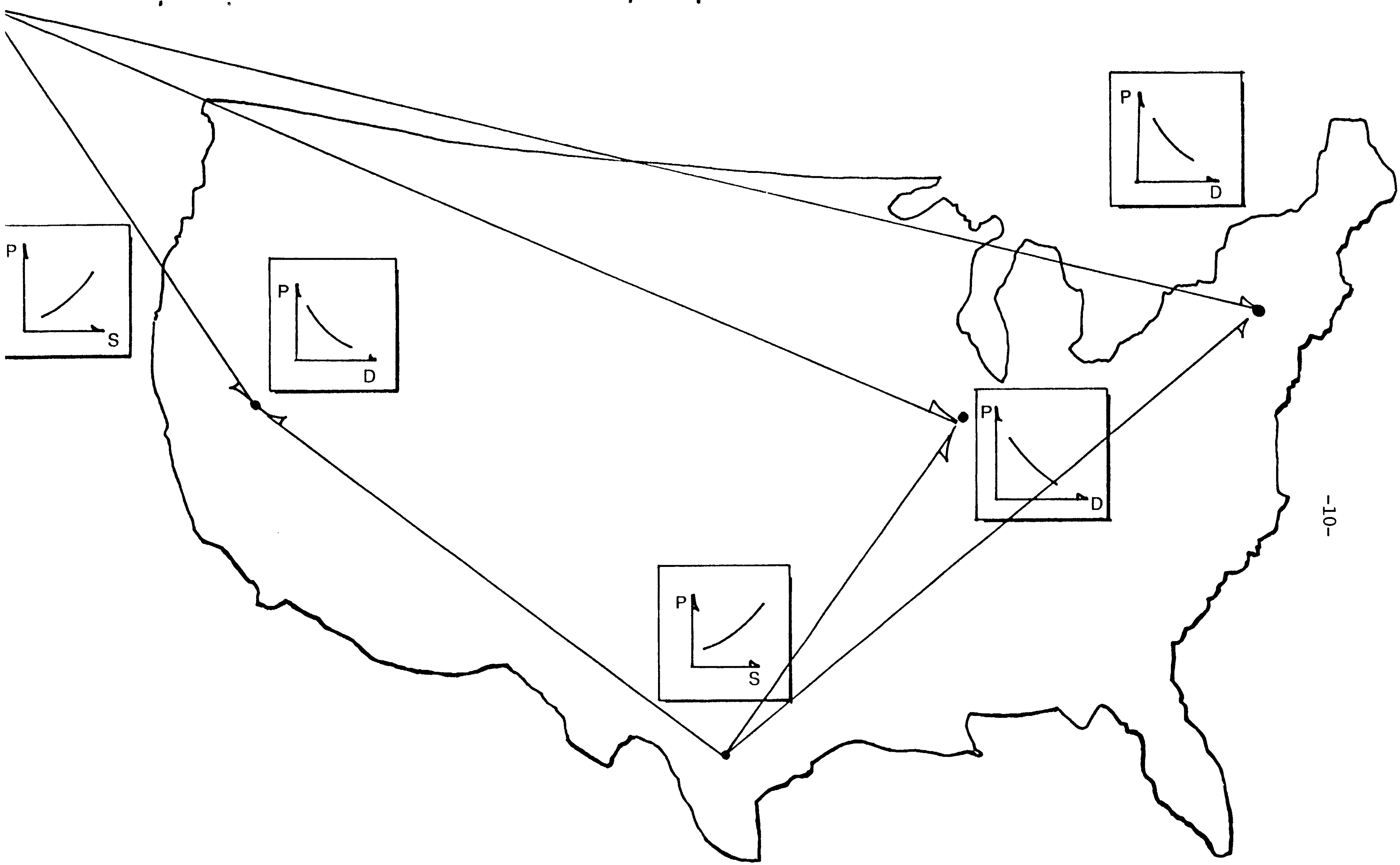

Fig. 4. Interregional Energy Distribution Network

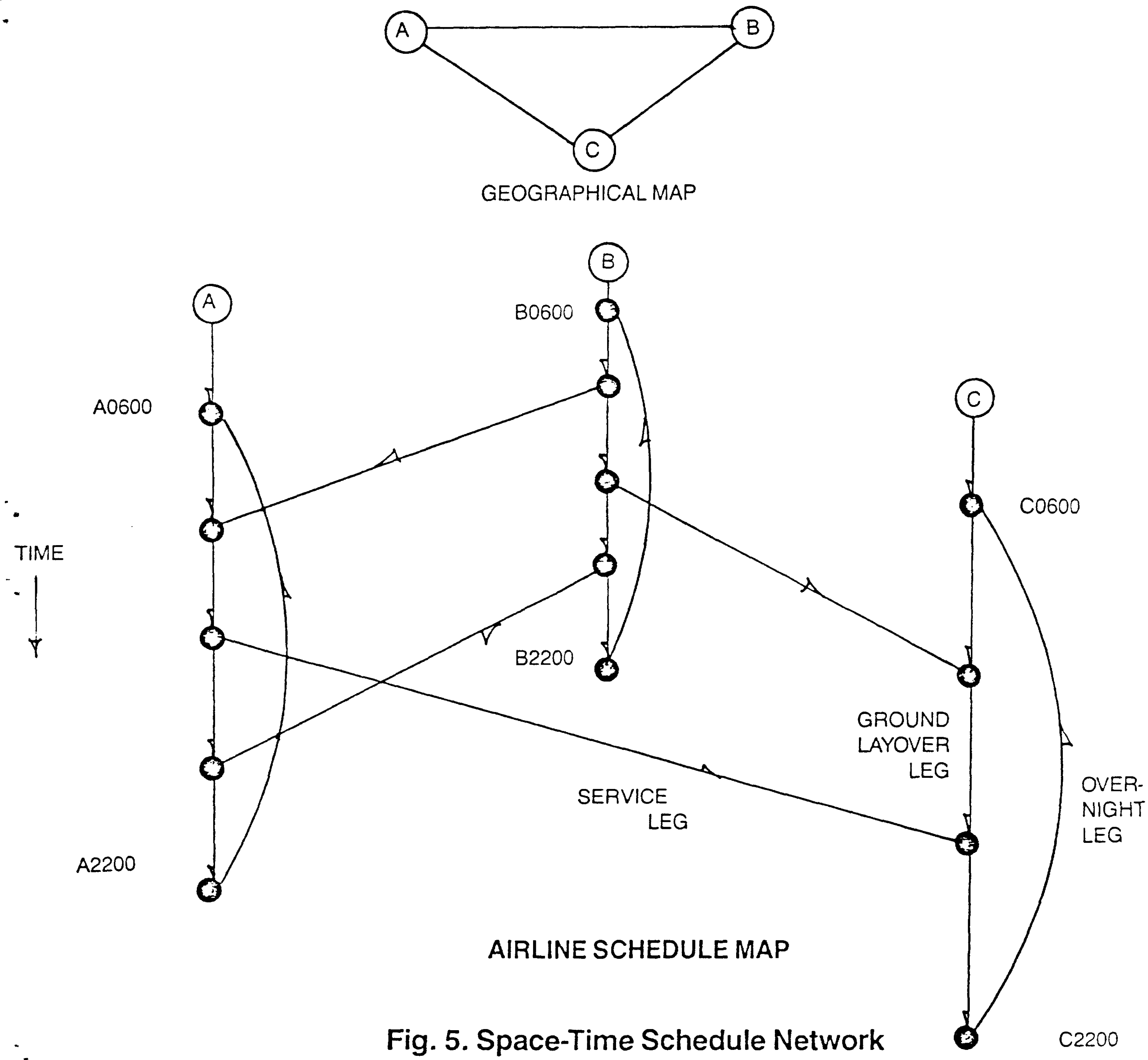

Fig. 5. Space-Time Schedule Network

legs joining these airports and choose the service legs that are most profitable to fly, an airline company might represent its service schedule in a network form as well (the schedule map in Figure 5). This network distinguishes nodes both by location and time of day. For example, the node labeled A0600 corresponds to airport A at 0600 hours. The schedule map defined on these nodes contains three types of arcs. Service arcs (e.g., connecting B0700 and A0900) correspond to potential flights. Ground layover arcs (e.g., connecting A0600 to A0900) permit planes to hold over at an airport for later flight legs. Overnight legs model layovers at the end of the day. By assigning revenues to the service legs and allocating capital costs for the planes to the overnight legs, this network can be used to find an optimal fleet size and an optimal selection of services to be provided. We simply solve a flow problem on this network with no exogenous input of supply or demand and with a restriction (flow bound) that no more than one plane fly each service leg. After solving the problem, we can then trace the flow of any plane as it circulates through the service, layover, and overnight arcs to determine its service schedule.

This use of network schedule-maps is not restricted to airlines. It has applications in most other modes to problems as varied as scheduling of street sweepers, school buses and oil tankers. In addition there are many embellishments on this basic vehicle fleet planning model (Bodin, Golden, Assad and Ball [1981], Magnanti [1981]).

NETWORK CAPABILITIES

Table 1 summarizes several different types of network optimization problems as well as current capabilities of computer systems for solving these problems. The simplest of these problems, the shortest path problem, assumes that a set cost is associated with traversing each arc of the network and finds the shortest (i.e., minimum cost) path joining nodes designated as origins and destinations for travel.

This problem is pervasive in transportation planning. First, when networks are operating below capacity and without congestion, the shortest

TABLE 1. NETWORK CAPABILITIES

MODEL	GENERIC NATURE	APPLICATIONS	CURRENT CAPABILITIES†
SHORTEST PATHS	GIVEN: SOURCE NODE, ARC ROUTING COSTS FIND: MINIMUM COST PATHS FROM SOURCE TO ALL NODES	• AUTO ROUTE CHOICE • ASSIGNMENT OF CUSTOMER TO FACILITIES	1000'S NODES & ARCS FRACTIONS OF A SECOND
MINIMUM COST FLOW	GIVEN: SUPPLY & DEMAND NODES, ARC & NODE CAP., ARC ROUTING COSTS FIND: MINIMUM COST ROUTING PLAN	• DISTRIBUTION SYSTEM PLANNING • VEHICLE FLEET PLANNING	1000'S NODES & ARCS FRACTIONS OF A MINUTE
MULTICOMMODITY FLOW	GIVEN: MIN. COST FLOW PROBLEM FOR EACH OF SEVERAL COMMODITIES, JOINT ARC CAPACITIES FIND: MINIMUM COST ROUTING PLAN	• MULTIFLEET VEHICLE PLANNING • MULTI-ITEM PRODUCTION/ DISTRIBUTION PLANNING	100'S OF CAPACITATED ARCS SEVERAL MINUTES
VEHICLE ROUTING	GIVEN: DEPOT, VEHICLE FLEET, DEMAND POINTS, ARC ROUTING COSTS FIND: MIN. COST ASSIGN-MENT OF VEH. TO ROUTES	• RETAIL TRUCK ROUTING • SCHOOL BUS ROUTING	100'S NODES FEW MINUTES, OFTEN SECONDS (HEURISTICS)
NETWORK EQUILIBRIUM	GIVEN: O-D DEMANDS, (NONLIN.) TRANS. COSTS (OR DELAYS) ON LINKS FIND: EQUILIBRIUM FLOW PATTERN	• PREDICTION OF URBAN TRAFFIC FLOW • PRED. OF GOOD FLOWS BETWEEN SPATIALLY SEPARATED MARKETS	100'S NODES FEW MINUTES, OFTEN SECONDS
FACILITY LOCATION	GIVEN: CANDIDATE LOC. FOR FACILITIES, FACILITY COSTS, DEMAND POINTS, ROUTING COSTS FIND: MIN.COST FACILITY LOCATION/CUST. ASSIGN.	• WAREHOUSE LOCATION • SITING OF URBAN EMERGENCY SYSTEMS	100'S NODES FEW MINUTES (GENERALLY HEURISTICS)
NETWORK DESIGN	GIVEN: CANDIDATE ARCS & THEIR COST, SUPPLY/DEM. NODES, ARC ROUTING COSTS FIND: MINIMUM COST NETWORK DESIGN/USE	• SERVICE NETWORK DESIGN (E.G., RAIL FREIGHT ROUTES) • ONE WAY STREET ASSIGNMENTS	100'S NODES FEW MINUTES (HEURISTICS)

† ON A MAINFRAME COMPUTER SUCH AS THE IBM 370/168.

path problem becomes an adequate representation for travel through the network. For example, shippers with adequate vehicle and depot capacities will distribute goods from source points to destination points along shortest paths. (If capacities are insufficient, they will be forced to use alternate routes). Second, the shortest path problem is also a key ingredient in many more complicated network models. For instance, the usual behavioral assumption of urban traffic equilibrium models is that users select the route from their origin to their destination that *minimizes their* delay time (or cost, or any other measure of disutility) with respect to the prevailing congestion imposed by other users.

As noted in Table 1, shortest path problems with thousands of nodes and thousands of arcs can be solved on mainframe computers such as an IBM 370/168 in fractions of a second--sometimes even milliseconds. And yet, when viewed algebraically, these problems become fairly large systems. Written in equation form, the shortest path problem could have thousands of equations, one for each node, and thousands of decision variables, one for each arc. And still, the problem can be solved very efficiently because of its special structure.

The second model in this table, the minimum cost flow problem, adds multiple sources and destinations, node and arc capacities, and/or node supplies and demands to the shortest path problem. Two prototypes of this problem are the Chrysler Corporation plant loading model and the airline schedule map model previously discussed. In each case, the model determines the flow pattern on the network that minimizes flow costs while honoring supply limits, demand requirements, and network capacities. Although the minimum cost flow problem may require an order of magnitude more computational time than a shortest path problem, it can still be solved very efficiently.

The minimum cost flow model assumes that flow in the network is a homogeneous good, be it a class of passengers, a single type of freight, a class of vehicles, or a homogenous crew. The multicommodity flow model represents situations in which several distinguishable commodities share the same network. As an example, instead of planning for a single vehicle type in the space-time scheduling network of Figure 5, a multicommodity flow model might consider a mixed fleet of vehicles -- what is the best mix and how is each vehicle type to be used? Other multicommodity flow applications arise in distribution and production planning systems when several commodities share the same resources. They may share costs, share capacities in railyards or truck depots, or share production facilities and a labor supply. Now the question is one of allocating resources to the various commodities and developing the best routing plan for each commodity. Because of the added requirement of sharing resources, the computational capabilities for multicommodity flow problems are inferior to those for simpler single commodity minimum cost flow problems. The essential factor limiting the computations in these applications is the number of arcs in the network that have capacities to be shared by the commodities. Problems with hundreds of capacitated arcs can be solved in a few minutes of computational time.

The vehicle routing and network equilibrium problems that we have discussed previously can be solved with similar computational effort, ranging from a few seconds to a few minutes. Vehicle routing problems are very difficult to solve optimally, however, and most procedures are heuristic. These are methods, based upon either some underlying theoretical construct or some intuitively appealing common sense practice, that provide "good" but not necessarily optimal solutions.

Each of the models discussed so far involve the analysis of existing networks. In contrast, facility location and network design models aim to synthesize networks by adding new nodes and/or new links. The classic example of the facility location problem is the location of distribution centers and warehouses that we have discussed briefly in the context of the Chrysler Corporation and Hunt-Wesson Foods distribution problems. The siting of fire stations, police stations, and other urban emergency facilities are other important applications of this problem type (Larsen and Odoni[1981]). The network design problem can model such varied problem contexts as one-way street assignments in urban road networks or the selection of services to be provided in rail freight planning. This last setting views arcs of the network as synonomous with rail service routes and views introducing a new service as adding an arc to the network. Generally, neither facility location models nor network design models can be solved efficiently by optimization procedures, though heuristic methods are able to find good solutions to problems with hundreds of nodes within a few minutes of computation time.

The literature on solution methods for each of these problem types is enormous. For example, a selected bibliography of five years ago (Golden and Magnanti [1977]) contains nearly 700 citations. Because network models are so practical, the number of publications continues to grow at a remarkable rate. Consequently, any detailed account of the literature would take us far beyond the scope of this paper. As a guide to the growing literature, the reader might consult any one of a number of survey articles and texts on network optimization, including Handler and Mirchandani [1979], Jensen and Barnes [1980], Kennington and Helgason [1980], and Magnanti and Golden [1978].

At this point, it may be reasonable to question the wisdom of operations researchers and transportation planners in placing so much emphasis on the computational efficiency of network methods. In some instances, this is a valid criticism. If these models are to be solved only a few times, then months of effort expended in modeling the underlying problem and in gathering data may overwhelm any computational considerations. The difference between a few seconds and a few minutes, or even a few hours, of computational time might be of limited importance. Computational efficiency may be critical, however, when these models are used as operational tools, particularly in an interactive or on-line decision-making mode. Computational considerations also assume increasing significance when the models are solved repetitively to perform a sensitivity analysis on the underlying data as when addressing contingency planning issues. Moreover, sometimes a model will be solved repetitively in the context of solving a more general problem. For example, most methods for solving network equilibrium problems will solve shortest path problems repetitively tens or even hundreds of times. In these instances, computational efficiency may be essential.

2. NETWORK MODELS AND MANAGERIAL PROBLEM SOLVING

How can the network optimization models that we have described in the last section of this paper be used to address the risks and uncertainties that are inherent in contingency planning? Can one classify contingencies and identify those for which network modeling might be most appropriate? Answering these questions requires perspective on the role of network models in managerial decision making in general. What are the strengths and weaknesses of network models? What is their role in increasing management effectiveness? What type of managerial issues are better served by other planning tools?

STRATEGIC, TACTICAL, AND OPERATIONAL PLANNING

Table 2 presents a celebrated categorization of planning decisions (Anthony [1965]) that helps to resolve these issues. This perspective views planning as a three-level hierarchy divided into strategic, tactical, and operational decision making. These correspond, roughly, to the resource acquisition, resource utilization, and execution decisions of an organization.

Typically, strategic planning decisions are so highly aggregate that detailed network knowledge is not an imperative for decision making. Decision makers do not require an elaborate network model, for example, in deciding upon whether or not to add an extension to an existing subway system. In this context, social and political issues are likely to dominate all but the most aggregate assessment of potential loading patterns on the extension and their effect on the transit network as a whole. Moreover, each of the network optimization models described in the last section assumes that the underlying data is known with certainty. Because of their broad scope and long time horizon, strategic issues are likely to be influenced by many uncertain events. As a consequence, network models are not responsive, at least directly, to one of the most essential characteristics of strategic decisions, their great uncertainty.

Nevertheless, network models can be of value in supporting certain strategic decisions. As we note in the next section, a broader view of network methods as combined with sensitivity analyses, scenario planning, and

TABLE 2. TAXONOMY OF PLANNING DECISIONS

CATEGORY	CHARACTERISTICS			EXAMPLES
	OBJECTIVES AND RESPONSIBILITY	EXTENT	DATA SOURCES AND REQUIREMENTS	
STRATEGIC PLANNING	RESOURCE ACQUISITION TOP MANAGEMENT	BROAD SCOPE LONG TIME HORIZON GREAT UNCERTAINTY AND HIGH RISK	EXTERNAL AND INTERNAL HIGHLY AGGREGATE	HIGHWAY, RAILBED, OR DEPOT CONSTRUCTION MARKET PENETRATION STRATEGIES (E.G. DEFINING ROUTES) GOVERNMENT REGULATORY POLICY
TACTICAL PLANNING	RESOURCE UTILIZATION MIDDLE MANAGEMENT	MEDIUM SCOPE INTERMEDIATE TIME HORIZON MODERATE UNCERTAINTY AND RISK	EXTERNAL AND INTERNAL MODERATELY AGGREGATE	SERVICE SCHEDULING (E.G. VEHICLES → SERVICES) AGGREGATE ROUTE CHOICE CREW SCHEDULING AND WORKFORCE PLANNING AGGREGATE INVENTORY AND WAREHOUSE PLANNING
OPERATIONAL PLANNING	EXECUTION MIDDLE AND LOW LEVEL MANAGEMENT	NARROW SCOPE SHORT TIME HORIZON LITTLE UNCERTAINTY AND RISK	INTERNAL DETAILED DATA	DISPATCHING ORDER PROCESSING DETAILED ROUTING AND SCHEDULING

simulation is capable of addressing risks and uncertainties in a meaningful way. In addition, some resource acquisition decisions, such as those involving vehicle acquisition, are so highly linked with the resource's network utilization that network methods are required in order to evaluate properly the investment's costs and benefits.

As our discussion of network applications has illustrated, one of the great strengths of network modeling is in supporting resource allocation decisions, such as vehicle deployment and allocation of limited plant and warehouse capacity to products. Because such tactical planning issues typically have medium term planning horizons of weeks, months, or possibly even a year or two, data will be much more certain and be more detailed than in longer term strategic planning. Consequently, methods such as network modeling that stress large-scale decision making but not risks and uncertainties are better matched with tactical decision making. Moreover, planners are much more likely to have access to meaningful statistical assessments of uncertainties and are much more likely to be able to assess possible contingencies at a network level in the context of tactical planning. That is, they are much more likely to have data upon which to base a network analysis. As a consequence, tactical planning has been a leading arena for network modeling.

Finally, in operational planning, data may be very detailed, so much so that even the mere development and calibration of a full blown network model might be prohibitive. For example, a detailed schedule map of an urban transit system with time as well as geographical dimensions could easily have tens of thousands of nodes. Moreover, because there is little uncertainty in many operational decisions, managers frequently feel that they can eschew sophisticated planning systems and react adequately to contingencies in an as-needed, management-by-exception basis by invoking established operating procedures. In addition, many managers feel that the need to respond quickly at the operational level precludes formal analysis of any nature. Nevertheless, network models such as vehicle fleet routing procedures are used for operational planning and react quickly to changes in the planning environment (Bodin, Golden, Assad, and Ball [1981]). As computer capabilities continue to grow and their costs continue to plummet, more organizations should be developing detailed computer information systems with operating data that is well-suited to network analysis. As this happens, network models should become increasingly attractive for operational planning and for responding to operational contingencies.

PLANNING VERSUS CONTROL

We can gain further insight into the potential and limitations of network analysis by viewing managers as engaging in two essential activities -- planning and control. As Anthony and Welsch [1981] note, "Planning is deciding what should be done and how it should be done. . . . Control is assuring that the desired results are attained." As they further note, desired results may differ from planned results because of changes in the environment.

Table 3 is a conceptualization of planning devised by Simon [1967], who divides this task into five stages. The first of these, the intelligence stage, identifies broad opportunities for decision making such as cost reduction, technological innovation, forward or backward integration, or product diversification. The subsequent design stage identifies specific candidates, e.g., specific products or product lines, for exploiting these opportunities. Both of these activities require substantial institutional knowledge, an awareness of an organization's current strengths and weaknesses, and an understanding of the organization's environment and of the competitive forces affecting its industry. These are the broad and often ill-defined ingredients of strategic planning. Accordingly, the insight for these planning efforts are more likely to arise out of intuition, judgment, and institutional awareness, rather than from network planning models. The many paradigms that are just emerging out of the burgeoning literature in strategic planning and such fundamental tools as industrial economics (Porter [1980]) are beginning to provide operational tools for dealing with these issues. Conceivably, network models will assume added value in these stages of planning as the field of strategy matures.

In the meantime, as a mechanism for allocating resources and for evaluating strategic plans, network analysis remains well-suited for the third stage of Simon's taxonomy -- choosing the best of the available alternatives. Several of our earlier remarks, and several of our examples of network applications, have already illustrated this point. Moreover, network models are also useful in the implementation and evaluation stages of problem solving, since they not only aid in devising plans, but also provide a data base against which to monitor and assess decisions and their consequences.

Table 3. STAGES IN PLANNING

- Intelligence - Identify opportunities for decision making.
- Design - Identify alternatives for decision making.
- Choice - Choose the "best" alternative.
- Implementation - Adopt and monitor the chosen plan.
- Evaluation - Assess decisions and the planning process.

Table 4. TASKS IN MANAGERIAL CONTROL

- Clarify and enunciate goals and performance measures.
- Adopt systems and incentives to achieve goals. Decide upon appropriate allocation of resources.
- Negotiate and establish budgets at all levels of an organization's hierarchy.
- Use information systems to monitor status, highlight critical indicators (symptoms), and signal action.
- Communicate information, review performance, and delineate plans for remedial action.
- Respond to contingencies via
  - policies and procedures,
  - reactive decision making.
- Reassess goals and control mechanisms, and reward performance.

The implementation and evaluation phases in Simon's taxonomy are intimately related to managerial control. This is the process for seeing a plan to fruition, for adapting to changes in the environment, and for adopting corrective action when the organization or one of the sub-units drifts off course. As indicated by the outline of the various tasks in managerial control specified in Table 4, control involves programming (planning and broad allocation of resources), budgeting, operating and measurement, and reporting and analysis (Anthony and Welsch [1981]). Although the details of managerial control will vary from one organization to the next, the tasks in this table capture the basic trust of the control process.

Network models can contribute to several of these tasks in control. First, tactical network models establish operating plans that often become the goals of managerial control. Second, as we have already noted, network models provide an information base for reporting and summarizing costs, revenues, and other accounting information as well as for summarizing operational plans. Consequently, they can function as a benchmark against which to monitor performance and for signaling departures from desired goals. For example, in the Chrysler Corporation plant loading and distribution model that we have considered earlier, the same information system that was used to devise the targeted operating plan could also be used to summarize the status of plant productions by carlines, summarize sales within each customer zone, and report performance and anomalies in the distribution system.

Networks can contribute to control in other ways as well. For example, many control systems must be able to respond to contingencies in the operating environment. By establishing operating procedures, organizations may be able to cope with many contingencies on a routine basis. It is, however, impossible to have procedures in place for responding to all contingencies. Some contingencies are so unlikely to occur that this effort is unwarranted. In addition, the vast number of potential contingencies often prohibits devising an a priori procedure for responding to each. Consequently, organizations must react to many contingencies as they occur. Because of their enormous computational capabilities, network models are attractive for this type of responsive decision making. Suppose, for example, that an airline were to lose the service of one of its vehicles for a short period of time. General operating policies might be able to guide airlines in dealing with such situations, and indeed they do;

an alternative would be to maintain an information data base for the airline's fleet as in the schedule map of Figure 5 and to run a network model to best redeploy the members of the fleet that remain operational. This alternative would permit the airline to find an optimal deployment of its fleet, accounting for the operating environment that it currently faces.

To recap, network analysis is nicely tailored for resource allocation, for tactical planning, and for the choice stage in planning. It can, at times, aid in evaluating strategic alternatives. In addition, networks provide an information base for monitoring and controlling performance of an operating transportation network and are often capable of responding readily to changes in an operating environment.

3. NETWORK OPTIMIZATION AND CONTINGENCY PLANNING

What can we distill from our discussion thus far? In particular, how might the range of network applications in transportation, the computational capabilities of network optimization, and the roles of network analysis in managerial decision making affect our view of contingency planning?

First, our discussion suggests that no single methodology is likely to cope with the full range of contingencies that arise in transportation planning. Contingencies are as varied as the plans that they affect; some require different treatment than others. Furthermore, our discussion suggests that network optimization could serve as a useful decision aid for helping managers to plan for, and respond to, particular types of contingencies. This section elaborates on these themes and suggests an approach to planning for those contingencies that lend themselves to network-based analysis.

TYPES OF MODELS AND CONTINGENCIES

By definition, any contingency planning effort must consider both the uncertainty of future events and a decision maker's attitude toward risk. Consequently model-based approaches to contingency planning should have predictive power. Moreover, since we wish to *plan* for uncertain events, the models should have normative power as well. That is, they should be able to develop plans or strategies that perform well when matched against the decision maker's objectives, or performance norms. And yet, as illustrated in Figure 6, most models in transportation planning have strengths in one, but not both, of these predictive and normative dimensions. On the one hand, econometric and demand models (Domincich and McFadden [1975]), whose normative capability is limited, are sophisticated and powerful tools for predicting consumer behavior in transportation systems and for predicting future events in the industry. On the other hand, normative models such as linear programming (Bradley, Hax, and Magnanti [1977]) and network optimization, whose predictive capabilities are limited, are equally powerful and sophisticated in allocating resources and in generating action plans. Of course, not all models, and particularly not all network models, fit nicely into one category or the other. For example, network equilibrium models of urban traffic flow as well as those of spatially separated markets are basically descriptive, but can be used for predictive purposes. In this instance, however, the network methods themselves have limited normative capabilities.

This dichotomy between normative and predictive models and the lack of integrating mechanisms for drawing concurrently upon the strengths of these two model types have been major obstacles inhibiting the development of analytic methods for analyzing contingencies.

The development of analytic models is further complicated by the fact that there are many different types of contingencies with essentially different characteristics. Figure 7 suggests a scheme for highlighting some of these differences. It divides contingencies into three groups: strategic, tactical, and operational. These three classes of contingencies are distinguished by the planning problems that they effect. This view places contingencies in a hierarchical framework consistent with Anthony's taxonomy of strategic, tactical, and operational planning.

Strategic contingencies are uncertain events that have long-term implications and effect the strategic posture of an organization or an industry. Changes in the technology base of industry, fundamental changes in the competitive environment due to new market entries or changes in industrial focus, and structural changes in the economic and regulatory environment would be examples. More specific examples would be changes in forms of containerization

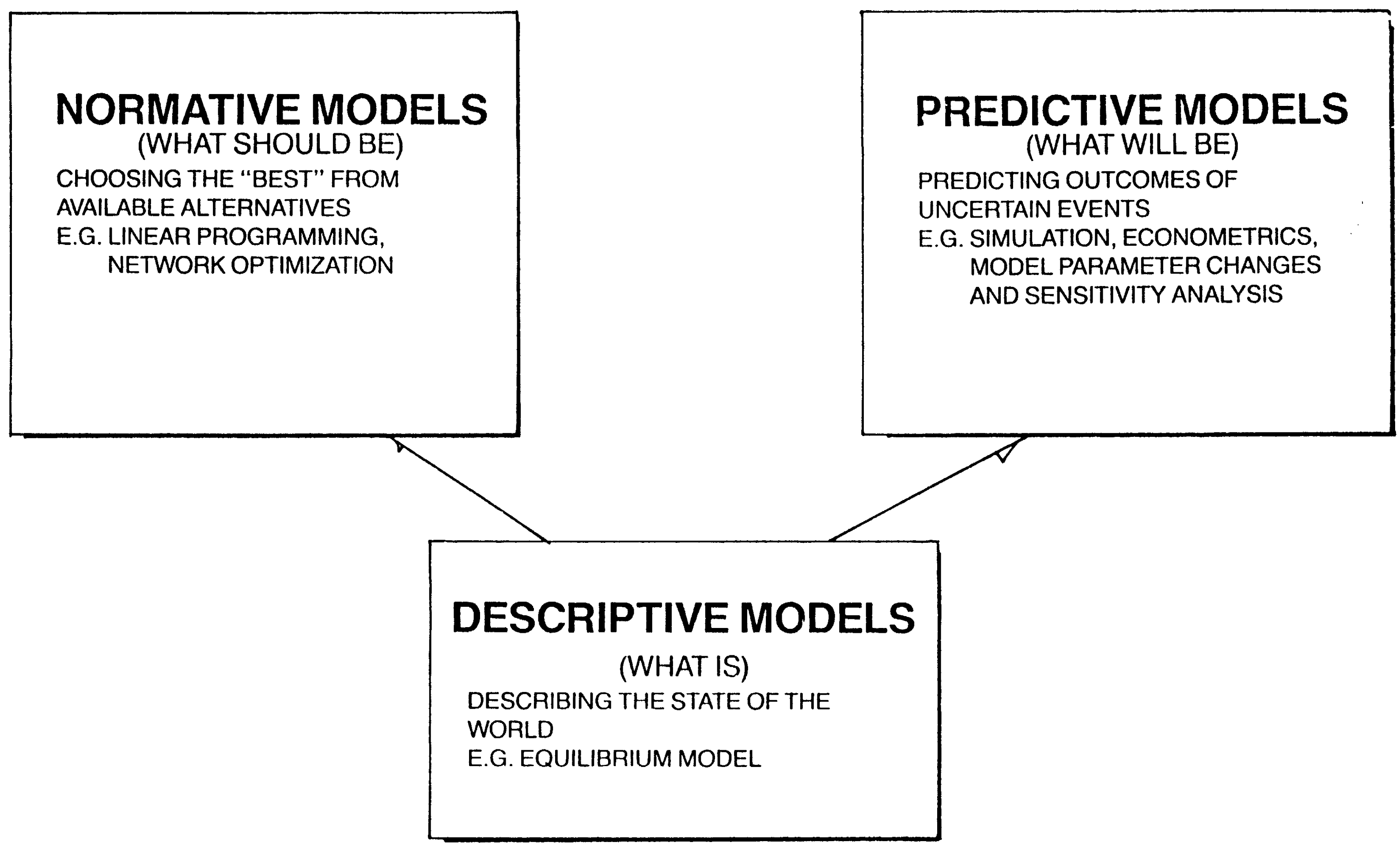

Fig. 6. Types of Transportation Models

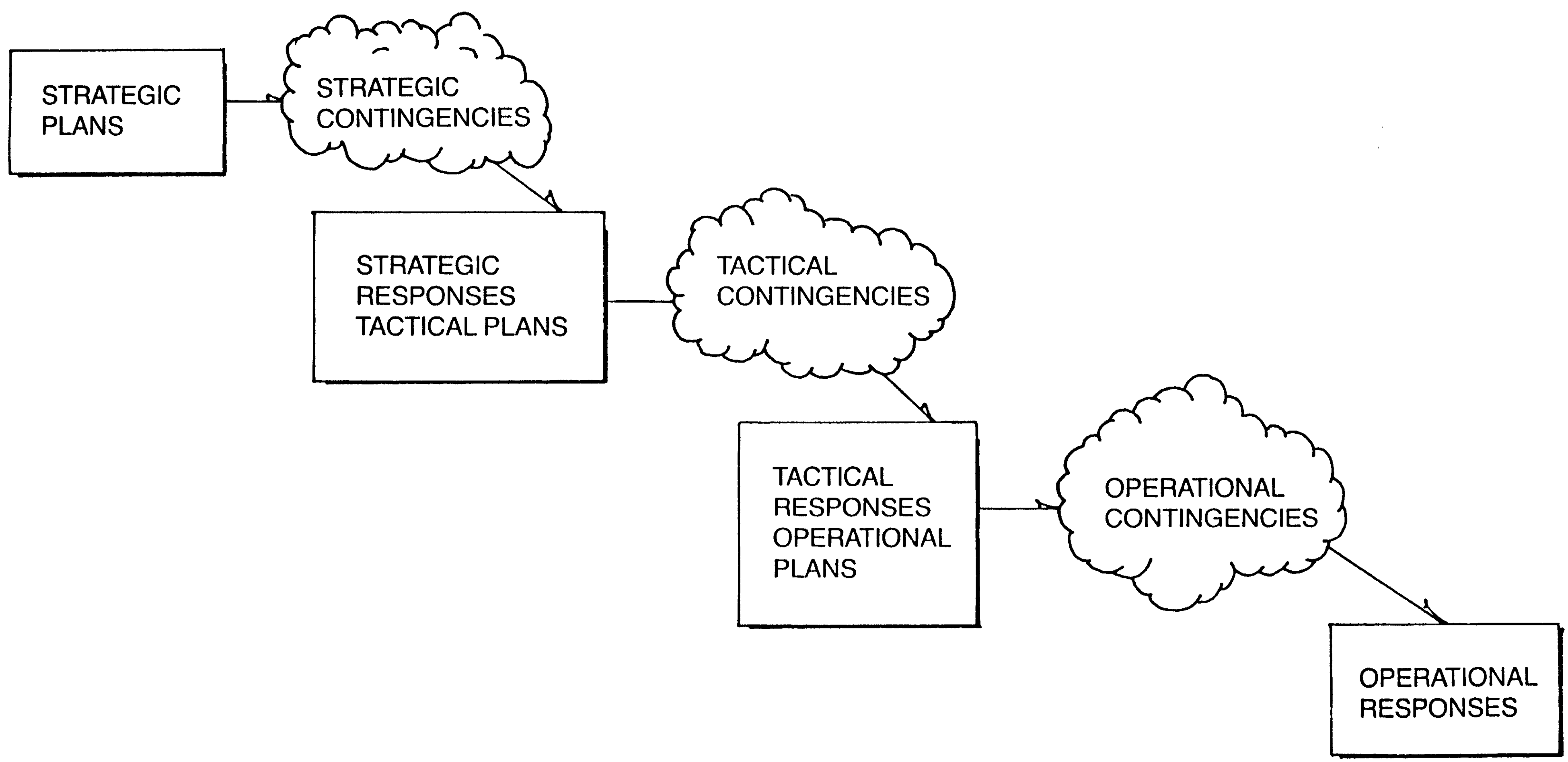

Fig. 7. Contingencies And Planning

in the maritime or trucking industry, or the airline industry's tendency to evolve toward hub and spoke service networks with most airlines concentrating their operations in a single or few major airports. Typically, the likelihood and impact of these strategic contingencies will be difficult to predict, except subjectively.

Tactical contingencies are uncertain events, such as changes in fuel prices, labor strikes, or changes in demand for a firm's products and services, that affect intermediate-term resource utilization. These kinds of events are much more structured than strategic contingencies and much more closely tied to prevailing market and economic trends. As such, they are much more amenable to statistical analysis and to analytic forecasting techniques. Moreover, because tactical contingencies are much more closely tied to an organization's current posture and its operating environment than are strategic contingencies, the act of merely enumerating contingencies, without even contemplating their probabilistic assessment, is likely to be more straightforward at the tactical level.

Finally, operational contingencies are events, such as unusual weather conditions or operating delays of vehicles, that affect day to day operations. Though predicting any particular event of this variety may be difficult, usually these contingencies are linked to historical patterns and therefore occurrences over any set time period of say a year could typically be estimated fairly accurately.

Although this categorization of contingencies draws somewhat arbitrary boundaries and does not recognize the full spectrum of contingencies as overlapping in scope and effect, it does emphasize the substantial variety of contingencies and their differing character. Approaches to planning should be responsive to these differences.

CONTINGENCY PLANNING

Figure 7 further illustrates the hierarchy and cascading of decisions and contingencies. At each level of this hierarchy -- strategic, tactical, and operational -- decision makers must make plans before contingencies unfold. They must, therefore, anticipate and devise plans for uncertain events. Moreover, they usually have opportunities to respond to contingencies. Decision making should reflect these opportunities as well. For example, in introducing a new service, a transportation firm should view the consequences of its decisions and the subsequent events that they might precipitate. Consequently, a strategy should have the following flavor: "Introduce a new service, and if the competition responds with a similar service, then . . . ." Stated in another way, decision makers should not view each action as an isolated event, but rather as part of a *scenario* of joint events and actions. These scenarios might be trajectories over time (i.e., a firm offers new services, its market share increases, a competitor responds, and then the firm's market share falls) or they might simply be a combination of events with no temporal connotations (i.e., fuel prices increase, market share grows, and interest rates climb) but which, nevertheless, may be dependent upon one another. In either case, decision makers should devise strategies that are contingent on the various scenarios that might arise.

The necessity for developing contingent plans that are tied with possible scenarios might appear to be self evident. But yet, as Bradley and Shapiro [1981] have observed "This is not a new idea but it remains one rarely followed in practice."

Scenarios are central to much of strategic planning. In this setting, planners frequently evaluate strategies by testing them against plausible scanerios (Hax and Majluf [1982]), which might be best, worst, or intermediate cases. Observe that identifying each of these cases hinges on the decision maker's subjective assessment of joint probabilities of the various uncertain events. Although these assessments might be stated euphemistically as "thinking of stories that hang together," they do nonetheless require a (possibly subconscious) subjective assessments of probabilities (Perold [1982]).

In many instances, the attributes of uncertain events (e.g., economic growth) are so aggregate at the strategic level that detailed modeling is inappropriate. Merely listing of plausible scenarios might be sufficient. In other instances, however, the uncertain events have direct consequences on an underlying network, which can then be used to *evaluate* strategies. For example, consider the airline fleet planning model embodied in the schedule map of Figure 5. A strategic decision in this setting might be the number of planes in an airline's fleet and a strategic contingency might be economic growth. Each scenario for economic growth translates into demands, and hence as revenues, on the service legs of the schedule map. With these in place, the network model could evaluate the strategy (the fleet size) by determining the best deployment of the fleet.

This use of networks becomes more pronounced at the tactical and operational levels where contingencies map more directly onto a network model and uncertainties can be better assessed statistically. For example, consider a typical 6-month or yearly tactical planning cycle for an application like the Chrysler Plant Loading and Distribution Model on Figures 2 and 3. This network model would require estimates (typically expected values) of costs and of demand by carlines and by customer zones, and use these to establish a targeted production and distribution plan. These steps correspond to the first three stages -- data generation (the types of data), data estimates (a scenario specifying the data values), and optimization -- of Figure 8.

Subsequent tactical contingencies such as variations in demand would alter the basic ingredients (parameters) of the network model. If the targeted production and distribution plans defined by the network optimization were locked in place, then the network model could evaluate these plans by testing them against (probabilistically) representative changes in the demand. That is, the model would simulate the plan (see Figure 8) against probabilistic assessments of demands and, in the process, evaluate it in terms of any of several desired measures of performance (e.g. costs, utilization of facilities). The network model could also generate other plans for testing by the simulation. For instance, it could generate alternate plans by solving the network optimization model with new data estimates (new scenarios) for costs and for demand. Frequently, network models generate and test certain of these new scenarios automatically by procedures known as sensitivity analysis or parametric analysis. In any event, by having the network optimization model generate plans and the simulator evaluate them, we combine the great strengths of both normative and predictive modeling techniques.

This same general approach applies when operational contingencies affect tactical decisions. In this instance, the simulator models the operating environment (e.g. detailed machine scheduling) rather than the tactical network

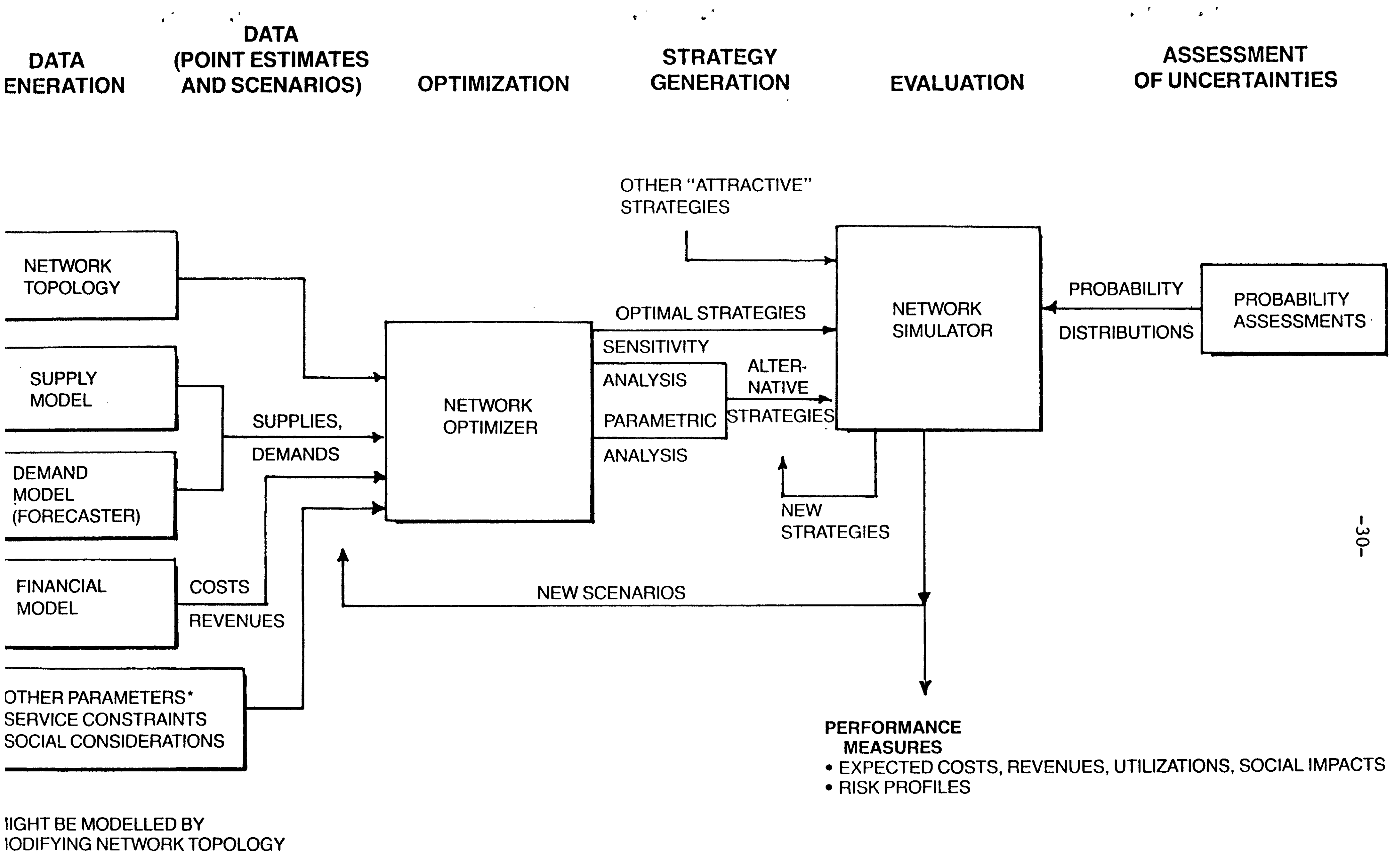

Fig. 8. Optimization Without Recourse

model (e.g. the aggregate production and distribution system) itself. The two-staged network optimizer/operational simulator thus assumes the form of a hierarchical model that links higher level tactical) with lower level (operational) decisions and contingencies. This hierarchical approach recognizes the inherent differences in scope, time frame, and degree of aggregation at each level of decision making. As such, it is responsive to managerial needs at differing levels of decision making, a characteristic that is attractive in analyzing not only distribution systems like the Chrysler Plant Loading problem (Hax [1974], see also Aggarwal [1973] and Connors et. al. [1972]) but many other network applications as well.

Figure 8 applies to situations in which contingencies affect plans that are already in place, but not to those situations in which decision makers have recourse that permits them to respond to contingencies. For instance, in our earlier example an airline had the opportunity to redeploy its fleet after having experienced changes in economic growth. Similarly, at the tactical planning level, Chrysler likely would be able to alter part of its plant loading and distribution plan after experiencing changes in its demands. In these instances, network optimization could be used within a simulation as shown in Figure 9. Here the contingencies affecting the original plan (the first stage decisions) define the parameters (a scenario) of a network model. By repetitively sampling these parameters in accordance with their governing probabilities and re-optimizing each time, the model can determine the probabilistic outcomes of the recourse decisions as used as adjuncts to the first stage decisions. In this way, we are able to combine both normative and predictive tools to develop, and to assess the consequences of, plans that are based upon contingent actions.

Note that Figures 8 and 9 are not unrelated. In fact, the entire simulation box in Figure 9 could be inserted into Figure 8 as the network simulator, thus permitting us to model two-staged decision making situations with network optimization performed within each stage. Combining these approaches in this way provides considerable flexibility in modeling. In particular, it permits us to model complicated scenarios with complex sequences of decisions and contingencies.

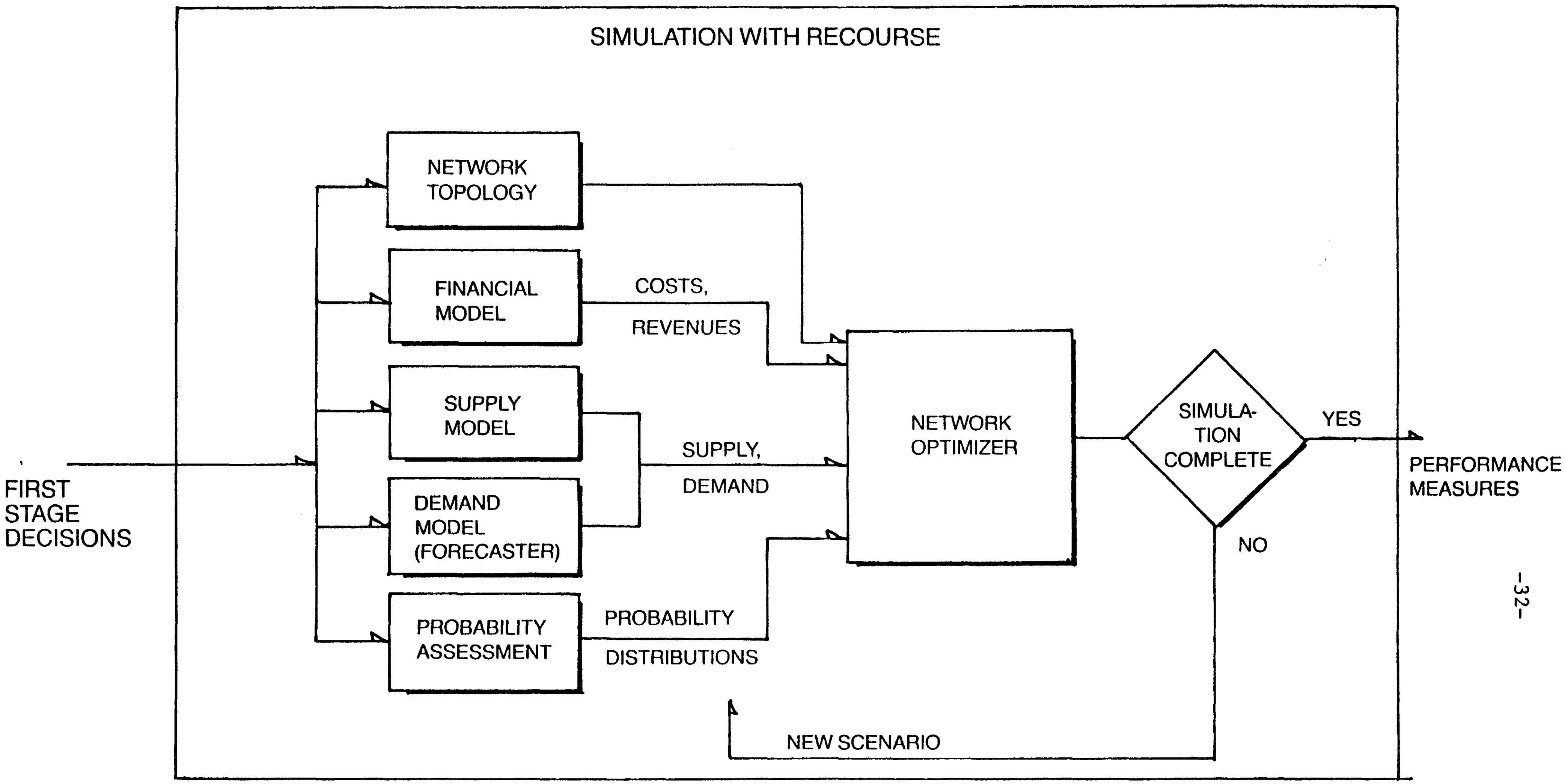

Fig. 9. Optimization With Recourse

Of course, effective practical application of this conceptual approach requires substantial refinement and considerable ingenuity in modeling. Since these refinements are usually problem specific, we will not pursue them here. We might close, however, by briefly commenting on a series of steps that should, it seems, be common to most contingency planning efforts:

1. DIAGNOSIS - Identify possible contingencies that are relevant to the decision(s) at hand.
2. SENSITIVITY ANALYSIS - Test each contingency in a probationary manner to develop a broad understanding of its effect on decisions and outcomes.
3. GENERATE AND TEST STRATEGIES - Use optimization or judgement to general strategies; test them against probabilistically determined or plausible scenarios.
4. POSTMORTEM - Perform further sensitivity analysis on the "attractive" strategies to determine their robustness to changes in probabilities and other problem parameters.

Diagnosis is analogous to the intelligence stage in Simon's taxonomy of planning. For ill-structured problems such as those that may arise in strategic planning, this step may be the most crucial element of a contingency planning effort, so much so that it might dominate the remainder of the analysis. In tactical and operational situations, diagnosis, while still essential, is likely to be more straightforward and function more as a percursor to subsequent, meatier analysis.

Sensitivity analysis tests the contingencies to identify which are most essential. For example, it might consider the widest variations in outcomes of a contingency and their effect upon the decision making situation. If the outcome of an uncertain event has little or no impact upon decisions, then analyzing that event in detail becomes unwarranted. In contrast, if an uncertain event has pronounced effects, then it merits our most serious attention. This step attempts to make these assessments with limited effort and hence to channel analysis in directions that would be most effective and most fruitful.

The strategy generation and testing step draws upon the ideas that we have discussed earlier. For strategic decisions, this analysis will tend to be less formal, based more upon intuition and judgment than formal planning tools. For tactical and operational planning, network planning and simulation methods will play a more significant role.

After generating good alternatives for contingency planning, decision makers should again assess the basic premises (i.e. probabilities) of their analysis. This postmortem should challenge these premises and test the performance of the strategies generated to change these assumptions. The strategies that emerge from this step should, consequently, not only perform well when pitted against the contingencies that might be expected, but also be robust against changes in the planning environment.

As this discussion has suggested, there are no panaceas for contingency planning. The balance between formal and informal analysis and the weight to be placed upon the various steps in a contingency planning effort should be tailored to the decisions and contingencies at hand. Our discussion has highlighted some of these differences; hopefully, in the process, it has provided a guide for choosing the most appropriate planning aid to bear upon any given problem.

4. CONCLUDING REMARKS

Networks are a rich source of modeling. In transportation, network models assume several different forms -- physical networks, route maps, and schedule maps -- and cover a wide spectrum of potential applications in both the private and public sectors. Our discussion in this paper has illustrated a number of these applications and has shown how network models are used as decision aids both in managerial planning and in managerial control. Moreover, it has suggested ways that network modeling might be combined with sensitivity analysis, with scenario planning, and with simulation to support contingency planning efforts.

Our discussion of network analysis, simulation, and contingency planning is, of course, far from complete. Designers of electrical networks frequently anticipate contingencies, and particularly component failures, by building redundancies into their systems (Boesch [1976], Frank and Frisch [1971]). Economists frequently use large scale econometric models to forecast demands for goods and subsequently use optimization methods for production and distribution planning (see Brooks [1975] for an example). Operations researchers (Pritsker [1979]) use network simulation for project evaluation and project planning. In still other settings, networks model specific contingency planning issues such as the evacuation of buildings in times of emergency (Chalmet, Francis, and Saunders [1982]). Each of these problem domains and methods provides even added opportunities for applying the methodologies that we have described in this paper.

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