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thesis entitled

SIMULATED PRODUCT SALES FORECASTING:
MATHEMATICAL MODEL,
COMPUTER IMPLEMENTATION
AND VALIDATION
presented by

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has been accepted towards fulfillment
of the requirements for

Ph. D. degree in Transportation

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Date November 6, 1978



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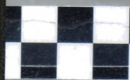
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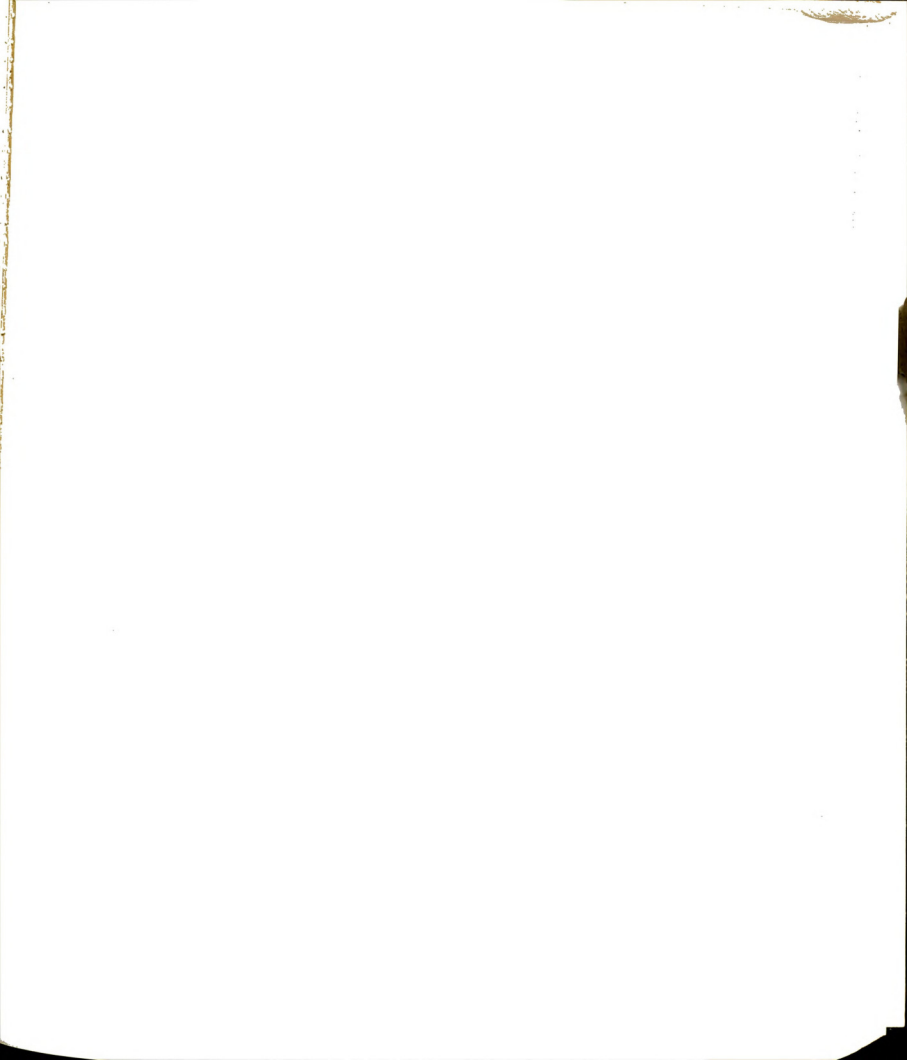
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SIMULATED PRODUCT SALES FORECASTING: MATHEMATICAL
MODEL, COMPUTER IMPLEMENTATION,
AND VALIDATION

By

David Joseph Closs

A DISSERTATION

Submitted to
Michigan State University
in partial fulfillment of the requirements
for the degree of

DOCTOR OF PHILOSOPHY

Department of Marketing and Transportation

1978

6108762

ABSTRACT

SIMULATED PRODUCT SALES FORECASTING: MATHEMATICAL MODEL, COMPUTER IMPLEMENTATION, AND VALIDATION

By

David Joseph Closs

The national distribution expense now consumes a significant proportion of the gross national product. Labor, fuel, and capital costs have increased dramatically. At the same time, customers have placed more stringent demands on the operation and performance of the distribution systems that supply their needs.

These converging factors are taxing the limits of existing distribution systems. The speed and size of current movement are rapidly approaching their physical bounds. The accomplishment of the distribution objective, while conserving scarce resources, requires the efficient operation of the distribution function. Optimal design and operation of a distribution system demands a detailed analysis of the system's performance characteristics.

This research addresses two weaknesses in the existing tools and methodologies for distribution systems analysis. First, although many models have been developed

to assist in this analysis, the firm's total distribution function has never been treated in its entirety. In particular, existing models have failed to consider either the firm's uncertain environment, the firm's interface mechanisms, or management's design and procedures. The uncertain environment replicates the uncertainty inherent in the demand and order cycle time elements. Forecasting procedures make up the interface mechanisms while the channel structure and operating policies provide management's controllable parameters. The second weakness addressed is the model validation and utilization methodology. Current distribution system analysis models have failed to provide methodologies for utilization. In particular, the assumptions and implication inherent in a modeling technique have often been forgotten when using the technique in distribution analysis. This research addresses these problems in three phases: model building, model validation, and model utilization.

The model building phase uses a review of past models and distribution operations literature to develop a model which integrates all aspects of distribution design and operations. The individual activities include demand processing, forecasting, channel structure, inventory management, and distribution operations. The activities are structured into events which are then incorporated into a dynamic

simulation model encompassing the firm and its environment. Since the model considers each aspect with a range of alternative operating procedures, it provides a unique testing environment for the study of physical distribution operations and planning.

The second phase utilizes existing literature discussing the philosophy and practice of model validation to build a framework for establishing model credibility. A procedure for testing initial model validity is developed and illustrated. The procedure includes statistical tests of random variate transformations, model stability, and model response. A qualitative analysis is used to test the operations of other model components. Such a procedure, when used in conjunction with model development or modification, provides a foundation for model credibility while remaining within the realm of practicality.

The third phase considers the problems encountered during model application to actual business problems. This segment, using actual business data, describes and illustrates a procedure which builds credibility in model applications through statistical tests of historical fit and stability. A more qualitative measure of model response to parametric changes is also included.

The research results include a description of the model and the procedures to be used in its application. In

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a more general sense, the research illustrates the process for use in constructing such a model. Thus, the research provides a tool and a methodology for analysis of the total distribution process.

ACKNOWLEDGMENTS

I wish to thank the many individuals and companies who have provided assistance in the completion of this work and the research it represents. It is impossible to acknowledge all those who have provided guidance and support, but some individuals merit special consideration.

The cooperation, patience, and insight of the project teams from the Johnson and Johnson Baby Products Company and the Whirlpool Corporation is greatly appreciated, as they provided the practical considerations for the research and the procedure.

I would like to express sincere thanks to the director of the SPSF Project and senior faculty advisor, Dr. Donald J. Bowersox. Professor Bowersox has provided much support and guidance through our long years of association. His values and integrity, as well as his concern for the student, have left a lasting impression on me.

I would also like to extend my appreciation to the members of my Reading Committee, Professors Douglas Lambert and Jeffrey Towle, for their valuable suggestions concerning the procedures and implications of this research.

The editing and typing has greatly added to the clarity and presentation of this report. For this, I am indebted to Ms. Felicia Kramer and Ms. Jan Duszynski, whose patience and skill were priceless.

A research effort of this size would be impossible to undertake alone. For this reason, the support of the other research team members, John T. Mentzer and Jeffrey R. Simms, is greatly appreciated. These individuals provided both the research assistance as well as the camaraderie necessary for a large-scale research project. The programming support and dedication of Dave Norton, Ray Rowland, and Steve Schumaker is greatly acknowledged.

Finally, I want to express my gratitude to my family, especially my wife, Noel Eve. She patiently provided encouragement and comfort during my graduate school years. Our most recent addition, Ellen Kay, also deserves recognition for bringing joy and happiness during the writing of the manuscript.

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CHAPTER I

INTRODUCTION

Integrated physical distribution has become a reality only during the past two decades. In earlier periods, managerial emphasis was directed to individual activities such as transportation, warehousing, and inventory. The task of measuring effectiveness and potential on an individual basis was not difficult. In contrast, planning and measuring integrated system performance offers a challenging managerial situation. This dissertation documents the development of a computer model of the integrated physical distribution process.

Physical distribution represents a major cost of business operations. In 1970, the ratio of total physical distribution costs to tangible gross national product was 26 percent.¹ The 1978 national expenditure is expected to exceed \$414 billion.² Heskett separates these distribution costs into three major categories: movement (transportation), inventory holding, and management costs.³ His categorization expands on the concept advocated by Converse, who described distribution as follows:

Marketing (distribution) has been defined as matter in motion. There are two kinds of motion in moving goods from the farm, the mine, and the factory into the hands of the ultimate customers. Goods must be moved through the trade channel and gotten into the possession of customers--that is they must be bought and sold [Second,] goods must be moved physically.⁴

Although transportation traditionally has been the primary subject of attention, integrated management has expanded to include raw material procurement, internal product and material transfer, and final product distribution. For each phase of movement, it is necessary to also include inventory investment, storage, and handling.

In addition to the emphasis on the cost of integrated physical distribution, customer service capability in terms of speed and consistency of delivery have become major concerns. Although customers are demanding more complete and consistent services, distribution technology can not always meet the desired goals within reasonable cost expenditures. Thus, in order to satisfy customer requirements, the physical distribution system must be designed to accomplish maximum capabilities within infrastructure and technology limits. The combination of cost and service requirements placed on the physical distribution system mandate that a systems perspective be utilized in the design and management of the overall process.

The National Council of Physical Distribution Management (NCPDM) recently refined its definition of physical

distribution to reflect these developments. NCPDM defines physical distribution as:

a term describing the integration of two or more activities for the purpose of planning, implementing, and controlling the efficient flow of raw materials, in-process inventory and finished goods from the point of origin to the point of consumption. These activities may include, but are not limited to, customer service, demand forecasting, distribution communications, inventory control, material handling, order processing, parts and service support, plant and warehouse site selection, procurement, packaging, return goods handling, salvage and scrap disposal, traffic and transportation, and warehousing and storage.⁵

The essence of the evolution of integrated physical distribution has been a steadily increasing emphasis on total system performance.^{6,7,8}

As the scope of physical distribution has expanded, a need has developed for quantitative methods of systems analysis. Existing literature reveals a wide range of quantitative models in the distribution field. In distribution system modeling, primary emphasis is placed on only one or two physical distribution components, as exemplified by the multitude of location and inventory models in existence.⁹ Recent literature, however, is beginning to place more emphasis on the total system model. Geoffrion identifies the important cost elements of an adequate distribution planning model as follows:

1. Transportation cost between plants, warehouses, and customers;
2. All warehouse and inventory costs;

3. Cost and savings of expanding, opening, and closing warehouses;
4. Production costs at the plants.¹⁰

Similarly, House and Karrenbaur list criteria for distribution planning models:

1. The representation should not violate viable theoretical conceptualizations of the logistics system unless its superiority to previous theory can be demonstrated;
2. The model should be applicable to a large number of logistics situations. It should represent adequately the wide variety of configurations that can be observed in operation;
3. The model should parsimoniously, but accurately, represent reality;
4. The model should optimize the system structure according to the appropriate goal set. Because system goals can vary widely, the model should be capable of identifying optimality conditions under alternative goals without extensive reformulation.¹¹

These authors identify the basic needs, as they view them, for model applications in distribution analysis.

The thrust of this dissertation is to use existing literature on distribution modeling, implementation, and validation to develop an integrated model and methodology capable of aiding in the analysis of total distribution situations. The development process will provide the tool, while the discussion of actual applications will identify the procedure to be used for validation and analysis.

THE BUSINESS PROBLEM

A review of the business situation is a useful aid in understanding the research. As stated earlier, the distribution function consumes a substantial percentage of the gross national product. Many components interact to fulfill the distribution objective and all must be considered and integrated to form a total system model. Such a model must incorporate the firm's physical distribution function components, the firm's physical distribution interface between the system and the environment, and the environmental components. Figure 1 illustrates these relationships. The problem can be understood best through a review of these individual structures.

FIRM PHYSICAL DISTRIBUTION SYSTEM COMPONENTS

The basic structure provided by the firm to meet its distribution needs includes a system of facilities along with a series of processes which perform the movement and storage of goods. Facilities may include manufacturing points, warehouses, storerooms, and retail outlets. The transportation activity may be included if the firm controls its own carriers. In addition to the physical components of the operations environment, the processes and policies which control this environment must be included as elements. The processes are exemplified by order processing and warehouse

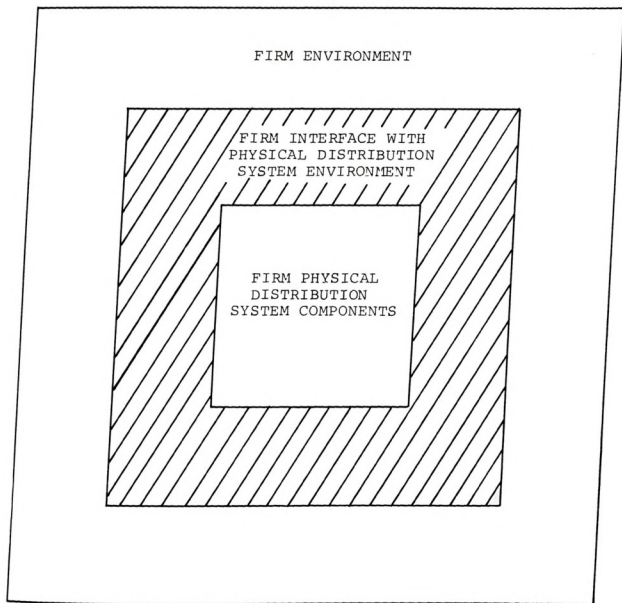


Fig. 1. Physical Distribution System and Environment

operations procedures, while policies might include inventory and stocking decisions. These elements dictate and control the transportation, inventory, storage, and material handling functions necessary to accomplish the distribution objective. However, such a structure would be adequate only under conditions of certainty for the firm. Since such conditions seldom exist, the firm must provide an interface which buffers the firm from its environment.

FIRM SYSTEM INTERFACE

Traditional forecasting methodologies provide the buffer for most physical distribution systems. The forecasts include predictions of replenishment order cycle times and cycle times within the system. However, a more critical environmental forecasting problem must be faced when estimating the demand environment of the firm. Many methods have been promoted to increase the effectiveness of this interface, but the results have ranged from disappointing to disastrous.¹² Many of the methodologies require extensive human interaction, which renders them impractical for multiple product applications. The primary function of the interface must be to predict or estimate the future in the non-controllable segments of the demand and operations environments. The prediction is then used as an input when establishing and controlling the operations of the firm.

FIRM ENVIRONMENT

The final critical element for analysis of an integrated distribution system is the demand environment. Satisfaction of that environment is the ultimate justification for the existence of the system. The demand environment includes the aggregate level of demand which must be satisfied by the integrated system. Only the aggregate level is critical, since the distribution system does not differentiate between serving one customer or another. The demand environment, as faced by the firm's physical distribution system, can be viewed as a series of orders for specific groups of products which must be satisfied within the guidelines established by the policies of the firm. For the most part, the firm can exert very little control over this environment. In addition, competitive firms attempt to neutralize the actions of the firm. This competitive interaction creates a highly volatile environment which must be considered in any analysis of distribution system performance.

In summary, total distribution system analysis involves controllable and non-controllable elements, as well as mechanisms to interface the two. An integrated approach requires that all aspects be considered when modeling system behavior and performance.

THE RESEARCH PURPOSE

The purpose of this research is threefold. The research can be made truly relevant only through consideration of all aspects. The first purpose involves model conceptualization and implementation. This phase requires an analysis of existing literature to identify the procedures for mathematically modeling the total system described in the business problem. A methodology for transforming the mathematical model into a computerized tool is also required in this phase. The second purpose considers the development of a methodology for validating such a model. The exact validation requirements depend on the type and scope of the model. The final research purpose addresses the problem of model application. Using guidelines from general modeling literature, a managerial procedure for model application is developed and illustrated. The illustration provides an ultimate test of whether the instrument and the methodology are acceptable.

The research goal is to develop a tool and a procedure which management can use for total systems analysis of the firm's physical distribution activities. The procedure includes a definition of the necessary components, indication of the required data elements, and specification of the steps necessary to build credibility.

To meet the broad purposes of the research, the specific objectives are as follows:

1. To identify the components required to model an integrated physical distribution system adequately and to develop mathematical specifications for creation of such a model.
2. To develop an integrating mechanism which can realistically control the operation of individual components.
3. To integrate the control mechanism with system components to create a computerized tool for total physical distribution cost analysis.
4. To define a procedure and to use contrived data to establish the basic validity of the model.
5. To gather and submit actual firm data to the procedures established above to demonstrate the research tool and the managerial validation methodology.

RESEARCH QUESTIONS

Fundamentally, three research questions form the basis for this investigation. Although these questions are integral to the development of any tool, they have not been addressed adequately for any existing physical distribution models. For existing component models, the treatment of at least one question has been inadequate.

The first question addresses the model concept and implementation. Question two concerns the methodology for validating an integrated distribution model. The final question pertains to the managerial process of utilizing the model.

CONCEPT AND IMPLEMENTATION

This question confronts the functions required when attempting to model an integrated physical distribution system. Once the conceptual model is defined, decisions must be made regarding the functional integration and implementation process. The question is as follows:

What functions are necessary for modeling an integrated physical distribution system and what process is appropriate for implementing that model?

VALIDATION METHODOLOGY

Once the model is successfully implemented, the second--and very often overlooked--question concerns the methodology used to validate the model itself as opposed to specific applications. The relevant issues here include basic statistical tests for transformation validity and manual inspections of model logic. Equally important is the performance of the model, using controlled data, in terms of stabilization and parameter estimation. The question asks:

What methodology is required for building the validity of the integrated distribution model?

MANAGERIAL UTILIZATION

The final question concerns accurate use of the model as an aid in managerial decision making. The basic issues include validation of a model application with base-line and experimental runs, and development of an information base for model performance. The managerial question is:

What should the procedure be for analyzing model applications and judging model performance?

RESEARCH QUESTIONS--CONCLUSION

Although the research questions are broadly stated, they form a framework for problem analysis. It is only through their joint consideration that a useful and credible research methodology can be developed.

SCOPE OF THE RESEARCH

The research described was part of a team effort involving three researchers and two actual firms. The author's responsibility included conceptualization, implementation, and validation of the model, as well as establishment of a procedure to validate individual applications. The process required a thorough review of existing literature on distribution modeling and extensive discussions with managers to maintain a real-world perspective. Following the specification phase, the model was computerized and a procedure was developed to outline the steps in model application for future researchers. The procedure was illustrated with actual firm data.

For model conceptualization and implementation, a fair amount of literature describes the components and processes of distribution models, but no existing model adequately addresses the systems concept in terms of the total environment. For model validation and usage procedures, general

modeling literature provides some guidelines, although no literature defines a methodology for use in the distribution sector. The process of developing such a model and its corresponding methodology is detailed in this research.

POTENTIAL CONTRIBUTIONS

The major overall contribution of this research is an environment and a methodology for the integrated analysis of physical distribution problems. The detailed contributions of the research include:

1. An integrated physical distribution environment which simulates and measures most activities associated with the distribution function.
2. A dynamic environment which incorporates temporal and spatial elements in a single model for a more accurate analysis of activities (such as inventory) which are affected by both elements.
3. An emphasis on demand estimation and forecasting activities to enable conduct of further research regarding the interfaces between demand expectation, forecasting, and physical distribution system performance.
4. A modular environment whose activities are semi-independent, allowing for ease of operation and change.
5. A "universal" environment which can replicate many types of distribution systems without major changes in the tool or the methodology.
6. A methodology which has been developed and illustrated for establishing the basic foundations of distribution model credibility.
7. A managerial process which illustrates a practical methodology for addressing important considerations when using a distribution model for actual applications.

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RESEARCH LIMITATIONS

The firms that participated in model development and analysis were limited in number. They were selected not at random but on the basis of their previous associations with Michigan State University. Therefore, it is conceivable that these firms are managed by executives who are more aware of, interested in, and knowledgeable about the distribution planning process. Processes or results which were judged credible by them may not be sufficient to convince less knowledgeable individuals. In addition, the participating firms are involved primarily in consumer products; therefore, the model assumptions and procedures have not been tested with non-consumables.

To provide for the scope of an integrated analysis and yet to include micro components, the model range was limited. The number of facilities and products subject to detailed analysis was constrained by limiting the research to a small number of products in a narrowly defined geographic area. Other geographic areas and products which interact with those under analysis may not have had their effects considered thoroughly.

The demand environment offered by the model does not pretend to predict reality. As such, the demand creation alternatives are offered only as methodologies to create a suitable and controllable demand environment.

Because of the model's general nature, its capabilities may be limited when addressing the peculiarities of a specific firm. In many cases, these limitations can be overcome with customized modifications to the general tool and procedure. An example of such a situation would be flexible shipping rules based on product availability.

Another limitation is the lack of a customer service feedback loop which would allow customer service to influence future demand dynamically. A substantial body of literature exists to establish such a loop, but there has been little success in quantifying it.^{13, 14}

Despite its acknowledged limitations, the model provides a methodology which expands the state of the art in terms of both an integrated physical distribution model and a procedure for utilization.

ORGANIZATION

The remainder of the dissertation is presented in six chapters. Chapter II contains the literature review which forms the theoretical basis for the research. Previous studies involving distribution modeling, implementation, and validation are reviewed to isolate the functions and processes required in a total systems model. Alternatives for accomplishing each of the steps are investigated.

Chapter III outlines the Simulated Product Sales Forecasting (SPSF) concept. The environment is defined in

terms of both the functions to be modeled and their scope. Model data requirements are also defined. The final part of the chapter addresses the general methodology for using the model.

Chapter IV describes the procedure used for conceptualizing and implementing the model. A discussion of the events and processes is included to explain model assumptions.

Chapter V discusses the methodological problem of establishing base model validity. The chapter describes the tests used to demonstrate that the model actually performs as it conceptually should. Initial model validity is thus established.

Chapter VI discusses the managerial problem of establishing the validity of the model for actual applications. A methodology is described and actual data are used to demonstrate the process and the ability of the model to treat the real environment adequately.

In Chapter VII, the research is summarized in terms of its implications for other research. Suggestions for future research are also discussed.

CHAPTER I--FOOTNOTES

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⁴Paul D. Converse, "The Other Half of Marketing," in Twenty-Sixth Boston Conference on Distribution (Boston: Boston Trade Board, 1954), pp. 22-5; reprinted in Alfred L. Seelye, ed., Marketing in Transition (New York: Harper and Row, 1958), pp. 114-21.

⁵National Council of Physical Distribution Management, Annual Conference Proceedings, 1976, inside front cover.

⁶Ronald H. Ballou, Business Logistics Management (Englewood Cliffs, N.J.: Prentice-Hall, Inc., 1973), pp. 22-6.

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⁸Heskett, Glaskowsky, and Ivie, Business Logistics, pp. 34-6.

⁹Bernard J. La Londe and Allan D. Schuster, Twenty Years of Distribution Modeling (Columbus, Ohio: The Ohio State University, Division of Research Working Paper Series, 1974).

¹⁰Arthur M. Geoffrion, "A Guide to Computer-Assisted Methods for Distribution Systems Planning," Sloan Management Review (Winter 1975):17-42.

¹¹Robert G. House and Jeffrey J. Karrenbaur, "Logistics System Modeling," International Journal of Physical Distribution and Materials Management (May 1978):194.

¹²Steven C. Wheelwright and Darral G. Clarke, "Corporate Forecasting: Promise and Reality," Harvard Business Review (November-December 1976):40-68.

¹³Harvey N. Shycon and Christopher R. Sprague, "Put a Price Tag on Your Customer Service Levels," Harvard Business Review (July-August 1975):71-78.

¹⁴Bernard J. La Londe and Paul H. Zinszer, Customer Service: Meaning and Measurement (Chicago: National Council of Physical Distribution Management, 1976).

CHAPTER II

LITERATURE REVIEW

Chapter II contains the literature review which forms the theoretical base for this research. The chapter is organized around three areas the dissertation addresses: conceptualization, implementation, and validation of an integrated physical distribution planning model. The conceptualization section discusses only those models within the field of physical distribution. Since only limited literature exists concerning implementation and validation, more generalized literature is reviewed for those phases.

LITERATURE REVIEW--DISTRIBUTION MODELING

During the past decade, the fields of physical distribution and market planning have attracted managerial attention because of the cost savings potential and the increased concern with customer service operations. Emphasis on the integrated system, as discussed in the previous chapter, has necessitated development of various analytical and heuristic procedures to assist in analysis. Since the mid-1950s, the number, complexity, and quality of logistical planning models has increased considerably.¹ Schuster and La Londe present

a brief overview of the past 20 years of distribution modeling. An outline of their paper (Table 1) illustrates the range of existing distribution modeling alternatives. The models of interest for this research are the generalized distribution system models, since these alone are capable of integrated analysis. The remaining models analyze operations for a specific mode. Although many of the procedures can be applied to alternative modes, the primary emphasis of those models is movement rather than the integrated process of movement and storage required in distribution operations.

Rather than presenting individual analyses of each model, the review examines model applications and characteristics and discusses their relevance to generalized distribution system modeling. Appendix A contains an annotated bibliography of individual model characteristics, flows, and applications.

The models currently used in industry to study generalized distribution systems range from basic formulations to complex methodologies using both mathematical and numerical methods. In order to evaluate the modeling requirements of a particular problem objectively and to establish the cost-benefit objectives for the analysis, one must understand the available model characteristics and their advantages. Kiviat summarizes this trade-off when he states:

. . . modeling is a continuous balancing of the costs of data collection and analysis against the costs (benefits) of precision, and program execution against the costs of model reprogramming.²

TABLE 1

DISTRIBUTION MODELING ALTERNATIVES

SECTION ONE:

- A. Generalized Distribution System Models
- B. Air Line System Models
- C. Motor Freight Models
- D. Railroad Freight Models
- E. Military Transportation Planning Models

SECTION TWO:

- A. Routing and Scheduling Models
- B. Air Line Models
- C. Motor Freight Models
- D. Water Freight Systems
- E. Vehicle Routing Models
- F. Air Line Routing Models
- G. Motor Carrier Routing Models
- H. Railroad Routing Models
- I. Water Carrier Routing Models
- J. Scheduling Models

SECTION THREE:

- A. Terminal Analysis Models

Source: A. D. Schuster and B. J. La Londe, Twenty Years of Distribution Modeling (Columbus, Ohio: Division of Research, College of Administrative Science, The Ohio State University, 1974), Table of Contents.

Two broad model categories exist for analysis of physical distribution systems--mathematical programming and simulation.³ House and DeHayes describe an alternative which combines the advantages of both methodological procedures.^{4, 5} However, they also point out that the combination methodology requires a problem that is basically concerned with a process operation.⁶ Since analysis of inventory requirements is not process oriented, the combination alternative is not considered further.

The primary differences between mathematical optimizing and simulation approaches are now discussed. The review defines the nature and characteristics of the models within the constraints of this research. The characteristics and applications serve as a basis for comparisons of existing model technology.

MATHEMATICAL MODELS

The mathematical or analytical process is initially demonstrated through the use of linear programming⁷ and algebraic solutions.⁸ Bowersox offers the following reason for this initial interest:

The unique feature of an analytical technique is the capability to isolate a precise mathematical solution to the problem under analysis.⁹

Even though the methodology identifies an optimum problem solution within the constraints imposed by the formulation, both the problem and the constraints may not reflect reality

adequately. In theory, therefore, the procedure ought to result in the cost minimizing warehouse configuration or order quantity. In order to develop or utilize a mathematical or analytical solution technique, however, the actual system relationships must be completely understood and quantified. Such an analysis can be a very difficult process. For example, although it is not difficult to quantify the relationship between total transportation costs and the elements contributing to total cost, it is very difficult to establish with any degree of certainty a quantifiable relationship between customer service and resultant sales. To the extent that relationships can be described realistically or approximated with a high degree of confidence, the mathematical modeling procedure is preferable to the non-optimizing approach since it is capable of producing an optimal solution for a given situation. Regarding the importance of the optimizing capability, Geoffrion states:

. . . assurance should be obtained that the computer program will have a true optimizing capability. That is, it should be able to sift through the multitude of alternate plans and find one which is best according to an appropriate criterion (usually minimum total cost) to achieve desired customer service levels for a given scenario.¹⁰

Nevertheless, the ability to optimize is not without its drawbacks. The constraints required, such as limits on problem size and functional form, are major deficiencies. As Bowersox states:

The optimality feature of the technique [mathematical programming] is relative, being only as valid as the design problem formatting. Too many simplifying assumptions can render the solution optimal but invalid.¹¹

House and Karrenbaur identify another major weakness of the mathematical programming approach--its inability to incorporate the dynamics of the situation.¹² Dynamic programming techniques may be used for considering aggregate changes over long time periods, but the technique cannot treat the day-to-day dynamics inherent in distribution operations. Distribution problems simply require too many variables, and current solution algorithms are not powerful enough.

Simple applications of analytical models include the "center of gravity" models used to minimize the cost of facility location.¹³ Another widely used mathematical model is Economic Order Quantity (EOQ), which determines the optimal replenishment order quantity while minimizing total inventory and procurement costs.¹⁴ Bender and Geoffrion discuss the more complex mathematical programming techniques to obtain minimum cost warehouse configuration.^{15, 16} However, the same characteristics that make these mathematical models easy to use, such as limited technical ability, standardized data requirements, and generalized procedures, also render the results impractical at times. Center of gravity facility location techniques may optimally locate a distribution center

in the middle of a lake or a desert. The pure EOQ model does not consider economies of scale or multiple products, thereby limiting its practicality further. Heuristic adjustments must be made to address these economies.

The more complex techniques proposed by Bender and Geoffrion require the use of linear programming and its various extensions. The most widely applied linear optimization techniques in distribution systems analysis are the simplex and the transportation methods. Although linear programming models are applied primarily to facility location and customer assignments, the models have been adapted to include capacity and allocation problems¹⁷ as well as vehicle routing and scheduling problems.^{18, 19} Carter and Ingall provide an example of an optimizing technique for inventory analysis.²⁰ The authors demonstrate use of the technique to minimize the sum of storage and stockout costs, although no consideration is given to the movement function or the interaction of multiple products and facilities.

However, as stated earlier, mathematical optimizing techniques have major limitations. Functional formulation requires much effort when the problem is complex. Measurement and specification of the variables becomes difficult when the behavior and sensitivity of the system are not completely understood. In addition, no techniques were found where mathematical optimizing procedures had been used when

considering both the movement and storage components of distribution operations. The apparent reason for the lack of an integrated optimizing model is that no algorithms and computers exist that can treat problems with the required number of variables and constraints. In addition, optimizing techniques generally do not include a methodology for considering various forms of uncertainty when evaluating alternatives. For example, uncertain demand and supply levels and the influence of stochastic cycle times or performance results cannot be introduced directly into the problem solution. Sensitivity analysis does have the potential to investigate the effects of uncertainty, but it does not illustrate the direct relationship between uncertainties of the controllable variables and the response variable.

SIMULATION MODELS

Numerical methods have been employed as alternatives to mathematical optimizing techniques for modeling complex situations. Bowersox offers the following generalized description:

A numerical model utilizes computational methods to replicate system design and performance. However, it contains no specific mathematical procedure that assures identification of the best possible solution. A numerical model does not attempt specifically to identify relationships within the model. Emphasis is placed upon the way the various components interact in terms of system performance.²¹

One popular numerical approach to large-scale distribution system modeling is computer simulation.²² Simulation itself can be performed using a number of host mediums; however, the digital computer is the appropriate tool for almost all distribution system models. Thus, all further references to simulation implicitly assume the digital computer is the medium.

Naylor's definition of simulation emphasizes that it is a numerical technique which involves mathematical and logical models that describe the behavior of a business or economic system.²³ Shannon takes a broader view of the subject by emphasizing the process rather than the technique itself. He states:

Simulation is the process of designing a model of a real system and conducting experiments with this model for the purpose of either understanding the behavior of the system or of evaluating various strategies (within the limits imposed by a criterion or set of criteria) for the operation of the system.²⁴

In another definition, House and Karrenbaur emphasize both the event orientation and the events required for distribution modeling.²⁵

The scope of each author's definition is probably dependent on that author's experience and interest. House and Karrenbaur include only a limited number of physical distribution applications within their definition. Naylor places more emphasis on the model while downplaying the

process and the potential. This research adopts the definition presented by Shannon which implies that development of a simulation model also requires definition of a validation and usage methodology.

Simulation models offer the ability to examine in-depth the performance of a distribution system specified by the user. However, this advantage has a corresponding deficiency. The very detailed nature of large-scale distribution system simulations requires a heavy investment for development and significant resource requirements for execution.²⁶ Unless a specific search algorithm is developed for optimization, simulation requires that the analyst identify the required changes in the controllable variables rather than allowing the model to do so. This characteristic indicates that simulation is an appropriate technique for analysis of "what if" questions, but is perhaps not as appropriate for searching for optimum systems. Another value of simulation models is identified by Ballou:

The simulation model usually replicates reality to a much better degree and requires fewer approximations than does a comparable algorithmic model.²⁷

Although it is true that simulations almost always provide a better model of reality, this author disagrees with the statement that simulations require fewer approximations.

MODEL COMPONENTS

Now that the two broad classes of models have been defined for purposes of this research, the literature is used to develop a framework for identifying the functions of an integrated model.

Components of an Integrated Physical Distribution Model

Existing distribution modeling literature contains no description or discussion concerning the functions of an integrated model. However, general distribution management literature does provide some direction and a good foundation for identifying a framework. As the model review demonstrates, past models addressed only one or two limited functions. The question regarding the components of an integrated model has never been answered.

Table 2 lists a series of distribution system decision components identified by Ballou.²⁸ Nine decisions are identified which are important to the functional areas of distribution management. Therefore, by extrapolation, they must also be important to total system performance. Rather than attempting to use such an enumerative list to classify existing distribution models, this author proposes a smaller number of inclusive components. The functional areas include: (1) demand generation, (2) forecasting, (3) location analysis, (4) operations, and (5) inventory. This compact framework

eases analysis and design while maintaining the general scope of the model.

To establish that this framework is both complete and valid, the proposed classification system must be matched against existing conceptions of the components of an integrated distribution system. The comparison is made on a general basis, without detail of individual daily operating decisions that may or may not be routinized. The parallelism is demonstrated by associating the components in existing classification systems with the proposed classification system.

The initial comparison reviews the categories proposed by Ballou. The transportation, order processing/information flow, materials handling, protective packaging, and production scheduling components are considered in the operations category of the proposed framework. Inventories and warehousing, as well as some aspects of materials handling, are incorporated in the inventory category. The forecasting category also considers some aspects of the inventory component. The customer service and facility location components are addressed by the demand generation and location categories, respectively.

To add another dimension of generality to the proposed framework, the categories are compared to the activities included in the definition proposed by the National Council

TABLE 2

PHYSICAL DISTRIBUTION SYSTEM DECISION COMPONENTS

-
-
- A. Transportation
 - 1. Mode and service selection
 - 2. Carrier routing
 - B. Inventories
 - 1. Stock policies
 - 2. Record keeping
 - 3. Purchasing
 - 4. Short-term sales forecasting
 - C. Customer service
 - 1. Needs and wants
 - 2. Response
 - D. Order processing/information flows
 - 1. Order procedures
 - 2. Information processing
 - 3. Data analysis
 - E. Warehousing
 - 1. Space determination
 - 2. Stock layout and dock design
 - 3. Stock placement
 - 4. Warehouse configuration
 - F. Materials handling
 - 1. Equipment selection
 - 2. Equipment replacement
 - 3. Order picking
 - 4. Stock storage/retrieval
 - G. Protective packaging for
 - 1. Handling
 - 2. Storage
 - 3. Protection
 - H. Production scheduling
 - 1. Aggregate production quantities
 - 2. Sequencing/timing of production
 - I. Facility location
 - 1. Location, number, and size of facilities
 - 2. Allocation of demand to facilities
-

Source: Ronald H. Ballou, Business Logistics Management
(Englewood Cliffs, N.J.: Prentice-Hall, Inc., 1973),
pp. 10-1.

of Physical Distribution Management.²⁹ The Council's customer service aspect is addressed by the demand generation category. Similarly, the demand forecasting aspect is the sole subject of the forecasting category of the proposed framework. Plant and warehouse site selection is addressed by the location category. Inventory control and warehouse and storage activities are integrated in the inventory category. The remaining activities defined by NCPDM can be grouped adequately within the operations category.

The specified framework accomplishes two objectives. As demonstrated above, the categorization includes all activities identified as factors in the distribution decision process by both an academic text and by a management organization. This scheme also corresponds with a mutually exclusive set of categories addressed by existing models. Current models do not always address only one category, but the activities they do consider can be divided logically into these five categories.

Now that the framework has been established, the following sections discuss in detail the considerations within each category. In most cases, a model incorporates more than one application area for a partial systems orientation.

Demand Generation

Just as customer demand generally provides the force variable for a firm's operations, the demand generation activity provides the force variable for the model of a firm. For distribution models, the demand activity generally does not attempt to predict the performance of individual customers. It does, however, provide aggregate demand which then drives the remaining system components. The activity's ultimate objective is order generation. Ideally, the model of the activity should be capable of providing orders with different characteristics so that the analysis can consider varying demand environments. Most models reviewed include some type of demand generation activity although few offer any degree of flexibility. Three types of demand generation activities are found in existing literature.

Random variates are used as the first method of order generation. Normal, lognormal, erlang, and poisson random number generators develop the quantities which are then used as order quantities for a particular customer or product. In this mode, data requirements for order generation are simple, but the results are not very realistic. The second and most common method reviewed uses historical data directly for model input. The demand consists of actual individual orders or reflects some level of aggregation, such as annual product flows. This methodology increases

the level of realism but also increases data requirements. In addition, the technique allows very little flexibility in terms of altering demand characteristics or patterns. In addition, the actual orders often do not provide a range of conditions which ought to be considered for reliable planning. The third methodology generates demand within the model using a combination of actual and experimental statistical data. This procedure combines the flexibility and limited data requirements of the statistical process with the realism of actual orders.

The only model which uses this methodology implements it as a two-phase procedure. The original LREPS model³⁰ uses a simplified version of this process, although the current version does not incorporate this feature.^{31, 32} The two-phase procedure uses a statistical methodology to develop an aggregate daily or weekly sales figure. Actual orders are then sampled until the periodic quota is met. The advantage of this process is that the statistical parameters of the first phase can be modified easily to initiate patterns, while the actual orders reflect reality adequately.

Two alternative methods have been used to generate periodic industry demand. The first alternative, used by Kuehn and Weiss³³ and Kotler,³⁴ develops an equation that is product specific. The Kuehn and Weiss model was originally developed for detergents, although the authors suggest that

the model could be used for most goods distributed through retail grocery stores. The method described by Weiss uses a multiple regression approach. Industry sales, the dependent variable, is regressed on what are considered to be leading indicators of industry demand. The predictions for these indicators, the independent variables, are used to estimate industry demand. A possible formulation of this model is:

$$S = b_0 + b_1X_1 + b_2X_2 + b_3X_3 + . . . + b_nX_n$$

Where:

S = the estimation for industry sales;

b_i = regression parameter as estimated through some statistical estimation procedure;

X_i = predictions for the leading indicators.

Typical indicators might include population, per capita income, births, housing starts, and industry indices. It should be noted that these methods may be used to estimate industry sales for any market area whether it is representing the entire country or only a limited geographical area such as a city.

The alternative method for developing a measure of industry demand utilizes an exponential regression analysis incorporating appropriate leading factors. Kotler's model³⁵ proposes:

$$\text{Industry sales} = A \times B \times C \times D$$

Where: A, B, C, D are any factors that might be related to industry sales.

An application of this approach is:

$$\begin{aligned} \text{Demand for new bicycles} = & \text{Population} \times \text{personal} \\ & \text{discretionary income per} \\ & \text{capita} \times \text{average percentage} \\ & \text{of discretionary income} \\ & \text{spent on recreation equip-} \\ & \text{ment} \times \text{average percentage} \\ & \text{of amount spent on recrea-} \\ & \text{tion equipment that is} \\ & \text{spent on bicycles.} \end{aligned}$$

Another step may be required to divide the industry demand into a suitable estimate of firm demand. This step is not necessary when the regression formulations are used to estimate firm, rather than industry, demand. Two such market share models were proposed by Krishnan and Gupta³⁶ and Kotler.³⁷ The proposed models are similar, with Kotler's model allowing more factors to influence the determination of market share. For a duopolistic market, the model presented by Krishnan and Gupta is as follows:

$$f_i = a_i s_i / (a_1 s_1 + a_2 s_2) + k(p_1 + p_2 - 2p_i) \\ \text{for } i = 1, 2$$

Where:

i = firm index;

f_i = firm's market share;

a_i = effectiveness per dollar spent on promotional effort of the i^{th} firm;

s_i = expenditure on promotional effort;

p_i = price of the commodity as sold by firm i ;

k = positive constant which reflects the effect of price on sales.

The formulation of the model could be extended to represent a multiple-firm industry. Kotler's model advances this two-firm, two-factor model to a multiple-firm, multiple-factor formulation. The primary difference between Kotler's model and that of Krishnan and Gupta is that Kotler's incorporates more variables for consideration in predicting market share. The factors include the preference rating for a firm, distribution effectiveness, and elasticity effects for each of these factors.

The second phase is a sampling procedure to build orders which provide the detail of the firm's demand. The initial LREPS model is the only process that operationalizes this phase.³⁸

Although this last type of demand generation activity employs a different method from the two previously discussed, all three have the same purpose: to provide a facsimile of market area demand. The first alternative provides more flexibility but may not reflect reality adequately. The second alternative reflects history accurately but offers little flexibility. The third alternative offers more flexibility and reality than the first two, but it also requires more data. Nevertheless, no existing physical distribution

models incorporate the third alternative. Appendix A provides a detailed discussion of each model.

Forecasting

Forecasting is another important component of the distribution system since it provides the interface between the firm and its demand environment. Many texts and articles have developed and promoted numerous methodologies for accomplishing this interface.³⁹ However, few models have been developed which allow a comparison of alternative techniques. Such a model would aid in evaluating the predictive capability of a forecast methodology given a particular demand pattern. In addition to evaluation of the technique itself, such a model would offer extensive possibilities to evaluate forecast parameters and their respective sensitivities.

The models that do exist fall into two classes. The first class includes models which match a specified demand pattern against alternative forecasting methods. The technique's accuracy is evaluated by measuring the difference between the forecasted demand and the "actual" demand. This class of models does not consider the effects that facility operations may have on the physical distribution system's ability to meet the forecast. The second class of forecast models includes operations and inventory management models.

However, since these models use only one forecast technique, no capability exists to evaluate alternative techniques in conjunction with a distribution operations environment. No models were found which included components for the analysis of alternative techniques along with the interaction of the firm's operations environment.

Distribution Management

The remaining activities can be grouped under the category of physical distribution management considerations. The firm has the greatest degree of control over these factors and, in fact, uses them as strategy components for its product offering. However, even though the activities jointly provide the firm's response parameters, management's actions can be segmented into three broad areas: location analysis, operations, and inventory management. The following sections treat each group independently.

Location Analysis. Location analysis is the most common objective found in distribution planning models. These models, primarily static, evaluate alternative warehouse locations and customer assignments by computing the cost and service characteristics of alternative systems. Two approaches are used for this analysis. One method uses an iterative approach to choose the best subset of warehouse locations from a set that has been previously defined to

the algorithm. Some mathematical and numerical models use this approach. This technique is often used when only a single echelon is under consideration. A second alternative evaluates the cost and performance characteristics of a prespecified distribution system configuration. Such a technique may identify the responses of a multi-echelon system. The model best suited for analysis depends on the characteristics of the problem. A locational analysis considering only a single echelon could be addressed best with the first alternative, while an analysis considering channel design could best be treated with alternative two. However, no models utilizing alternative two include an optimizing algorithm.

Operations. Operations is a seldom used modeling application. Of the models reviewed, only two provide a framework for analyzing the effects of alternative operating policies. An operations model considers questions involving shipment consolidation, review period frequency, shipment scheduling, cycle time control, and channel coordination. Bowersox has identified these questions and others as important operational considerations in policy formulation.⁴⁰ The models that consider operations are simulations, although neither model addresses all of the questions identified above. One of the primary problems in operations modeling

observed in the literature and in this author's experience is the difficulty of establishing generalized algorithms for modeling a specific situation. For example, the rules used for shipment consolidation usually differ by organization and include much exception processing.

When analyzing operations procedures, the entire physical distribution network, or at least a representative share of it, must be modeled because of the interdependence of facilities. A systems orientation requires that the nodes (facilities), the links (both communication and physical), and the flows be modeled and observed. Restrictions or delays are placed on the entities to approximate actual operations or alternative operations.

The models that consider operations utilize dynamic simulation techniques which incorporate both spatial and temporal dimensions.

Inventory. Although inventory modeling could be considered a segment of operations models, the amount of research in this area deserves special attention. These models address problems considering alternative inventory levels and policies. Sensitivity analysis to establish the necessary levels of stock inventory and safety stock is also a subject of this model category.

A demand generation routine generally provides the force variable which impacts on a single or multiple facility

distribution network on a period-by-period basis. The model measures performance characteristics for each set of policy parameters in order to evaluate alternatives. The most common service measurement used is the percentage of demand filled without back-ordering. All of the inventory management models reviewed use dynamic simulation. Because of the temporal dimension involved in meeting the customer's needs, any models considering this component must use the dynamic simulation approach.

A special category of inventory-related models that deal with time-sequencing of material is not treated in this review. The materials requirement planning (MRP) models do not have a direct relationship to the SPSF objective since they deal with derived demand rather than independent demand, which is the case with finished goods distribution. The derived, or dependent, demand situation is appropriate for raw material procurement. Orlicky provides a detailed discussion of the MRP concept.⁴¹

MODEL CHARACTERISTICS

Now that a framework has been established to aid in categorizing the objectives of physical distribution models, a second classification system is proposed to describe the model characteristics used to meet research objectives. Identifying and discussing selected attributes is critical

since the capability of a particular modeling technique depends directly on those characteristics. For example, a deterministic model may not provide an efficient tool for the analysis of uncertainty in the distribution system. Emshoff and Sisson provide a partial framework for the analysis by defining the following characteristics: (1) static-dynamic, (2) aggregate-detailed, (3) continuous-discrete, and (4) deterministic-stochastic.⁴² The authors also include the following: (1) physical-behavioral, (2) computer-human, and (3) recursive-quasi-equilibrium. However, this author does not consider the last three classifications applicable to distribution models. Shannon defines a similar classification system for models: (1) static (cross-section)-dynamic (time series), (2) deterministic-stochastic, (3) discrete-continuous, and (4) iconi-analog-symbolic.⁴³ One additional characteristic that this author feels is important when reviewing current models is the degree of flexibility of the model. House and Karrenbaur also identify this feature as important.⁴⁴

The remainder of this section of the review defines the characteristics and demonstrates the manner in which they have been used in existing distribution models.

Static-Dynamic

Within the field of physical distribution modeling, the characterization between static and dynamic models

generally can be established by the degree of temporal consideration. Naylor, et al., state:

Static models are those models which do not explicitly take the variable time into account . . . [while] . . . mathematical models that deal with time-varying interactions are said to be dynamic models.⁴⁵

The static model is much easier to design and implement than a comparable dynamic model. The static model is acceptable for many applications in logistical analysis, particularly when facility location is the target variable. Bowersox summarizes the function of static analysis procedures:

The static simulation procedure seeks to estimate the outcome of a specified plan or course of future action. If the potential [distribution] system design is identified, the primary purpose of the simulation would be to quantify total cost and threshold customer service. Used in this sense, the static simulator provides a tool for rapidly measuring the capabilities and costs related to system designs and related sensitivity analysis.⁴⁶

Although Bowersox refers directly to simulation, the same holds true for static mathematical optimizing models.

Most models which analyze warehouse configurations are static. Location oriented linear programming models are primarily static. The output of the model provides the optimum design, given the levels of the aggregate exogenous variables. The static nature implies that the logistical activity occurs at one instant in time rather than over a series of time periods. As an example, when a static model is utilized to analyze the structure of a warehouse

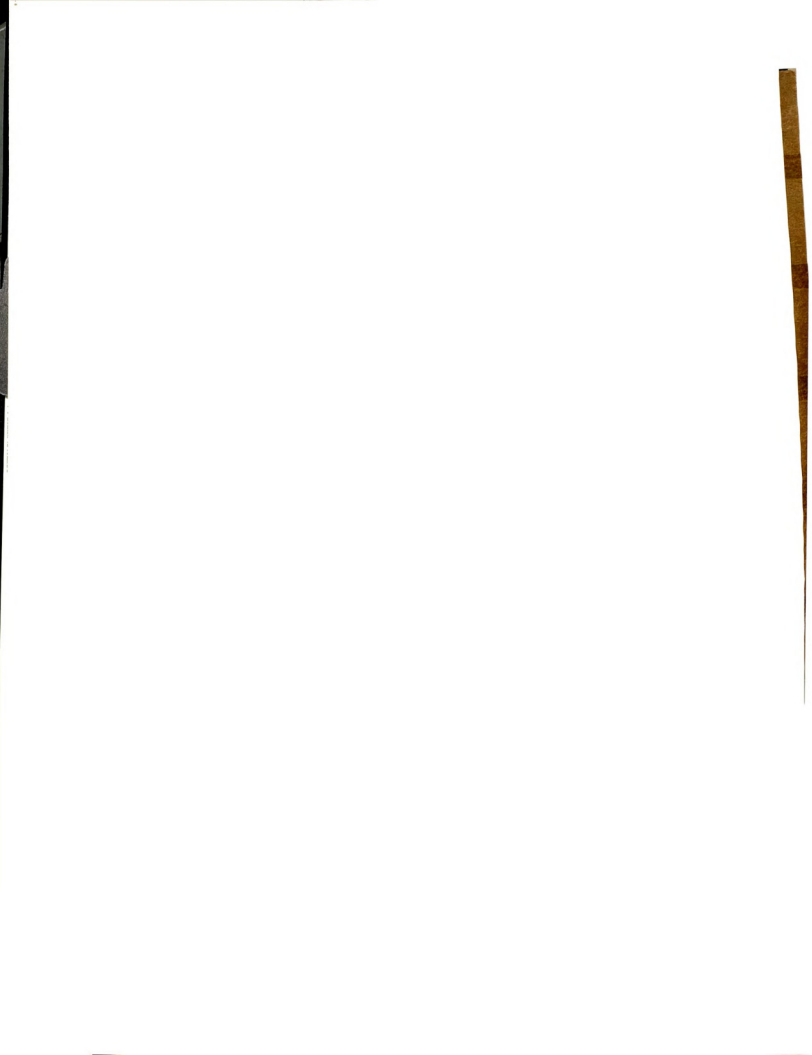
configuration, most models reviewed use aggregate annual product flow on a static basis.⁴⁷ Each customer's aggregate demand is assigned to the warehouse which provides the lowest cost or best service or a combination of both.

Dynamic models generally incorporate the temporal dimension. Dynamic analysis is particularly valuable for considering the effects of alternative policies on time dependent events such as inventory replenishment or freight consolidation. Without the feedback mechanisms provided in a dynamic model, the effects of changes in model operations could not be passed to subsequent operating periods. Models which address operations procedures or inventory policy incorporate dynamics. Generally, detailed daily or weekly data are used. The model state changes as a result of the demand and the new state conditions then provide the beginning status for the following period.

The determination as to whether the model should be static or dynamic depends on the proposed uses of the model. Existing literature and knowledge of the needs of distribution analysis suggest that models which perform detailed operations or inventory analysis must include dynamic components so that temporal interaction may be considered.

Aggregate-Detailed

According to Emshoff and Sisson, "one of the most important characteristics of a simulator is its degree of



aggregation."⁴⁸ This feature determines whether the model can be expected to provide answers to macro or micro problems. The degree of detail required depends on the objectives of the modeling effort and the level of accuracy desired. To ensure efficiency in development, implementation, and use, the model should be made as parsimonious as possible consistent with the objectives of the analysis. A detailed model may not be appropriate for study of an overall distribution system configuration because it would be too expensive to construct and execute in relation to the level of information needed. On the other hand, establishment of inventory policy for individual products may require a very detailed analysis to provide an accurate measure of the inventory-service tradeoff.

Most models reviewed as the basis for this research are detailed. As would be expected based on the previous discussion, the models intended for operational or inventory analysis tend to be more detailed than models which address distribution system configuration. In almost all cases, the models consider individual product and warehouse detail for aggregate groups of customers. Although customers are often aggregated for the analysis, a fair amount of detail remains due to the large number of customers which must be considered initially by the analysis. The emphasis on detail may not be necessary in all cases, but the degree of past emphasis

can probably be attributed to the background of the project managers involved in model utilization. The operating experience of those managers has taught them to be extremely cautious when using an aggregate level of information.

Continuous-Discrete

The dichotomy between continuous and discrete reflects the type of time increment mechanism used by the model.

According to Shannon:

Continuous change models use fixed increment time advance mechanisms and are appropriate when the analyst considers the system he is studying as consisting of a continuous flow of information on items counted in the aggregate rather than as individual items.⁴⁹

On the other hand, discrete change models are appropriate when the analyst is interested in what happens to individual items in the system. Pritsker allows for the possibility of a simulation which contains both continuous and discrete mechanisms.⁵⁰

Shannon outlines some important considerations in reaching a decision concerning the time increment mechanism: (1) the purpose or goal of the model, (2) the precision of results required, (3) computer run time required for different methods, (4) computer storage required, and (5) programming effort required.⁵¹ These guidelines provide valuable insight but are not absolute criteria to be relied on since the last three considerations almost require that the

implementation be completed before accurate answers are available. Emshoff and Sisson provide a general rule for the use of alternative time increments.⁵² They suggest that continuous variables lead to valid, low-cost models for studies of whole enterprises and of socio-economic phenomena. However, they claim:

For more detailed models, the discrete nature of the real world becomes evident; there are individual orders, machines, people, and transactions. These models will be discrete in both values and along the time dimension.⁵³

Using the guidelines outlined by both Shannon and Emshoff and Sisson and considering the objectives of the model, the most appropriate time increment mechanism is the discrete alternative. The detailed level of analysis required, such as treatment of individual transactions and shipments, calls for a discrete analysis. In addition, the level of record maintenance for most firms would not support the data required for a continuous analysis using less than daily increments. On the other hand, utilization of increments greater than one day would cause the model to lose some of its accuracy due to the level of aggregation.

Deterministic-Stochastic

This characteristic describes the model's capability to deal with uncertainty observed in both the environment and in the functional relationships within the model. The terms "deterministic" and "stochastic" represent polar

extremes. Shannon identifies the characteristics of the two model types:

Deterministic relationships are identities or definitions that relate certain variables or parameters where a process output is uniquely determined by a given input. Stochastic relationships, on the other hand, are those in which the process characteristically has an uncertain output for a given input. Both types of relationship usually take the form of a mathematical equation relating the endogenous and status variables to the exogenous variables.⁵⁴

Although analytical models are usually deterministic, stochastic programming models do exist. However, no analytic models were found which addressed distribution problems while considering uncertainty. Among the models reviewed which specifically address the spatial design of distribution systems, none were found which considered any degree of uncertainty.

Models in which at least one relationship is described by a probability function are considered stochastic.⁵⁵ Stochastic, or random, variables and relationships provide a means for considering the uncertainty inherent in accomplishing the distribution objective. Common stochastic variables encountered in the simulation models of distribution systems include customer demand, order cycle time, and product availability. Stochastic models are also useful for generating random samples of data from the simulator to be used in either the "observation" or "testing" stages of

scientific inquiry.⁵⁶ The use of stochastic relationships between the exogenous factors and endogenous variables provides a more realistic model of the distribution system. For example, a deterministic model would require that an average be used when some measure of the order cycle time is needed. However, the use of a stochastic model allows introduction of random order cycle times. In prior work, it has been concluded that the variation, not the average level, causes the primary problems in distribution system performance.⁵⁷ Almost all models which simulate distribution operations employ some type of stochastic variable or relationship. For example, when policies influenced by the uncertainty of order cycle time are being analyzed, the order cycle times used are often generated stochastically using an appropriate probability density function.

In summary, the literature review identified both deterministic and stochastic models. Deterministic characteristics were found in almost all models which address the design of the distribution system. The remaining physical distribution components are almost always treated using a stochastic model.

MODEL ANALYSIS

This section of the simulation literature review classifies the individual models used for analysis of distribution problems. The proposed framework, in terms of

both functions and characteristics, is used to demonstrate the character and weaknesses of current distribution modeling technology. Appendix A contains a detailed analysis of individual models. Table 3 summarizes the distribution functions addressed by existing models. The entry for the model-function pair briefly describes the capabilities of the model within the particular area. In some cases, the model may handle a functional area in great detail, while in others the treatment may be cursory. Table 4 provides a summary of simulation characteristics used in addressing individual functions. This analysis should provide some insight into the characteristics necessary for use in a distribution model.

CONCLUSION--DISTRIBUTION MODELING REVIEW

The state of the art for distribution models is quite advanced when the distribution configuration problem is considered. However, the areas of demand generation, operations, and forecasting have not been included in most analyses.

The demand generation alternatives listed in Table 3 either do not provide enough flexibility or do not provide enough realism. The exogenous input alternative provides a great deal of realism, but it is difficult to create alternative demand environments for analysis. The stochastic

TABLE 3
DISTRIBUTION MODEL FUNCTIONAL SUMMARY

Model	Firm's Environment	Distribution System to Environment Interface	Distribution System Components Under Management Control		
	Demand Generation	Forecasting	Location and Structure	Operations	Inventory
Ballou ⁵⁸	Exogenous annual quantities		One echelon network		
Ballou ⁵⁹	Exogenous orders	Single technique	Fixed	Alternative processing policies	Alternative levels
Bender ⁶⁰	Exogenous annual quantities		One echelon network		
Buffa ⁶¹	Exogenous monthly quantities				Constrained optimal safety stock
Camp ⁶²	Exogenous annual quantities		One echelon network	Alternate sourcing	

TABLE 3 (Cont'd.)

Distribution System Components Under Management Control						
Model	Firm's Environment	Distribution System to Environment Interface	Location and Structure	Operations	Inventory	
DPM ^{63, 64}	Demand Generation	Forecasting	Multi-echelon network			
DSS ^{65, 66}	Exogenous annual quantities	Single technique	Multi-echelon network	Offers alternative policies	Alternative levels and policies	
Forrester ⁶⁷	Stochastic generation		Single location			
Geoffrion/ Graves ^{68, 69}	Exogenous annual quantities		One echelon network			
GPFS ⁷⁰	Stochastic generation	Limited alternative techniques				
Kuehn/ Hamburger ⁷¹	Exogenous annual quantities		One echelon network			

TABLE 3 (Cont'd.)

Distribution System Components Under Management Control						
	Firm's Environment	Distribution System to Environment Interface				
Model	Demand Generation	Forecasting	Location and Structure	Operations	Inventory	
	Exogenous annual quantities		One echelon network			
LREPS ^{73, 75} ₇₆	Exogenous orders	Single technique	Multi-echelon network	Alternative sourcing and policies	Alternative levels and policies	
Markland ^{77, 78} ₇₉	Exogenous monthly orders		One echelon network	Alternative sourcing and policies	Alternative levels and policies	
Packer ⁸⁰	Stochastic generation	Alternate smoothing techniques	One location		Alternative levels	
Shycon/ Maffei ⁸¹	Exogenous annual quantities		One echelon network			
WHAMOL/ Whirlpool ⁸²	Stochastic generation		Multi-echelon network	Alternate sourcing		
Whybark ⁸³	Stochastic generation	Alternate smoothing techniques	Single location			

TABLE 4
DISTRIBUTION MODEL ATTRIBUTE SUMMARY

Model	Static/ Dynamic	Aggregate/ Detailed	Continuous/ Discrete	Deterministic/ Stochastic	Mathematical/ Simulation
Ballou ⁵⁸	S	D	D	D	S
Ballou ⁵⁹	D	D	D	D	S
Bender ⁶⁰	S	D	D	D	M
Buffa ⁶¹	D	D	D	D	M
Camp ⁶²	S	D	D	S	S
DPM ^{63, 64}	S	D	D	D	S
DSS ^{65, 66}	D	D	D	S	S
Forrester ⁶⁷	D	D	D	S	S
Geoffrion/Graves ^{68, 69}	S	D	D	D	M
GPFS ⁷⁰	S	D	D	S	S
Kuehn/Hamburger ⁷¹	S	D	D	D	S
LOCATE-House ⁷²	S	D	D	D	S
LREPS ^{73, 74, 75, 76}	D	D	D	S	S

TABLE 4 (Cont'd.)

Model	Static/ Dynamic	Aggregate/ Detailed	Continuous/ Discrete	Deterministic/ Stochastic	Mathematical/ Simulation
Markland ^{77, 78, 79}	D	D	D	D	S
Packer ⁸⁰	D	D	D	S	S
Shycon/Maffei ⁸¹	S	D	D	D	S
WHAMOL/Whirlpool ⁸²	S	D	D	D	S
Whybark ⁸³	S	D	D	S	S

generation alternative provides a greater degree of flexibility in demand generation, but the orders may not be characteristic of actual orders.

Although not many distribution models address operational questions, those that do so consider flexible sourcing, shipment consolidation, and order processing alternatives. Consideration of this function has not been weak; however, the effect of operational procedures has not been considered in most models.

The forecasting function has been seriously overlooked in terms of its effect on other functions. Models strong in operations or inventory areas offer only a single forecasting technique for evaluation. This design implies that the forecast process is essentially external to the performance of the distribution objective and, thus, no interactions exist in either direction. On the other hand, the models that provide alternative forecast techniques do not adequately consider the operations and inventory components. This design also fails to consider interactive effects.

The need exists to develop an integrated distribution model to address these deficiencies and to provide a tool for analysis of total physical distribution system performance. In particular, the model ought to have a demand generation capability which is flexible yet realistic.

This capability would provide easily obtained alternative demand environments which could be matched against the distribution system structure and policies to estimate the performance characteristics of the system. In addition, inclusion of the other four components (i.e., location, operations, inventory, and forecasting) provides a tool for analysis of the interactive effects of individual functions. No models exist which provide a flexible environment along with individual, yet interactive, consideration of each of the component functions.

LITERATURE REVIEW--IMPLEMENTATION

The literature review now addresses the model implementation process. Although the process is somewhat dependent on the specifics of the model, many general simulation texts have outlined the basic steps. Some texts provide broad directives, while others address detailed questions or alternatives. However, existing literature describing distribution modeling offers little insight concerning the procedures utilized.

The review discusses three topical areas regarding the implementation process: general issues, language, and specific implementation procedure. The areas are necessarily interdependent, since each affects the others.

GENERAL ISSUES

Each general issue must be addressed before initiating the implementation process since the answers have broad implications for the scope and capabilities of the model. The four basic issues important here are: (1) introduction of uncertainty, (2) method of response estimation, (3) computer resource requirements, and (4) model portability. Each issue is discussed in terms of its implications for the modeling process.

Introduction of Uncertainty

The first issue concerns the introduction of uncertainty into the model. As pointed out earlier, one of the primary advantages of simulation is its ability to convolute the interactive effects of various sources of uncertainty. When considering the uncertainty, two sub-issues merit reflection: the degree and source of the variance and the algorithms used to generate this variance.

The degree and source of the variance depends on the real-world system being modeled. Emshoff and Sisson state:

If historical data or direct observation suggest that unexplainable variations exist in the value of some phenomena, then the phenomena should be represented in the simulator as a stochastic process.⁸⁴

Even with this somewhat obvious statement concerning where and when a stochastic process should be utilized, the answer is not as simple as it might seem. In many cases where only

two or three alternatives require evaluation, the stochastic nature of the environment may not require consideration since only the aggregate differences in model response are important. As an example, since aggregate cost is the most significant consideration in a location model, the introduction of stochastic variables to approximate order lead times is not necessary. Another consideration in selecting the degree and source of variance is the validation process. When an adequate stochastic process is not available to model a variable, validation of the integrated model may be difficult. Emshoff and Sisson suggest that all variables be deterministic initially.⁸⁵ Following sensitivity analysis, some variables are gradually converted to stochastic in a systematic manner until the model performs realistically.

The second sub-issue concerns the mechanism to be used to generate the stochastic or random variates. Naylor et al.⁸⁶ and Emshoff and Sisson⁸⁷ provide detailed discussions concerning the requirements for suitable random numbers along with algorithms for creating and testing them. The algorithms generally provide uniformly distributed random variates between 0 and 1. When other than uniformly distributed variates are desired, a transformation process is necessary for conversion to an appropriate distribution. Emshoff and Sisson describe three processes suitable for use when no explicit functional form could represent the

probability density function: (1) inverse transformation, (2) rejection method, and (3) rectangular approximation.⁸⁸ When a theoretical functional form such as a normal or poisson is appropriate, Naylor et al. and Pritsker illustrate FORTRAN subroutines that can be used to generate random variates with the appropriate characteristics.^{89, 90}

The literature discloses two basic decisions that must be made for each variable. First, each variable must be evaluated individually to determine whether it merits stochastic consideration. The important points to consider for the analysis include the degree of uncertainty in the variable and the variable's effect on overall model response. Second, for the variables that do merit stochastic consideration, the appropriate process for stochastic variate generation must be selected.

Response Estimation

A related issue for simulation models which incorporate stochastic variables is the means of establishing the confidence intervals for the response variables. Since a single simulation provides only one estimate of the true system response variable(s), multiple simulations must be run to establish the confidence interval for each estimate. Numerous methods exist for obtaining these estimates, with varying degrees of efficiency. One method described by Emshoff and Sisson proposes that multiple simulation runs

be made, each with a different random number stream.⁹¹ The estimates from each replication are then pooled exogenous to the model to establish an estimate for the response variable as well as the confidence limits. A variation on this methodology offered by Pritsker is to allow the simulator to make multiple passes with a different sequence of random number variates.⁹² The model would then endogenously perform the statistical analysis for response estimation. The "fixed" cost or overhead for a simulation is thus spread over more response estimations. Another alternative, also offered by Emshoff and Sisson, suggests that the simulation be broken into blocks or segments which are assumed to be independent.⁹³ The response variable from each segment can then be used to estimate the true parameter. The presence of autocorrelation, or time dependent variables, would eliminate this method from consideration. A method which can be used in conjunction with any of the above three to establish a better estimate is described by Carter and Ignall.⁹⁴ The method, known as virtual measures, is one type from a broader class of processes known as variance reduction techniques. The basic principle of such techniques calls for using knowledge about the structure of the model and nature of the inputs to change or distort the original problem so that special algorithms may be used to obtain desired estimates at lower costs.⁹⁵ Incorporation of the

proposed algorithms within the simulation reduces the variances of the response variable so that either the confidence level is increased or the number of random number streams required is decreased when attempting to establish the validity of a particular response variable estimation. Shannon has cautioned that while these techniques appear to be very powerful for simple, artificial problems, the gains are not as significant when addressing more complex, real world problems.⁹⁶

The method of response parameter estimation must be established prior to the development of the simulator since the selection may have implications for the simulator control mechanisms. The internal statistical analysis and the variance reduction techniques may serve to improve the efficiency of the simulation process under some circumstances. However, the increase in development time must be weighed against the possible efficiency increase.

Computer Resource Requirements

The existing computer resource restrictions must also be considered prior to model implementation. Reitman points out that the principal cost of the simulation is not computer time but the manpower required to develop, assemble, and attain the problem definition and system design.⁹⁷ Nevertheless, host computer limitations are an important

constraint, even with current technology. The basic considerations include the execution speed of the model as well as the amount and configuration of memory required.

With the current advancements in computer hardware, speed considerations have become less important since few programs are constrained by computation speed. Minimization of the delay times associated with input and output functions is a more important consideration. Judicious use of file access methods reduces file access times which in turn affects execution time most significantly. Lehman points out other considerations which are important for minimizing computer time.⁹⁸ He includes suggestions for utilizing arithmetic operations, control statements, loops, and subscripts, as well as input and output. His suggestions provide insight into the computation process so that the most efficient coding techniques may be utilized. For the most part, however, the suggestions only reflect good programming practice and are not significantly different from what an experienced programmer would do. In any event, without an extremely thorough analysis, the effectiveness of these considerations is very difficult to measure. With these two limitations in mind, execution time efficiencies are not considered further.

Storage considerations, on the other hand, may have a significant influence on model performance, even with the

present technology of virtual memory. Minimized storage requirements implies that the model must wait less time to obtain its required memory and that the model will not be swapped out as often. In addition, the associated computer charges will be lowered with the reduction in memory size. To emphasize the significance of this consideration, the Manager of Information Services for a firm with a large virtual memory computer pointed out that the program and data must be organized in a manner which would minimize the paging required.⁹⁹ Pages contain segments of the program and data which may be stored periodically on a peripheral device rather than in the main computer memory. In particular, Lehman outlines the important considerations for utilizing memory overlays or virtual memory as mechanisms for core reduction.¹⁰⁰ In the case of overlay utilization, he points out that the design and grouping of overlaid routines can significantly influence the operation of the model. For virtual memory machines, the essential considerations include referencing large data arrays as well as the structure of extended loops and subroutines.

With current technology, no major problem exists with model implementation on a large-scale computer. The sheer power of current machines may be used to accomplish almost any task. However, for large-scale models requiring great amounts of resources, particularly if the model is

run repeatedly, the considerations pointed out in this discussion are important.

Model Portability

Model portability is another important issue which must be addressed during the implementation phase. Reitman identifies two aspects of this issue as: (1) the flexibility of the program to handle other problems, and (2) the ability of the program to be utilized by other user teams.¹⁰¹ House and Karrenbaur also point out that model applicability is an important issue for implementation.¹⁰² A fourth important sub-issue is the model's capability to be transported to other hardware types.

No easy answers exist for the portability issue. To the extent that individual aspects of portability are important for the model, a corresponding priority must be placed on the appropriate sub-issue. Generally, a tradeoff exists between program efficiency and portability. The implementation process must decide where the model is directed on the efficiency-portability continuum.

LANGUAGE

Many books and articles have addressed the topic of simulation languages, including both general purpose and special purpose languages. Earlier texts provide detailed descriptions of the syntax and capabilities of particular languages. These texts are more appropriately considered

handbooks, complete with extensive examples, for utilization of that language. Pritsker and Kiviat provide such manuals for use with the FORTRAN-based GASP simulation language.^{103, 104} Kiviat, Villanueva, and Markowitz provide the same information for SIMSCRIPT.¹⁰⁵ Similar texts by IBM¹⁰⁶ and Pugh¹⁰⁷ are available for the GPSS and DYNAMO languages, respectively. More recent texts describing the widely used GPSS language include Greenberg¹⁰⁸ and Schriber.¹⁰⁹ The handbook approach provides detailed characteristics for a single language, but it complicates the process of evaluating tradeoffs among the languages.

Many recent general simulation texts have discussed tradeoffs in detail. Some texts preface the specific language discussion with a broad overview of the positive and negative characteristics of both general and specific programming languages. Texts by Reitman¹¹⁰, Shannon¹¹¹, and Emshoff and Sisson¹¹² demonstrate this concept. In each book, a rather brief discussion of the characteristics of computer programming languages is followed by a detailed review of the most commonly used general purpose simulation languages. On the basis of reference and use, the most common general purpose languages used for simulation include FORTRAN, GASP, DYNAMO, SIMSCRIPT, SIMULA, and CSMP. Each of the above-mentioned texts provides a good overview of the common languages, with Shannon providing a flowchart for evaluating alternatives.

Naylor et al. also discuss general purpose simulation languages. They provide a framework for evaluation of alternatives, but the authors point out that economic considerations are most important in the final analysis. The authors include the following economic factors:

1. Availability of computer hardware
2. Availability of programmers knowledgeable in particular computer languages
3. Cost of programming per unit time
4. Cost of computer time.¹¹³

Given the framework provided by all of the above authors, there is no reason to believe that further development is required to provide a language for model implementation. At least as an initial phase, the implementation process should evaluate existing languages in terms of their capabilities and then evaluate economic considerations. If no existing language meets the needs of model implementation, then perhaps a modified version of an existing language would provide adequate capabilities. Further development should be considered only as a last resort.

PROGRAMMING PROCEDURE

The final requirement for the implementation phase is definition of a procedure for converting the specific model to a computer program. Very little has been written about the implementation process of specific distribution

models, although many texts have outlined procedures for implementing models in general. In particular, Emshoff and Sisson describe three methods of analysis for implementing individual system segments.¹¹⁴ These authors suggest the flow approach for systems ". . . having dynamic properties determined by the flow of physical or information entities through the system." The second method, the functional approach, is ". . . commonly used when there are no directly observable flowing elements in the system, but when there is a reasonably clear sequence of functions to be performed." The third, or state-change, approach is ". . . useful for a system that has a large number of interdependent relationships for which no specific sub-grouping can be observed."

Since it is possible to subgroup the systems that accomplish the distribution objective, either of the first two alternatives provides an acceptable procedure. In particular, the flow analysis alternative would treat the individual physical and communication flows as they emanate through the system while the functional alternative would treat the individual events with their interrelationships. A precedent has been set with existing dynamic distribution models using a functional approach. Both LREPS¹¹⁵ and DSS¹¹⁶ use a functional or event orientation.

CONCLUSION--IMPLEMENTATION REVIEW

The literature review for computer implementation of the research has not demonstrated, nor was it expected to demonstrate, any substantial deficiencies in existing work. The intent of this review was to disclose the issues and questions that must be addressed as part of the implementation phase. This was done by reviewing the limited discussion concerning implementation of existing distribution models as well as the general modeling procedures outlined by other texts.

The resultant questions include four broad general issues, the programming language, and the analysis method for use in implementation. Each question must be answered before the implementation process.

Once the computerized model is implemented, the final step for model development is validation. The procedure is complex and multi-faceted, with relatively rich supporting literature. The following section discusses some of the considerations and procedures that have been reported.

LITERATURE REVIEW--VALIDATION

The model validation process has many dimensions which must be isolated and treated individually. Some individuals feel that a valid model must simply replicate reality while others feel that more stringent requirements are necessary.

Three levels of review are appropriate for this research. The first level addresses the broad theory of validation. It asks the philosophical question of what is necessary to establish the validity of a model. Deficiencies are not likely to be encountered in this area. The second level addresses the applied problem of validating a simulation model in particular. General simulation texts are reviewed to establish this criterion. Again, it is doubtful that this research will encounter deficiencies here. The third level looks specifically at the validation processes used for existing distribution models. The section addresses the question of how the methodologies proposed in the first two levels have been applied to distribution model development.

PHILOSOPHY OF VALIDATION

The basic purpose of the validation process is to establish the "truth" of the model. However, it is virtually impossible to establish the "truth" of any model since the criteria for "truth" or "non-truth" are themselves difficult to establish. To overcome this problem, Popper suggests that ". . . efforts should be concentrated on determining the degree of confirmation rather than verification."¹¹⁸ This implies that the model be subjected to types of situations which would be encountered in the actual system's environment. Then, as Van Horn suggests, validation becomes

the ". . . process of building an acceptable level of confidence that an inference about a simulated process is a correct or valid inference for the actual process."¹¹⁹

The confidence building process itself cannot be defined and accomplished easily. The question must still be asked: What is the most appropriate means of establishing an acceptable level of confidence? To address this question, even on a philosophical level, Naylor and Finger have summarized three major methodological positions on validation: rationalism, empiricism, and positive economics.¹²⁰

The rationalist view defines a model as a "system of logical deductions from a series of synthetic premises of unquestionable truth." Under this assumption, validation becomes the process of confidence building in the assumptions. This approach is more appropriate for the hard sciences where it is possible to establish universal axioms and theory.

The second major position, empiricism, reflects the opposite point of view. In this case, the model and the corresponding validation process should be based on facts, not assumptions. To meet empirically established criteria, model performance must be based on and correspond with the observed facts. This approach provides the basic validation procedure for use in the social sciences since there is no requirement for the "premises of unquestionable truth."

The final view, championed by M. Friedman, proposes that the validity of a model depends on its ability to predict the behavior of the system and not on the basis of its assumptions. Although this approach is very pragmatic, this author believes that the methodology does not offer enough potential for utilization of existing theory and facts.

If one were to select only one of these proposed methodologies and proceed with the validation, this author, and others, believes that the process would leave much to be desired. Naylor and Finger¹²¹ and Bowersox et al.¹²² propose instead a three-stage approach which incorporates aspects of all three methodologies. Stage one calls for construction of hypotheses and postulates for the process using all available information--observations, general knowledge, relevant theory, and intuition. Stage two uses empirical testing to attempt to verify the assumptions of the model. The final stage tests the predictive capability of the model by comparing the model results with those generated by the real world.

This multi-stage approach incorporates the positive features offered by each of the methodological positions while overcoming the weaknesses of an individual approach. Utilizing this approach, no weaknesses are found in the philosophical approach to validation.

The process of validating analytical models is not discussed in detail, since the derivation of the model itself must be based on postulates of "unquestionable truth." Thus, the only question of validity for analytical models concerns the correspondence between model assumptions and reality. On the other hand, simulation models require validation of both the assumption and the methodology. The following discussion reviews how this validation process has been operationalized for simulation models.

SIMULATION VALIDATION

This section of the review discusses the validation process as presented in generalized simulation literature. In most cases, simulation authors operationalize the methodology outlined in the previous section, although some variations exist, as Emshoff and Sisson demonstrate.

Emshoff and Sisson prescribe the positive economics view for the validation process. They state:

The only possible evidence of validity for a simulation model that has been developed specifically for a situation is that the model has made satisfactory predictions in the past. If this is the first time the model is being used, such evidence is not available.¹²³

These authors may be correct in the long run; however, intermediate steps exist that may be used to lend credibility to an "unvalidated" model. Emshoff and Sisson themselves suggest that Hermann's five preliminary approaches to

validation may be used for establishing the credibility of a "first-time" model. Hermann's tests include:

(1) "internal validity," (2) "face validity," (3) "variable-parameter validity," (4) "hypothesis validity," and (5) "event or time-series validity."¹²⁴ To operationalize

this extended test for validity, Emshoff and Sisson suggest the following four-step procedure:

1. The analyst assures himself that the model performs the way he intends it to, using test data, and if available, real historical data. This is debugging.
2. Reasonableness is checked by:
 - a. showing that key subsystem models predict their part of the world well (using historical data);
 - b. showing, where parameter identification is required, that parameters can be fit (that the search terminates with a close match to historical data), and that the parameters have reasonable values;
 - c. having people who are knowledgeable about the situation (preferably including the decision maker) review the model in detail and agree to its structure and parameters.
3. The decision maker has an opportunity to explore the use of the model to become familiar with its predictions and to examine the interactions it implies. At this point the analyst and decision maker may be able to agree as to what is a close enough fit between simulator output and actual data.
4. The model is used for decision aiding. Careful records are kept of its predictions and of actual results. (This may involve a time span of years so the evaluation procedure has to be set up carefully.)¹²⁵

The above procedure illustrates a good general approach which may be used to complete the overall validation process of any model. However, it does not specifically address the problems inherent in validating a simulation model, such as how it is possible to convert steps two and three into actual tests. The problems of statistical hypothesis testing and parameter estimation must still be confronted.

Lehman suggests two approaches which he feels are appropriate for establishing the validity of models.¹²⁶ One approach uses the Turing or Extended Turing Test for investigating the indistinguishability of the model from the actual system. The basic methodology implies that the model is valid if a "knowledgeable" individual cannot distinguish between the responses of the model and those of the actual system. Another test described by Lehman uses the criterion of "matching to known results" to establish validity. As one would expect, this test compares the actual with the simulated responses to establish the degree of fit through either inspection or statistical measure. According to Lehman, the procedure is less cumbersome than the Turing test since it utilizes existing theory and information about the system. In addition to a lack of operational detail, the tests described by Lehman do not provide insight into the range of extremes that ought to be tested.

Although Meier, Newell, and Pazer do not provide a unique procedure for model validation, they do point out some important considerations. Specifically, they identify two sources of response which must be controlled. According to them:

When models are evaluated on a statistical basis, differences in statistics that are obtained when experimental changes are made may be attributed to:

1. Effects of starting conditions
2. Random fluctuations in behavior caused by random processes in the model
3. Effects of experimental changes that are made in the model.

Since the experimenter is primarily interested in (3), it is desirable to plan experiments to control the effects of (1) and (2).¹²⁷

The above statement provides some insight into operationalizing the four-step procedure outlined by Emshoff and Sisson. The establishment of reasonableness in step two requires that the transient effects of the model be isolated and controlled. Step three requires the same type of evaluation.

At the procedural level, Shannon proposes a three-step process to establish confidence in the model.¹²⁸ The steps correspond exactly with the three positions discussed in the previous philosophy section. Shannon then presents a detailed discussion of the statistical methods and tests that could be used to establish confidence in the model. He suggests statistical techniques such as tests of means,

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analysis of variance and covariance, goodness of fit tests, and regression and correlation analysis to establish the internal structure and hypothesis validity of the model. Using observations, previous research, relevant theory, and intuition, the tests should assure that the model is based on sound assumptions and adequately reflects existing data. The second analysis step Shannon proposes addresses his third criterion of validity. The comparison of model transformations attempts to establish the degree of correspondence between the real world system and the model. Shannon offers two approaches to address the comparison problem. When only a single response variable adequately reflects system performance, then the solution is concerned with a univariate two-sample problem. In cases where the generated output reflects an autocorrelated time series, "... spectral analysis has been suggested to test the conformance of the two time streams."¹²⁹ Spectral analysis also requires that only a single response variable be analyzed. Shannon's other approach addresses the multiple response problem when no single variable can adequately reflect the performance of the model. To address this situation, Shannon suggests that the experiment be decomposed into multiple mini-experiments or, as another possibility, reduction of the problem to a univariate case by transformation of the response into a composite measure of performance. The composite

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measure from the actual system and the model may then be tested using univariate techniques for conformance.

Shannon provides the best detailed treatment of the validation problem when concerned with simulators; however, the four-step procedure by Emshoff and Sisson provides a better overall guide. A normative approach would integrate the detail of Meier et al. and Shannon with the broad plan suggested by Emshoff and Sisson. The objective of this validation discussion is to define a procedure based on the literature to build confidence in such models. The next section of this review examines some existing simulation models to establish how such models were validated. The dynamic simulations are of particular interest since all previous models addressing operations and inventory have been dynamic.

DISTRIBUTION VALIDATION REVIEW

This last section reviews the literature discussing the validation process used for existing physical distribution models. However, in many cases, very little is written concerning the validation for many existing models.

Ballou¹³⁰

The combination dynamic programming and location model proposed by Ballou did not provide a documented validation procedure. Although the details were not provided,

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the author implied that the model results were compared against actual data.

Ballou¹³¹

Ballou's second model, which dynamically addresses time delay effects on inventory, was validated by matching the output of the model with the actual system response. Since the simulation was stochastic, the model was also tested extensively with multiple random numbers to establish the sensitivity of the model. In particular, it was found that using the model deterministically would result in the same general conclusions as were found stochastically.

Bender¹³²

The discussion of Bender's optimizing model provides no insight into the validation process other than a brief review of the potential of sensitivity analysis.

Buffa¹³³

The Buffa optimization model for setting safety stock does not discuss the validation effort.

Camp¹³⁴

Camp's dynamic model for analysis of the interactive effects of safety stock and variable lead times utilizes a four-step validation procedure. The tests include: (1) careful inspection of logic, (2) comparison of model results

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with observed logistics network data, (3) model predictive ability, and (4) a combination of all three. Although these steps correspond with the general requirements outlined earlier, the actual implementation was not rigorous. Testing was accomplished through manual checking of: (1) the logic and equations, (2) the individual assignments, (3) sample calculations, and (4) non-summary output variables.

DPM¹³⁵

Nothing is written about the validation procedure used for the Distribution Planning Model. However, since this author was personally involved in its development, it can be said that the validation was accomplished using a comparative approach. The model response was compared against the real world response on a non-statistical basis. The level of accuracy desired was situation dependent.

DSS^{136, 137}

Neither the Connors article nor the program documentation provided by IBM discussed model validation for the Distribution System Simulator. Specifically, no information is provided on how the concept of the model was validated. In addition, the authors do not discuss a procedure that would be applicable for validating the model for a particular problem situation. It is possible that this deficiency in model literature was one of the causes for the lack of interest in the DSS model.

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Forrester¹³⁸

Forrester presents a broad discussion of validation in his book describing the industrial dynamics concept. He stresses the same factors that were outlined in section two of the validation literature review. Forrester's views on validity are summarized in the following quotations:

Validity as an abstract concept, divorced from purpose, has no useful meaning.¹³⁹

The ability of a model to predict the state of the real system at some specific future time is not a sound test of model usefulness.¹⁴⁰

Data may serve to reject a grossly wrong decision-making hypothesis, but they can scarcely prove a correct one.¹⁴¹

In summary, although Forrester believes that the model must be controlled to agree with the real world, very little detail is presented about the validation procedure. In particular, no information is provided on the validation methodology used for the production-distribution system model.

Geoffrion/Graves¹⁴²

The article describing the distribution system location optimizer by Geoffrion and Graves provides no insight into the validation process used. Since it is a mathematical programming technique, there is no need to validate the generalized model. However, no guidance is given for validation of an application.

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Even though the model is a stochastic simulator, no information is provided on the validation procedure used for the general model or for specific situations.

Kuehn/Hamburger¹⁴⁴

The literature describing this heuristic location model does not discuss the procedure used for validation of either the model itself or a specific case.

LOCATE--House¹⁴⁵

House's location simulator literature does not describe the validation procedure for the model itself or for specific applications.

LREPS¹⁴⁶

The validation procedure described for the LREPS model involved a three-stage process. The first stage tested whether the time series of the endogenous variables were statistically under control. In particular, did the data streams examined demonstrate persistent behavior over time? The second stage compared the model output with the actual historical data. The third step examined the sensitivity of specific model assumptions. Statistical methods were proposed for testing the product sampling and the demand generation method.

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The LREPS validation procedure is one of the most detailed described for distribution models. However, some major weaknesses are apparent. No tests were attempted which would isolate the effects of random occurrences or initial conditions within the model. In addition, the model was tested only for a single case, which is a limited base for establishing model credibility. No generalized validation procedure was proposed for use when the model is applied to different problems.

Markland¹⁴⁷

Since the warehouse location model was not used in a statistical sense and no historical data were available, model validity was largely considered in terms of: Have we adequately described the distribution system we (Markland) are trying to model? The procedure, then, amounts to a test of reasonableness on the part of the user and management. The real test for the model in general as well as for specific applications was thus a qualitative measure.

Packer¹⁴⁸

The literature describing Packer's inventory and precasting management model does not discuss a validation procedure for either the model itself or for any particular application.

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Shycon/Maffei¹⁴⁹

The validation process for the Shycon/Maffei location model does not describe a model or an application validation procedure.

WHAMOL/Whirlpool¹⁵⁰

The validation procedure used for the model or its application is not discussed in any existing public literature.

Whybark¹⁵¹

The literature describing the forecast technique testing model does not include a validation procedure for either the model in general or specific applications.

CONCLUSION--VALIDATION REVIEW

Although extensive literature describes the philosophy and general considerations appropriate for the validation process, existing distribution models have made little use of it. Some models have used a quantitative approach which emphasized statistical rigor but lacked any insight into the validation of the overall model or a specific application. The other extreme reflects a qualitative approach which tests the model's ability to match historical data. From this review, two primary weaknesses can be isolated. First, existing literature does not describe distribution model

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development or applications which prescribe and demonstrate the procedure to be used in building credibility either in the model itself or an application. The second deficiency is demonstrated by the type of data used to validate existing models. In some cases, historical data were used, while in others contrived data made up the test conditions. Although historical data are realistic, the model is not adequately tested to its limits. On the other hand, contrived data does not always reflect reality. A validation design using both types of test conditions overcomes the weaknesses of using either alternative alone.

Credibility is a serious problem for those using models to analyze distribution problems. The model must gain the confidence of both the developers and the users. For the technology-oriented developers, the problem is to define test conditions such that the model can be tested statistically. The training of a management scientist provides the tools and capability to accomplish this adequately. For the user, however, the problem is much more difficult. The user knows little about testing models but is experienced in distribution system performance. The user needs direction in order to specify the types of experiments that will aid in evaluating the credibility of the model. Existing literature does not provide such a guide.

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LITERATURE REVIEW--CONCLUSION

The primary deficiencies of existing distribution modeling research lie in the areas of model design and validation. The model design phase has often overlooked the interactive effects of the various components of the distribution system. Either one or a number of the demand, forecasting, or operating environments have been left out. One possible reason for this lack of consideration of the overall system might be the difficulty of integrating all of the components into one model. Lack of motivation may be an additional reason, since it is only recently that the dysfunctional effects of the interactions have become known. Since no models are available which provide a totally integrated testing environment, there has been little need to prescribe a validation process for evaluating them. In fact, relatively little interest at all exists in the validation process when one considers the history of distribution modeling. The deficiency may be a result of the two points of view that intersect in the field of distribution. The management scientist is interested in statistical validation, while the user is interested in a qualitative measure of application validation only. However, sophisticated techniques for analysis of an integrated system require an elaborate validation procedure since qualitative methods alone may not isolate the problems.

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The following chapter describes a methodology which addresses both of the above problems. The design of an integrated distribution testing environment is introduced briefly and is followed by a validation procedure which considers both statistical and applications validity.

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CHAPTER III

SPSF CONCEPT

Simulation literature reveals no models capable of creating the integrated distribution process. Particularly from a distribution modeling perspective, the demand generation, forecasting, and operations simulation components have often been overlooked. Although these components have been modeled individually, distribution researchers have failed to consider interactive effects. However, as the systems perspective points out, total system performance can be analyzed and tested adequately only through the use of a total systems model. A truly integrated model must not only include the three components identified in the literature review, but must incorporate the interactive effects as well.

One problem that has not been treated adequately in the past, due to the lack of a systems perspective, is shortage operational forecast accuracy. A distribution center warehouse utilizes an operational forecast to establish and maintain stocking levels for individual items. In the past, any difference between forecasted sales and actual sales was attributed to a forecasting technique error. Articles by Whybark,¹ Gross and Ray,² and Wheelright and

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Makridakis³ attest to this fact. However, using a systems perspective, one can see that many other types of errors may demonstrate themselves as forecast errors. For example, cycle or lead time uncertainty may cause the physical supply process of the firm to fall short of the forecasted system demand. Thus, although the forecast may have been 100 percent accurate, total demand was not met due to a failure in replenishment system performance. Other situations in which a complete systems orientation may be necessary would include multi-echelon inventory and forecast interaction as well as dependent versus independent demand forecasting. To address the problems of component interaction, this research develops, implements, validates, and proposes a usage methodology for a model of a total distribution system which contains each component identified in the literature review.

GENERAL MODEL DESIGN

Consistent with the concept of the physical distribution system and its environment, the model can be segmented logically into three modules. The demand module represents the uncontrollable aspects that face the firm. The forecast module provides the interface with which the firm buffers the uncertainty for operational planning. The operations module simulates the firm's activities as it attempts to satisfy the demand.

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The demand module replicates the uncertainty of the firm's environment. It uses detailed exogenous data to create surrogate customer orders which are used to test the distribution system.

The forecast module, which utilizes existing forecasting techniques, provides the interface between the firm's operations and its environment. The operational component of the model uses one of the forecast techniques to anticipate the demand level that may be encountered by the system. The forecast module utilizes only the limited amount of information normally available to forecast techniques. A large amount of detailed information is not feasible for use in an operational forecasting model because of the many products and locations that must be treated.

Operationally, the distribution system that forms the subject of the analysis includes communication and product movement from the production facility to the firm's customers. The network structure may be single or multi-cheloned, incorporating any combination of the following full or partial line institutions: manufacturing facilities, wholesalers, distribution centers, and retailers. The operations module, allowing for all of the above features, addresses management decisions such as location analysis, operational policy, and inventory policy.

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The model must maintain very detailed information to allow for analysis of the interactive effects. Because of the level of detail required, the model concentrates its analysis on a limited channel of customers and distribution facilities. Once the behavior and interactive effects of the reduced channel can be understood in detail, the conclusions and prescriptions must be extrapolated to the firm's total distribution system. The extrapolation process is not within the scope of this dissertation. However, the model does provide for multiple products to allow for an evaluation of their interaction within distribution operations.

Within the above guidelines, this research describes the design and utilization of an integrated model which may be used for analysis of distribution problems. Figure 2 identifies the major model subsystems along with the components of each of the modules. Although individual module performance is important, the real model benefit lies in its ability to consider and report on the interactive effects of the modules.

The next section of this chapter briefly discusses the modules--demand, forecasting, and operations--and their interaction. (Chapter IV presents detailed specifications.) A brief discussion of corresponding data requirements is also provided.

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DEMAND MODULE

The demand module, the force variable for the testing environment, develops surrogate customer orders. Through this module, the modeler creates the type of demand environment desired to facilitate observations of system performance. The module creates orders representative of actual orders for a limited number of demand points. The order characteristics may be based on either history or expectations, which allows the modeler to consider demand situations which may not have occurred previously. Utilizing a combination of detailed economic, demographic, competitive, and historical information for a demand point, the demand module provides a stream of daily orders.

Three alternatives are available for demand generation in the SPSF Testing Environment: (1) the use of existing orders from sales history, (2) the use of Monte Carlo processes or probability distributions to create individual orders, and (3) the combined use of regression and simulation analysis to develop periodic sales levels which can then be reduced to individual orders. The SPSF Testing Environment includes a procedure using each of these as alternative demand generation approaches.

The first method of demand generation, use of actual historical orders, is employed as Procedure One in the demand module. The direct use of sales history is the most realistic

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and simple method of demand replication. However, this procedure has the serious shortcomings of requiring more data than alternative methods of demand generation and a general difficulty in creating experimental test conditions.

Procedure Two employs basic statistical generating functions such as normal, log-normal, erlang, and poisson distributions to create total daily sales. Although easy to implement, this approach offers no assured approximation of market reality. Even if the probability distribution used is fit statistically to historical sales, the model parameters are static.

Once the periodic sales level is identified, the total sales level must be decomposed to daily orders for use by the operations module. The general procedure is to select orders randomly from a sample order base until daily demand is complete. Several sample order sets may exist, each containing a group of orders from individual seasonality periods. Pseudo orders can be structured to permit experimental conditions or to test events such as new product introduction.

The third technique for demand generation utilizes the correlation between past demand and other economic variables to provide an estimate for the periodic sales level. Procedures Three and Four of the demand module offer alternative correlation procedures.

In a typical test situation, it is often possible to identify several economic indices that can be correlated to sales. Such factors can be determined through basic statistical analysis of past market and company data. Typical factors which may be considered include population, net income, gross national product, and number of housing starts, as well as other selected indicators of the state of the economy depending upon the specific product in question. It is conceptually possible to simulate numerous market conditions using economic indices as independent variables. In addition to simulation of the current market condition, indices may be projected to estimate future or alternative conditions to test experimental situations.

For Procedure Three, firm sales level is projected using multiple linear regression. First, the effect of various factors upon firm sales is measured using least squares regression. Then, given estimates for selected factors, a linear regression equation is used to predict the firm sales level for a particular period. Daily sales are then determined by factoring this periodic sales level.

In Procedure Four, industry demand is generated for the market area using the economic factors as independent variables in a regression equation of the general form:

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Where:

IS = industry sales for the period;

a = the vertical axis intercept;

$X_1 \dots X_n$ = the independent variable influencing industry sales;

$b_1 \dots b_n$ = the respective weights of the independent variables.

This form of generalized equation permits the inclusion of any independent variables deemed relevant to the estimation of industry market area sales. It also allows specification of different variables for different product situations.

The regression formulation provides an estimate for industry demand which is then factored to reflect historical seasonality. Next, specific market share is determined using the approach proposed by Kotler.⁴ The Kotler approach uses a ratio of the firm's "marketing effort" to the industry "marketing effort" to arrive at specific market share.

The final result of the regression analysis for Procedures Three and Four is an estimated monthly or weekly sales level. Next, a normally distributed random variate is used to factor the periodic sales to daily sales. Given a value for daily sales, individual product orders are created using the method outlined for Procedure Two.

The extent of the demand module data depends on the procedure utilized. Under the first procedure, a complete

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file of actual historical or experimental orders is required while the remaining procedures require only a sample of orders. In addition to the sample, Procedure Two requires the input of the level and variance of daily sales. Procedures Three and Four require the values for each predictor variable as well as a factor to decompose periodic sales level to daily sales level. The precise form and type of data needed depends on the industry being modeled. Through the use of one of the procedures, the module can provide individual orders which approximate any type of environment. Fulfillment of these orders and the resulting profit potential provides motivation for the existence of the forecast and operations modules of the actual firm.

FORECAST MODULE

The forecast module provides the firm's interface between the demand environment and the operationalization of its policies and actions. For the distribution system to obtain perfect results, the firm must forecast correctly and operations must allocate the resources to meet that forecast. The source of the prediction may be a knowledgeable individual or it may be a sophisticated forecasting technique. For the general case, where multiple facilities and products are involved, the sheer number volume requires utilization of a numerical technique. However, a vast number of quantitative techniques is available ranging from simple

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averaging to the more complex Box-Jenkins methods. The forecast module includes a range of alternative techniques to allow for evaluation of existing capabilities as well as alternatives. The module design also allows for integration of additional techniques as desired. Each technique uses a limited history base to generate a forecast for individual distribution facilities and products. As the literature review indicated, most forecasting techniques are tested for their ability to respond to fluctuations in demand, but little is known about the interaction of the technique and other types of uncertainty in the integrated system. Only through development and research with an integrated model can the interactions be addressed adequately. In conjunction with the SPSF basic research undertaken at Michigan State University, Sims identified four forecasting techniques as representative of those used by industry for short-range multiple product situations.⁵

Brown's Simple Exponential model⁶ is the most basic forecasting technique provided in the module. This technique, which is not adaptive, allows for a level component only; it does not consider trend or seasonality.⁷ Adaptive capability refers to the technique's ability to consider the past error level when projecting future forecasts. Trigg and Leach's Adaptive Exponential Smoothing model⁸ provides the next level of technique complexity. Although the algorithm

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is adaptive, it still considers only the level component and relegates trend and seasonality to the status of noise factors. Winters' Exponential Smoothing with Trend and Seasonals⁹ provides the third level of complexity. Winters' model explicitly considers the trend and seasonal components but it does not have adaptive capabilities. The most complex method offered in the module is the Roberts and Reed Self-Adaptive Forecasting Technique.¹⁰ The level, seasonal, and trend components of the forecast are all considered in an adaptive manner.

The data required for the forecast module depend on the technique to be utilized. For the simple techniques, only the level component history is required, while the level, seasonal, and trend component histories are required for the more complex techniques. Histories are required for each facility and product for which forecasts are to be generated. Both the demand and forecast modules require historical data to accomplish their stated objectives. The forecast module is limited in the amount and type of information it can use since the data storage and maintenance requirements must be minimal. On the other hand, for the testing environment, the demand module can use a great deal of information since it is required for only a limited number of demand points. The demand module provides the potential for the distribution system while the forecast

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module provides the firm's best estimate of the potential. Management's operational policies must satisfy these expectations.

OPERATIONS MODULE

The operations module is a dynamic simulator that integrates input from the forecasting module and the demand module. The simulator models individual activities required for the physical distribution process. Typical activities might include order processing, order shipping, inventory management, production, and transportation. Each event occurs independently, with the dynamic characteristic of actual operations achieved through activity interaction. For example, the output of the inventory management event is the input to the inventory replenishment event, which in turn creates a requirement for the shipping event.

In the linkage of events, the introduction of performance time uncertainty through probabilistic time variables is critical for the model to capture the dynamic realism of distribution operations. Typical components requiring probability variables are order processing, communication, and transit time.

In addition to incorporating modular interaction and temporal uncertainty, the operations module design allows for multiple plants, distribution facilities, and products,

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as well as alternative operating policies. The operations module may be used to simulate up to fifteen locations and can handle up to ten individual products or groupings of products.¹¹ The locations may be arranged in any number of echelons, from manufacturing plants to final customers.¹² Customer locations can represent specific accounts or areas of aggregate demand.¹³ These capabilities permit the operations module to replicate the typical physical distribution configuration used to replenish inventory to a specific geographic area.

Figures 3 and 4 illustrate the structural flexibility provided by the operations module. The simplified distribution structure in Figure 3 illustrates inventory stocking at three locations with product shipment from a manufacturing plant to a distribution center and ultimately to the customer via a retailer. Although such a simplified distribution structure would be found rarely in actual market situations, it provides a useful basis for analysis of specified policies. Typical policies capable of alternative testing are illustrated on the right side of Figure 3. Figure 4 provides an example of a more complex distribution structure consisting of 12 facilities in four echelons. This example also illustrates multiple source destinations and direct or bypass shipment capabilities from the manufacturer to the distribution center location. The letters within the symbols denote

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which of the five products (A, B, C, D, and E) are stocked at a facility.

It is important to note that these examples illustrate only potential system configurations which can be structured within the operations module. Figures 3 and 4 do not include the total simulator or SPSF Testing Environment in that the forecast, demand, and analysis modules are not illustrated.

The operations module requires primarily two types of input. The first type defines the network configuration in terms of facilities and linkages between facilities. As a part of this data type, the stochastic nature of the link performance must be quantified. The second data type consists of the policy alternatives for use in system operation. For each facility and product, the input must include inventory and stocking policies as well as the corresponding level parameters.

Once the operations system configuration has been defined and the demand and forecasting modules have accomplished their objective, the operations module processes the firm's demand through the major activities of an integrated physical distribution system including inventory control, order processing, materials handling, and transportation. Only through the interaction of all three modules can the actual system sales be determined.

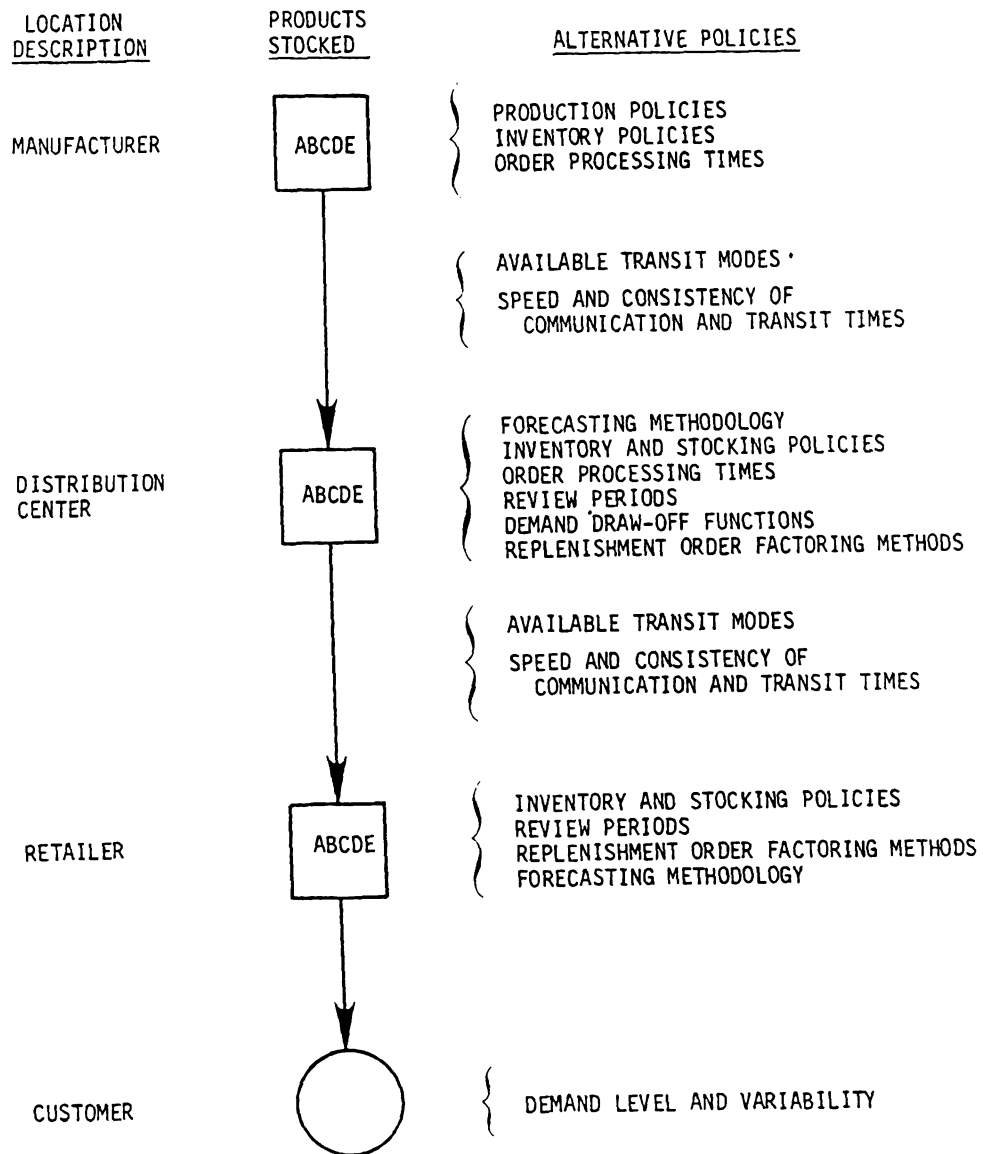


Fig. 3. Example of Simplified Distribution Structure

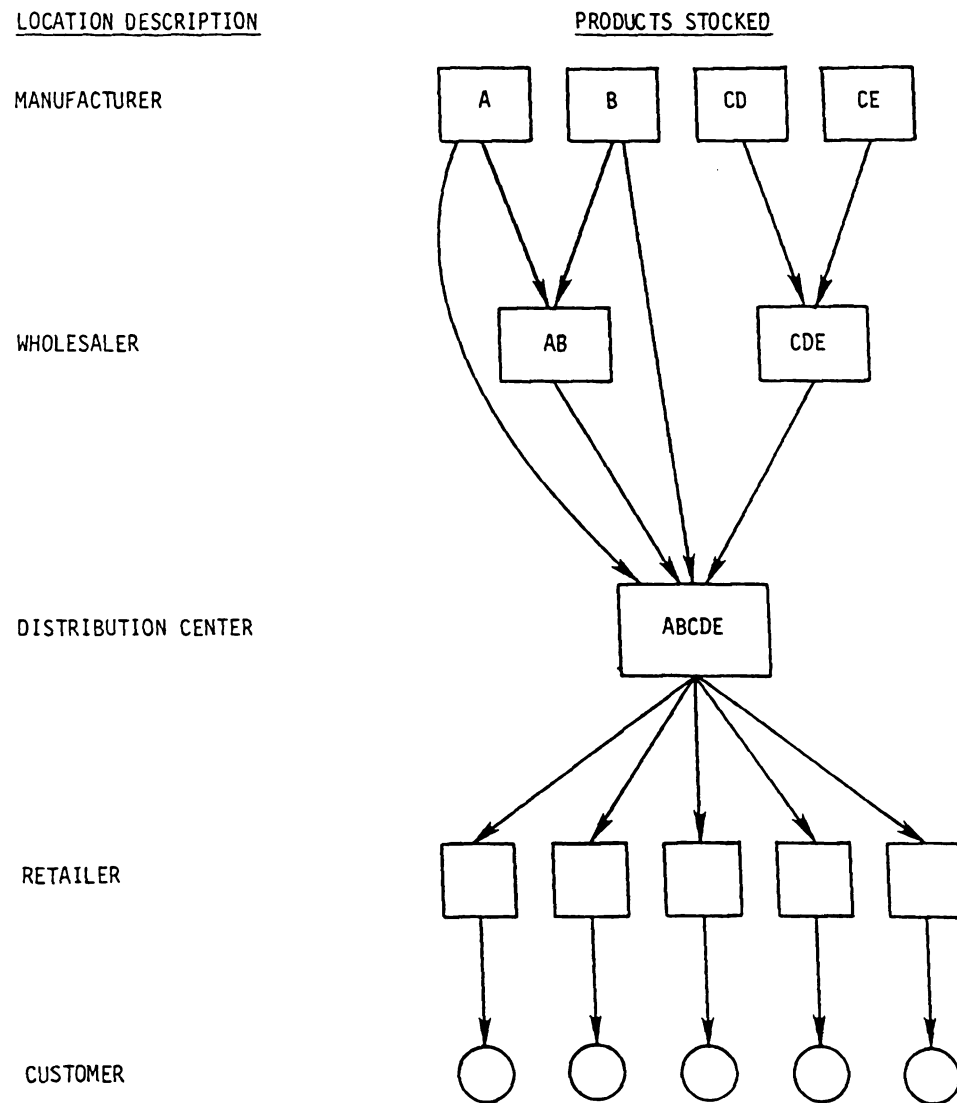


Fig. 4. Example of Complex Distribution Structure

The final integration of the actions of all three subsystems is reported through the routines of the SPSF analysis module. The routines provide the management reports that allow for isolating the correct source of system discrepancy.

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CHAPTER III--FOOTNOTES

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²Donald Gross and Jack Ray, "A General Purpose Forecast Simulator," Management Science (April 1965):119-35.

³Steven C. Wheelwright and Spyros Makridakis, "An Examination of the Use of Adaptive Filtering in Forecasting," Operational Research Quarterly (March 1973):55-65.

⁴Philip Kotler, Marketing Decision Making: A Model Building Approach (New York: Holt, Rinehart, and Winston, 1971), pp. 92-9.

⁵J. R. Sims, "Simulated Product Sales Forecasting: Analysis of Forecasting and Operating Discrepancies in the Physical Distribution System" (Ph.D. dissertation, Michigan State University, 1978).

⁶R. G. Brown and R. F. Meyer, "Fundamental Theorem of Exponential Smoothing," Operations Research (September-October 1961):673-85.

⁷For a complete definition and discussion of the level, trend, and seasonality components of a forecast, see Donald J. Bowersox et al., "Short Range Product Sales Forecasting," National Council of Physical Distribution Management Proceedings, 1976, pp. 193-215.

⁸D. W. Trigg and A. G. Leach, "Exponential Smoothing With an Adaptive Response Rate," Operations Research Quarterly (March 1967):53-9.

⁹P. R. Winters, "Forecasting Sales by Exponentially Weighted Moving Averages," Management Science (April 1960): 324-42.

¹⁰S. D. Roberts and R. Reed, "The Development of a Self-Adaptive Forecasting Technique," AIIE Transactions (December 1969):314-22.

¹¹These limits, fifteen locations and ten individual products or groupings of products, correspond to the current program limits available to the SPSF research at Michigan State University. These limits were set to minimize core and time requirements for current research; however, minimal effort is required to alter those limits.

¹²The number of echelons in a specified structure is limited only by the maximum number of locations as input by the user.

¹³Up to ten individual accounts and/or areas of aggregate demand may be employed in any network.

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CHAPTER IV

SPECIFICATION AND IMPLEMENTATION

Chapter IV discusses the procedure used and the problems encountered in model specification and implementation. In particular the research question is:

What functions are necessary for modeling an integrated physical distribution system and what process is appropriate for implementing that model?

Four sub-questions provide the basis for treatment of the broad question. Analysis of the individual questions and performance of the appropriate actions lead to model specification and implementation. The specific questions for this phase are:

1. Which of the three model building procedures is appropriate for model implementation to obtain flexibility in both use and modification?
2. What is an appropriate means of interfacing the individual activities within the model? What are the appropriate linkage mechanisms between the subsystems?
3. Can the model be implemented so that it can be installed on other computer systems with ease? If it can, what are the general requirements of potential systems? Which programming language(s) is most suitable for implementing the model?
4. What physical distribution functions are necessary for a model designed to perform distribution systems analysis? What are the individual function specifications in terms of the variables and transformations required?

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For each question, the discussion includes a detailed problem definition, literature considerations, and problem resolutions or results.

MODEL BUILDING PROCEDURE

The first question that must be treated during conceptualization concerns model formulation. As discussed in the literature review, Emshoff and Sisson identify three alternatives for the analysis of systems: the flow approach, the functional approach, and the state-change approach. Selection of a specific approach is important since it dictates the form of the analysis. The following sections present a discussion of the alternatives and select the most appropriate one for this analysis.

PROCEDURE DISCUSSION

To establish a basis on which to discuss the alternatives, the following paragraphs review the details of each approach.

Flow Approach

According to Emshoff and Sisson: "The most common method of grasping a situation is to follow the flow of the major items being processed."¹ Under this approach, the flow of individual entities, such as products or information, is followed to isolate the situations where the entity is

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changed or moved. The processes can then be analyzed independently as subsystems. The flow approach places emphasis on the entity itself as it is processed through the system; therefore, all information is based on the performance of the system as recorded for an entity. Queuing problems adapt well to the flow approach.

Functional Approach

In cases where there may not be an obvious flowing element, Emshoff and Sisson suggest the functional approach.² This approach is more appropriate in situations where identifying a sequence of specific functions is easier than tracing the flow of an individual entity. Once the functions have been isolated, they can be studied in detail to determine which facilities and information are required, which transformations are made, and which outputs result. The functional approach is well suited for production control problems.

State-Change Approach

The state-change approach studies changes in variable values between two points in time. Once the variables are identified, the second task is to "define the relationships that describe how the state [of each variable] changes as time moves from one instant to the next."³ When using the state-change approach, two steps are important when analyzing the relationships. The first step requires the definition

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of a procedure to determine whether a variable should change. The changes may be difficult to isolate since they may be dependent on a series of prior or conditional states. The second step requires the definition of an algorithm that actually accomplishes the changes in the variables. According to Emshoff and Sisson: "The state-change approach is particularly suited to problems destined for simulation analysis, but it can be used in any situation."⁴

PROCEDURE SELECTION

As stated earlier, the requirement of the conceptual problem is to define the approach(es) to be used. A single approach must be selected for analysis of a particular system or subsystem, although individual subsystems may use alternate methods. Only a single approach may be used for analysis of a particular component since it is not possible to place equal emphasis on the flow, functional, and state-change aspects at the same time. For example, it would be difficult to conceptualize a manufacturing process by analyzing the product flow and the functions concurrently. The method of analysis provides a framework for organization. It is not possible to organize around two different concepts at the same level.

The work of Bowersox et al. offers a precedent in the selection of an analysis method. An activity (functional)

approach was used for LREPS development.⁵ In addition, management texts describing the physical distribution process use a functional approach.^{6,7,8} The texts generally decompose the distribution process into transportation, inventory, and storage and handling functions. In addition to these precedents, four other factors suggest the use of the functional approach.

First, the flow approach could logically be used to analyze product flow through the system. However, at some points in the system, the importance of product flow is superseded by the importance of order integrity since many system performance characteristics are measured using orders. The use of either entity would require a transformation from one unit of measure to another, although no easy conversion exists. In addition, tracing the flow of individual products would require more detail than necessary for the analysis. The flow of an individual item is not important when computing system performance.

Second, for either the flow or state-change approaches, the number of variables for analysis would be very large due to the large number of products. Analysis of the flow or state-changes of individual products would be difficult and could lead to erroneous results when attempting to explain system behavior, since the sum of the individual item's performance may not reflect aggregate performance.

The third factor, and one of the most significant, is that decision makers are accustomed to treating the physical distribution system within a functional framework. It would be difficult for them to adapt to a flow or state-change approach from an analytical and applications point of view. Since the decision makers are the ultimate users, they must have confidence in model performance. Adapting to a new organizational concept such as flow or state-change would be difficult for them.

The final factor leading to selection of the functional alternative is the degree of flexibility offered. The functional approach allows for definition of an isolated procedure which performs transformations on specific input to generate output. The procedures do not interact except through common input or output parameters. Thus, individual functions can be inserted or modified easily without a substantial amount of change in other functions.

The previous four factors, as well as limited precedents, suggest that a functional approach is appropriate for the analysis of a physical distribution system. The overall system should be analyzed functionally, followed by an analysis of the individual subsystems. Such an analysis defines the inputs, transformations, and outputs of the individual subsystems.

Once the individual functions and their operations have been defined, the next phase of the conceptualization process must define the vehicle and the means of modeling the individual functions. The following section addresses that question.

FUNCTIONAL INTERFACING

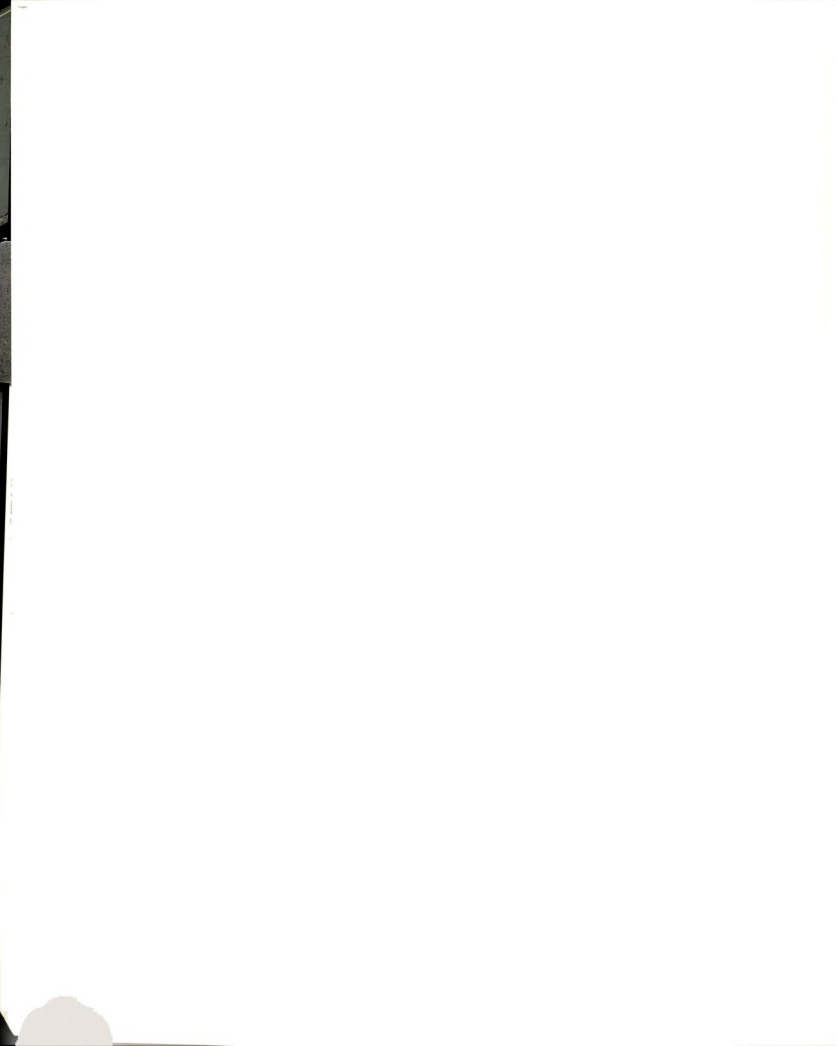
As a first step in establishing the functional interfaces of the model, the model type and general characteristics must be defined. In particular, the model characteristics, as discussed in the literature review, must be defined. The critical considerations include the following: (1) mathematical-simulation, (2) static-dynamic, (3) aggregate-detailed, (4) continuous-discrete, (5) deterministic-stochastic, and (6) model structure. The following sections discuss the option or combination of options appropriate for an integrated distribution model.

MATHEMATICAL-SIMULATION

The first question addresses the basic model type appropriate for the analysis. While the mathematical approach offers the potential for an "optimal" solution, it does not have the flexibility with regard to assumptions that is offered by the simulation approach. The assumptions regarding the nature of the transformations are rigid for mathematical models. In addition, with a mathematical model, even

small changes in model functions or constraints could mean a major reformulation of the model. Another major factor suggesting the use of simulation is the degree of uncertainty inherent in distribution operations. Also, the number of variables required for such a formulation would quickly become unmanageable, even with today's large mathematical packages, due to the number of facilities and products involved as well as the number of different states in which an entity may exist. In addition, on the basis of the literature review, Table 4 showed that existing physical distribution models which address the inventory or operations problem have been simulators.

Considering both practical and historical factors, a distribution model which addresses all of the previously described components must be a simulation. However, future research with the model may lead to integration of mathematical search procedures, such as steepest descent,⁹ for the selection of "optimal" policies or alternatives. The application of such a technique, while theoretically appealing, would be limited in its capability and would be successful only with the insight provided by a great deal of model experience, since it may require approximations of complex functional relationships.



STATIC-DYNAMIC

The question addressing the feedback characteristics of the model must be addressed next. According to the definition found in the literature review, dynamic models are those which explicitly consider the temporal variable. An adequate analysis of the inventory and operations components requires consideration of the time element since both place and time must come together to meet customer service. Consideration of time in this case implies that some type of feedback exists. Modeling inventory or operations without feedback would be equivalent to saying that today's results do not affect tomorrow's potential. Such a structure would not replicate the actual situation since feedback does exist in the environment. As with the previous attribute, the literature demonstrates that existing models considering either the inventory or operations component are dynamic.

Both the limited historical precedents and the practical considerations suggest that a model which considers the five components identified earlier must be dynamic. Only through an analysis integrating the time element can overall system performance be analyzed adequately.

AGGREGATE-DETAILED

The nature of this analysis is very detailed. The analytical subjects include individual facilities, products,



and orders. The only way to measure system performance adequately as dictated by channel design and policy considerations is to observe the processing of the individual entities within the system. Since distribution problem situations are firm oriented, a micro analysis is appropriate. Therefore, the model designed to conduct research within the realm of the firm's distribution system must be detailed.

CONTINUOUS-DISCRETE

As suggested by Emshoff and Sisson, a detailed level of analysis such as for individual transactions and shipments ought to be discrete in character. The information base and the nature of the decision makers would not support any alternative other than a discrete simulation using daily time increments. In many cases, both customer and replenishment orders are processed only once daily. Firms rarely maintain performance time data in anything less than daily increments if they are maintained at all. On the other hand, the use of a time increment any longer than one day would decrease model precision since many activities can occur over one day's time.

All existing distribution models use the discrete timing mechanism. When dynamic models are considered, all models except one use a daily time increment. Markland uses monthly increments, but this writer feels that would be too long for this level of analysis.¹⁰



Considering these practical and historical reasons, a simulation model describing the performance of an integrated physical distribution system ought to use a discrete time mechanism with daily increments. Decision makers can easily relate to such a system since it is very similar to the one they face every day. However, definition of such a mechanism implies that all activities within the model must occur an integral number of days apart. Activities are 0, 1, 2, or 3 days apart, not 1.5 days.

DETERMINISTIC-STOCHASTIC

The final consideration concerning model characteristics addresses the degree of uncertainty that the model ought to include. Within the components defined as part of the distribution function, many activities exist which historically have demonstrated a great deal of uncertainty, such as demand and cycle time elements. As identified by Speh¹¹ and Wagenheim¹², the inconsistent system components are the source of more system discrepancies than the slower components. Since system variance is a major source of error, and one of the major research objectives of the overall SPSF research is to identify sources of intercomponent error, the model that analyzes the situation must be stochastic. In particular, the processes that model the demand and cycle time entities must be probabilistic since a great deal of uncertainty may be associated with these elements.



STRUCTURE

Now that the basic characteristics of the model have been identified, a basic structure must be developed that is consistent with the functional approach and the model attributes. Also included within the structure is a mechanism for time-phasing the individual functions.

The logical extension of the functional approach in terms of a structure is an event-oriented model. Each function is transformed to an individual event which performs the processes normally assigned to the particular function. The decision makers can relate well to this approach since it corresponds directly with the functional orientation they are accustomed to. The event orientation also provides a great deal of flexibility since additional events can be integrated without affecting the logic of other events, provided that the events are programmed to be autonomous. The other option for structure could be an activity-oriented mechanism where one does not schedule actual events but denotes the conditions under which an activity may occur. The use of an event orientation is more efficient when its use is possible, since it schedules an event only when the model knows that proper conditions exist for its occurrence.¹³

Once the event orientation is designated, time-phasing simply becomes a scheduling problem. The individual



events must be scheduled to occur in sequence and to process the correct input. Existing simulation languages provide the facilities for event scheduling. In particular, Shannon identifies SIMSCRIPT, GASP, SIMCOM, and SIMPAC as offering executive programs to sequence the scheduled events automatically.¹⁴

One additional problem exists that is not as easily solved, however. Even though the scheduling can be accomplished relatively easily, the problem of passing parameters between individual events still exists. Events may be on the schedule a number of times with different inputs. Another problem area is that some events require very little input while others require a substantial amount. For example, a report event may require no specific input for its processing; however, the replenishment order event requires an entire order as input. In fact, many replenishment orders may be in process, even some for the same source and destination. Maintaining this information is not a problem since it could simply be stored in an array as is done in the GASP simulation language. Such an approach would not be very efficient, however, since the array would have to accommodate the longest entry and would leave much unused space for the short entries. Therefore, the use of linked list processing allows the basic entries to be much shorter while providing the potential for indefinitely long

entries. The linked list structure would contain the parameters for all events. Variable length parameter blocks are important for distribution models since the existence of multi-line orders causes parameter needs to fluctuate considerably. None of the reviewed languages offered this flexibility. Such a consideration is important in model development since it makes the model more efficient in terms of core while providing the flexibility to change parameter storage easily if additional parameters are required.

FUNCTIONAL-INTERFACING CONCLUSION

The structure and the characteristics of a model suitable for integrated distribution planning have now been defined. They include the following attributes:

1. Simulation
2. Dynamic
3. Detailed
4. Discrete
5. Stochastic
6. Event-oriented

The development of these criteria has been general enough to apply to the development of any model whose objective centers on physical distribution systems. Any model that addresses the integrated distribution process and, in particular, the SPSF Testing Environment, must have these characteristics.



MODEL IMPLEMENTATION

The third question addresses the technical requirements for model implementation. The main points to be considered include the language to be used and the computer resources required. These points are interdependent since there is a certain amount of hardware-software interaction. As a first step in the analysis, the desirable characteristics of such a computer model are defined.

A significant model consideration is its ability to be transferred readily to alternate computer systems. In order to promote model usage, it was desirable that the model be implemented in a language which could be easily transferred across systems. The portability issue also implies that only universal hardware and software functions be used. For hardware, this would include input and output from the following devices only: card, disk, tape, and printer. Exempted would be devices such as extended core storage or virtual memory, which are not available with all systems. For software, portability considerations drastically limit the use of such techniques as word-packing and assembly language coding. Considering the above, the model ought to be implemented with a standard language, whether general or simulation, on a computer with a moderate amount of memory. For our purposes, moderate memory requirements are defined as 512K decimal bytes of memory. If the model were any

larger, it would be too cumbersome for most non-virtual machines. In particular, the machine on which the model was developed at Michigan State University, a CDC 6500, is not a virtual machine.

Now that the basic hardware requirements have been defined, the language must be identified. In addition to the general requirements that the language be adaptable across hardware, it must also have the capability to manage the parameter array efficiently as described earlier. An inefficient process could waste memory resources.

With the above considerations and the four possible languages suggested by Shannon in mind, the final step in the analysis requires selection of a language. The SIMCOM and SIMPAC languages are not acceptable since they are compatible only with the IBM 709 and IBM 7090 computers, respectively.¹⁵ Of the remaining two alternatives, GASP and SIMSCRIPT, both are very general and have a high degree of availability. The two advantages offered by GASP for this research include the researcher's past experience and the language's capability to be used on any machine with a FORTRAN compiler. The FORTRAN compatibility allows for easy modifications to the simulator control routines. In particular, the linked list structure can be integrated with the remainder of the FORTRAN-based routines. Use of the FORTRAN-based GASP also implies that the model can be implemented on any machine with a FORTRAN compiler and sufficient memory.

In summary, the two features that dictate the use of the GASP simulation language include portability and flexibility for change. With such a structure, the model can be adapted to changing situations and hardware environments.

FUNCTIONS AND VARIABLES

The last question asks what individual physical distribution functions ought to be modeled and what variables and processes should be used to model them. To answer this, let us investigate the functions that would be necessary to model each of the five components of the logistical system identified earlier. As a review, these components include: (1) Demand Generation, (2) Forecasting, (3) Location Analysis, (4) Inventory Management, and (5) Operations Management.

COMPONENT ANALYSIS

The Demand Generation component functions should logically include a methodology for generating individual daily orders and then processing them. The demand processing function corresponds to the customer service activity identified by the National Council of Physical Distribution Management (NCPDM). As a part of this operation, the model must maintain records of demand and sales since this component provides the demand potential measure of the testing environment.

The second framework component directly identified by NCPDM is the Demand Forecasting activity. The objective of this activity is to predict future demand for use in anticipating inventory needs. Thus, the predicted demand must be used as an input to establish the appropriate inventory levels.

The Location Analysis component must include the capability to model and operate any network of facilities along with the corresponding inter-relationships. The function must consider the stochastic nature of replenishment order transmission and shipment. Another important task for the Location Analysis component is validation of network consistency in terms of product stocking and sourcing. The set-up and consistency checks for the network comprise a one-time-only process since the channel design would not be changed continuously throughout a model run.

The Inventory Management component has the task of inventory control as identified by NCPDM. According to Bowersox: "Inventory control is a mechanical procedure for implementing an inventory policy."¹⁶ Therefore, the objective of the Inventory Management component is to monitor inventory levels and initiate appropriate actions when necessary.

The last component identified includes the system aspects which model the firm's operations. Returning to

the definition offered by NCPDM, the functions involved in the firm's operations would include distribution communications, material handling, order processing, packaging, return goods handling, salvage and scrap disposal, traffic and transportation, and warehousing and storage. The functions of packaging, return goods handling, and salvage and scrap disposal are not considered in this model since the procedures involved are often specific to the application. However, even though these functions are not considered further in the general design, model flexibility ought to allow for consideration of specific applications. Keeping the remaining functions in mind, let us follow the processes that the distribution system must perform to provide delivery for goods from a facility. It is only through this shipment that physical distribution meets its objective of satisfying customer demand. Before shipping, the firm must either order the goods from another facility or produce them. Thus, a replenishment order must be generated and transmitted to an appropriate source. The time delay incurred during the transmission may be stochastic. Once the replenishment order is received at the source, the order processing operation begins. Again, a stochastic delay may be involved. When the order processing activity is completed, the order is shipped and then ultimately arrives back at its ordering destination. The four-step process of (1) order, (2) process,

(3) ship, and (4) receive recurs again and again throughout the system. The functions identified by NCPDM are contained within these four activities. Distribution communications is order transmittal. Warehousing, storage, and material handling are included within the shipping and receipt activities. Traffic and transportation are included within the shipping activity. Thus, all of the operational elements included by NCPDM within their definition of distribution are addressed by the four activities discussed above.

Through an analysis of the framework identified in Chapter II and the definition of distribution offered by NCPDM, nine activities have been identified as necessary for modeling a physical distribution system. Table 5 provides a list of the activities. A tenth activity is included since it directly affects distribution management. The Production activity provides a mechanism for introducing goods into the system while maintaining a material balance. As a matter of convenience, the Replenishment Order Initiation and Inventory Management activities are combined since one of the functions of inventory management is to initiate replenishment orders to maintain inventories at their policy-dictated levels.

Two additional adjustments are proposed to the basic activities identified earlier. The first activity is necessary since the model replicates the environment of only a

limited geographic area. However, in most cases, the modeled facilities are designed and operated to serve customers from a larger area. To allow the facilities to operate as

TABLE 5
REQUIRED ACTIVITIES FOR MODELING
DISTRIBUTION SYSTEMS

1. Demand Generation
2. Customer Order Processing
3. Network Configuration
4. Replenishment Order Initiation
5. Replenishment Order Processing
6. Replenishment Order Shipping
7. Replenishment Order Receipt
8. Inventory Management
9. Demand Forecasting
10. Production

though they were faced with the higher demand level while still maintaining primary emphasis on the limited geographic area, a Demand Bleed-Off activity is proposed to create an outlet for this "excess" stock. The second adjustment is proposed for the order processing activities for both customer and replenishment orders. As a function of order processing, it is sometimes necessary to place orders on

back-order status. When stock becomes available, the back orders are processed and shipped. Even though the order is processed similar to a regular order, the fact that it must be retrieved from the back-order queue changes the operation slightly. For convenience, therefore, this specific segment of the ordering activity is treated as an independent activity.

From an implementation point of view, input and output activities are also necessary for utilizing the model. These activities, subsequently called Data Read and Report, allow for introducing control data and reporting all model output. With the inclusion of these four activities and the consolidation of two others, Table 6 lists the activities required for implementing a total distribution planning model. The listing has been modified to reflect the order in which the activities are most likely to occur, although it should not be necessary to require the model to operate in any specific sequence.



TABLE 6

SPSF EVENTS AND FUNCTION

Event	Function
Data Read	Accepts parameters and variables, market and warehouse definitions.
Network Configuration	Configures the distribution system by integrating nodes, links, and the geographic market area as managerially specified.
Demand Forecasting	Uses one of the pre-defined forecasting techniques to forecast product sales for the market area. This forecast can either be built up through the system back to the manufacturing facility, or each echelon can be forecasted independently. The forecasts will be offset by the lead times when necessary.
Demand Generation	Generates pseudo customer orders for use in approximating the uncertainty of the demand environment.
Customer Order Processing	Processes the customer demand for each simulation period. The demand is provided via a call to the demand module.
Demand Bleed-Off	Due to the fact that all of the locations receiving shipments from a warehouse or manufacturing location may not be included in a desired configuration, this event automatically reduces the inventory available to simulated locations according to the percentage of the total inventory at the stocking location that the simulated locations receive in actuality.
Inventory Management	Accumulates the daily state measurements so that averages may be reported. In addition, this event initiates replenishment orders when the inventory level drops below the designated reorder point.

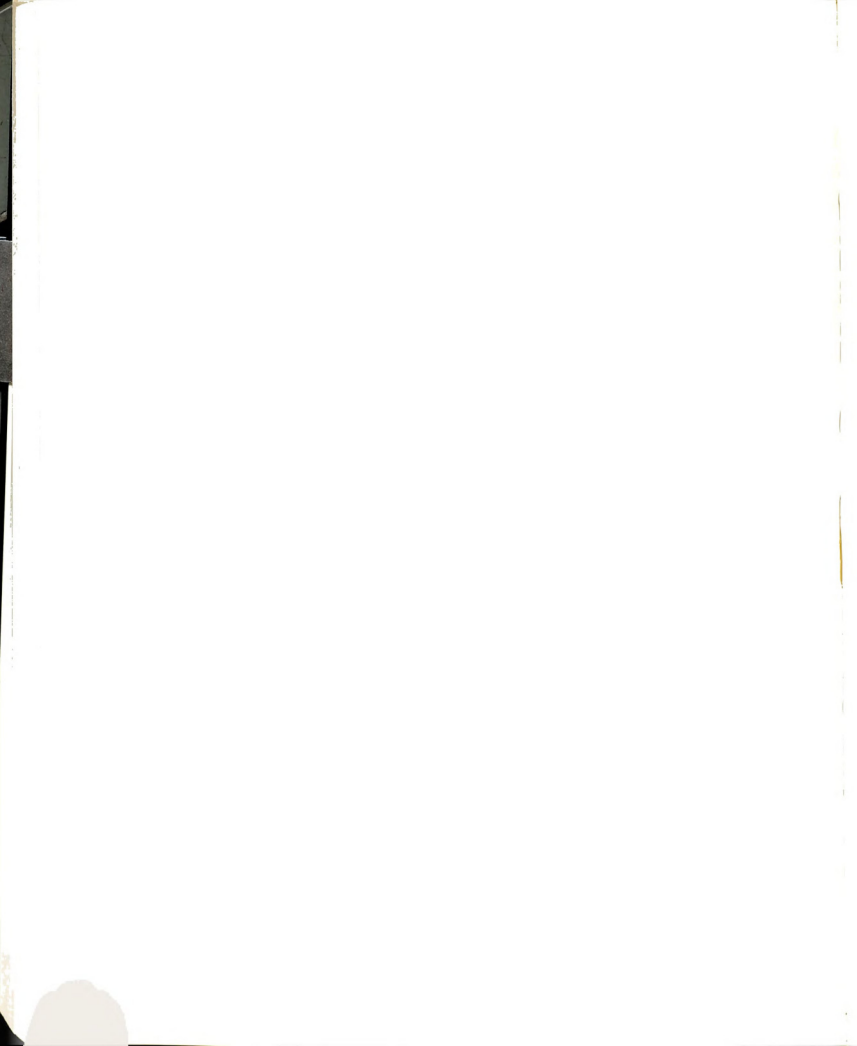


TABLE 6 (Cont'd.)

Event	Function
Production	Simulates the production function by incrementing the product inventory at the manufacturing facilities when scheduled or necessary, with or without uncertainty.
Replenishment Order Processing	Initiates the order processing phase for replenishment orders at the source location.
Replenishment Order Picking	Completes the processing of the replenishment order and initiates the shipment of the order.
Shipment Arrival	Simulates the arrival of the replenishment order through adding the quantities into inventory-on-hand.
Back-Order Checking	Reviews the back-order queue after the arrival of additional inventory to determine if any of the back-orders can now be filled.
Report File Generation	Reports the current values of all status and flow variables to a file that is suitable for input to the cost or report modules.

The flow of the operations module is controlled by the GASP event sequences. All activities are initiated through this control mechanism and ultimately return to it. Figure 5 illustrates an aggregate flow chart of the events that simulate the firm's operations.

The following sections briefly describe the model logic used. The overall scheduling logic is discussed first.

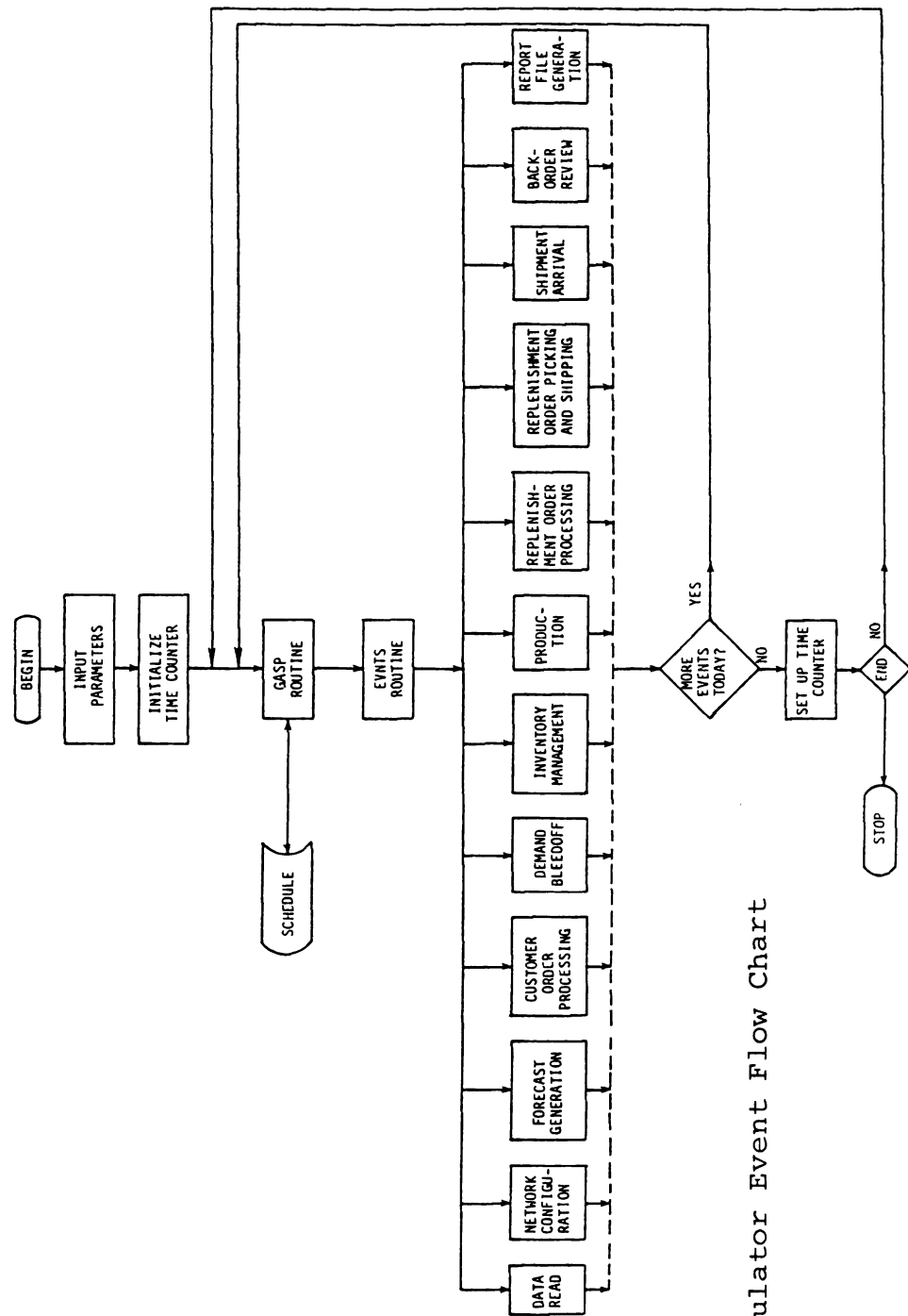


Fig. 5. Simulator Event Flow Chart

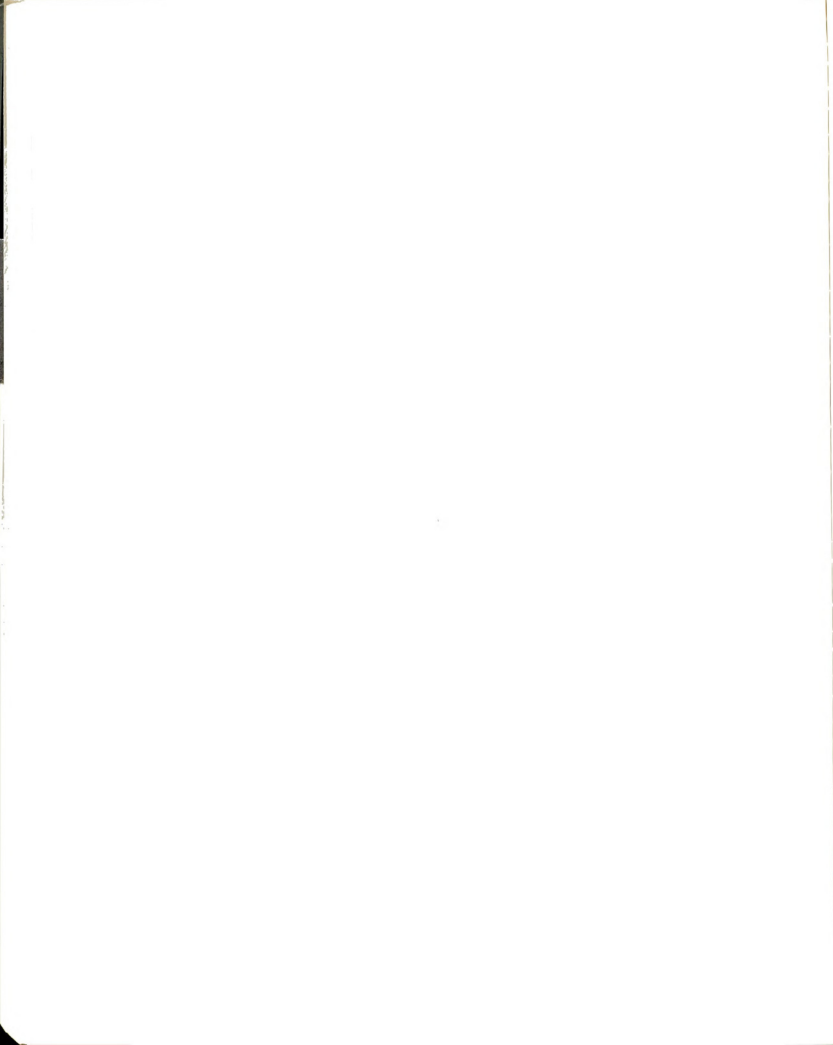
The second section addresses the logic of each individual activity.

SIMULATOR LOGIC

The simulator initially interprets input variables which provide parameters and system definitions for the test environment. This includes specifications concerning the forecast and demand modules since the operations module provides the integrating and control mechanism for the overall simulator. When the parameters have been interpreted, the TIME variable is initialized and the simulation begins. During each time period, the EVENTS routine interrogates the schedule to determine whether or not an event is to be performed and at what time during a period.

To illustrate the scheduling process, two events are compared. The ORDER event is scheduled for each period since it is likely that customer orders will be encountered during each period. On the other hand, the REPORT event is usually scheduled to occur at the end of a series of periods such as a week or a month.

When all of the events scheduled for a particular period are completed, the simulation period counter is incremented by one. The value of this counter "clock" is then checked against the predetermined ending period number for the run. If more time remains to be simulated, the model returns to the EVENTS routine and "begins a new day."



ACTIVITY LOGIC

For each activity identified above, a three-component analysis is provided. The first part addresses the broad activity purpose in terms of distribution management. The second part develops the logic used to model the activity, including inputs, transformations, and outputs. The final part illustrates the conceptual activity flow.

Data Read

The Data Read activity interprets the simulator parameter input. To allow for changing model parameters at any time during execution, the activity may be scheduled at any time.

The Data Read activity is independent of all other activities within the model. It neither schedules other activities nor is it scheduled by others. Whenever the activity is performed, it begins by reading and interpreting the next logical set of cards.

The only input to the Data Read activity consists of the data sets themselves which must be arranged in contiguous groups. The Data Read activity performs three functions after it has read each card from the model's standard input file. The first function determines whether or not the end of a data set was encountered. The second procedure checks the validity of the card format. Errors

encountered through this check might include an invalid card type or an improper format. When an error is found, the card information is ignored and the card is printed out with an appropriate message. The final procedure step passes the routine control to the section of the routine that processes the specific card type. At this point, additional checking is performed to test whether the variables are within specified limits. After the information is loaded into the correct variables, the routine flow returns to the read procedure to obtain another card. Figure 6 illustrates a simplified flow diagram of the procedure.

The Data Read activity, although basic to any computer model, has been expanded to provide more flexibility and ease of data entry than would be necessary for a basic model. The cards are order independent and parameters may be changed at any time during the run. This capability aids the decision maker in model utilization since more emphasis can be placed on the modeling process rather than on the technical problems of model use.

Network Configuration

The Network Configuration event performs the setup and checking of the system being simulated. The general Network Configuration framework provided by the model

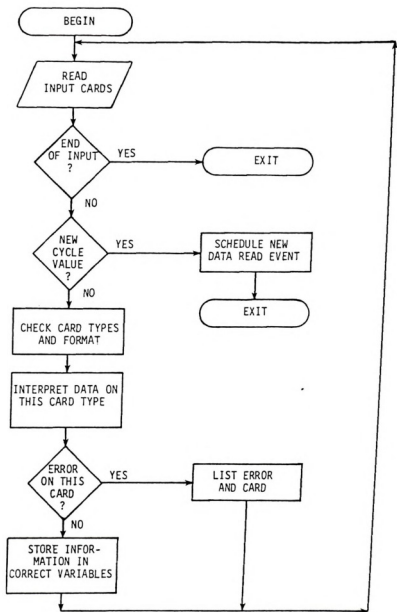
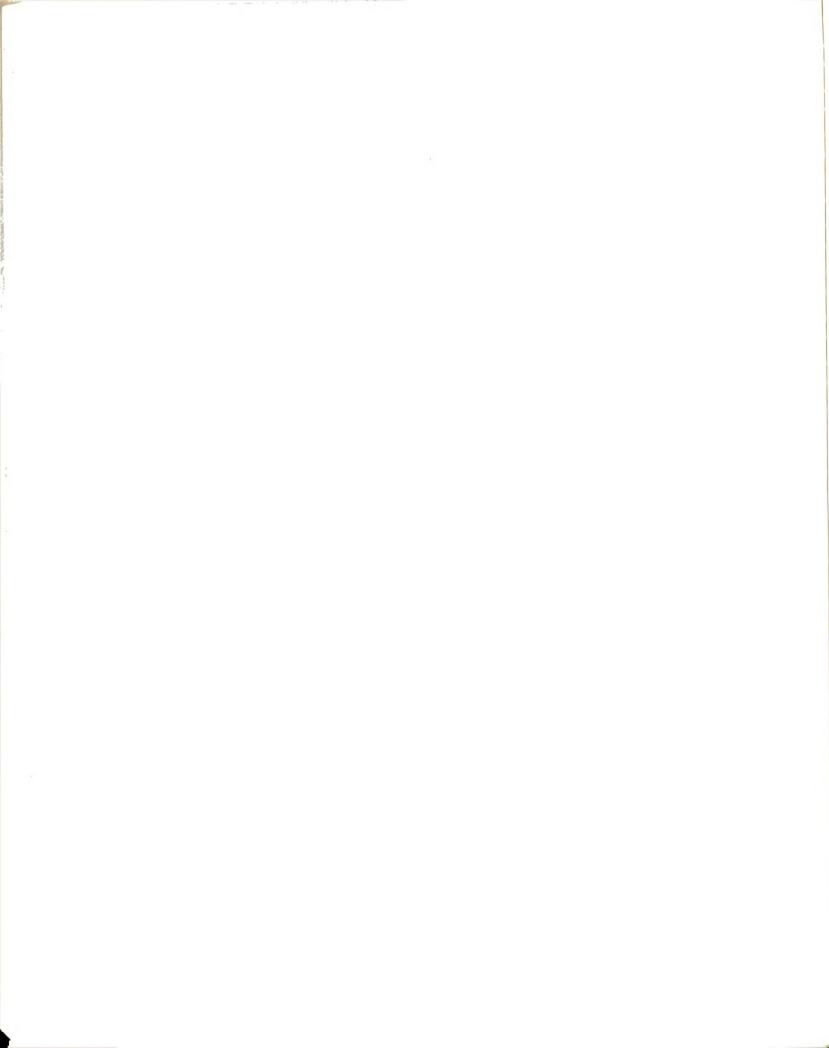


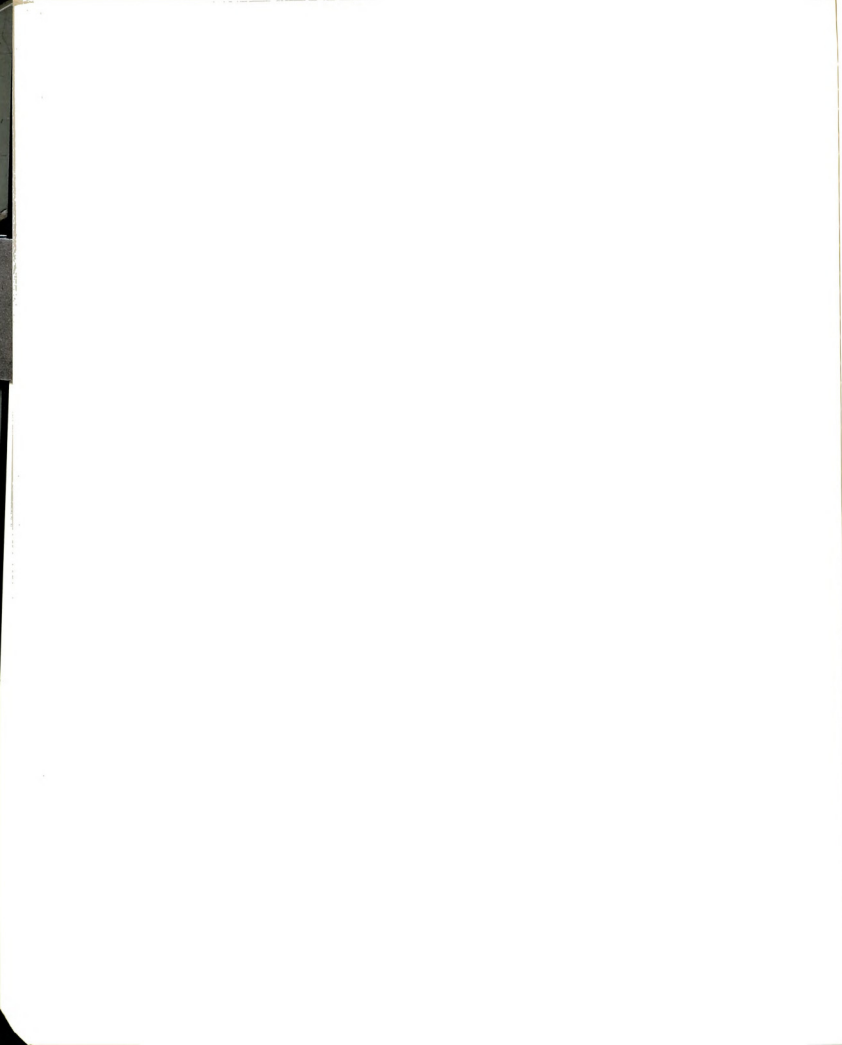
Fig. 6. Data Read Event Flow Diagram



consists of a combination of nodes (which represent facilities) and links (which represent channels of information and physical flow). Nodal points can represent any facility that maintains inventory within the distribution system, including manufacturing locations, distribution centers, warehouses, retailers, or vendors. The current configuration of the model permits a maximum of fifteen nodes and ten customers. The links allow interaction between facilities in terms of inventory and physical flow and provide the primary source of model dynamics by including the uncertainty experienced under normal operating conditions. The uncertainty for communication and transit links is replicated by stochastic cycle time components.

Within the configuration defined for the model, multiple product flows are allowed, including the capability for multiple and alternate sources. Policy specification and measurements of performance are maintained by product detail.

A primary function of the Network Configuration routine is to interpret and validate product stocking and sourcing information. The Network Configuration activity is required only at the initiation of a model run. Similar to the Data Read event, configuration is independent and does not interface with any other model activity.

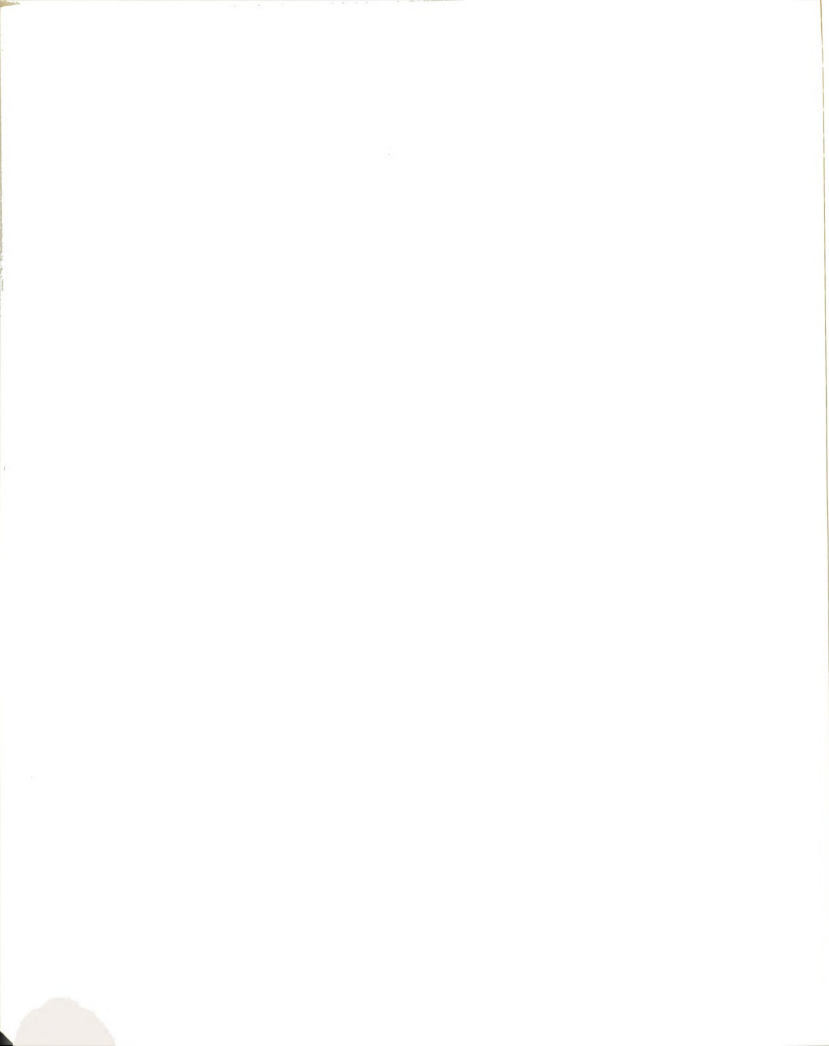


The Network Configuration logic assumes that the user has defined the echelon structure for the model. The echelon number for each of the facilities is stored in an array LEVEL which specifies that the network be configured beginning with product sources and ending with facilities performing final product disposition.

Another variable used throughout the process is the error flag LOCKIL. Whenever an error in the configuration process occurs, this variable is set to one. When control of the simulator returns to the EVENTS routine, this variable is reviewed. If the user specifies that the run is to be terminated in case of configuration errors, model execution is aborted.

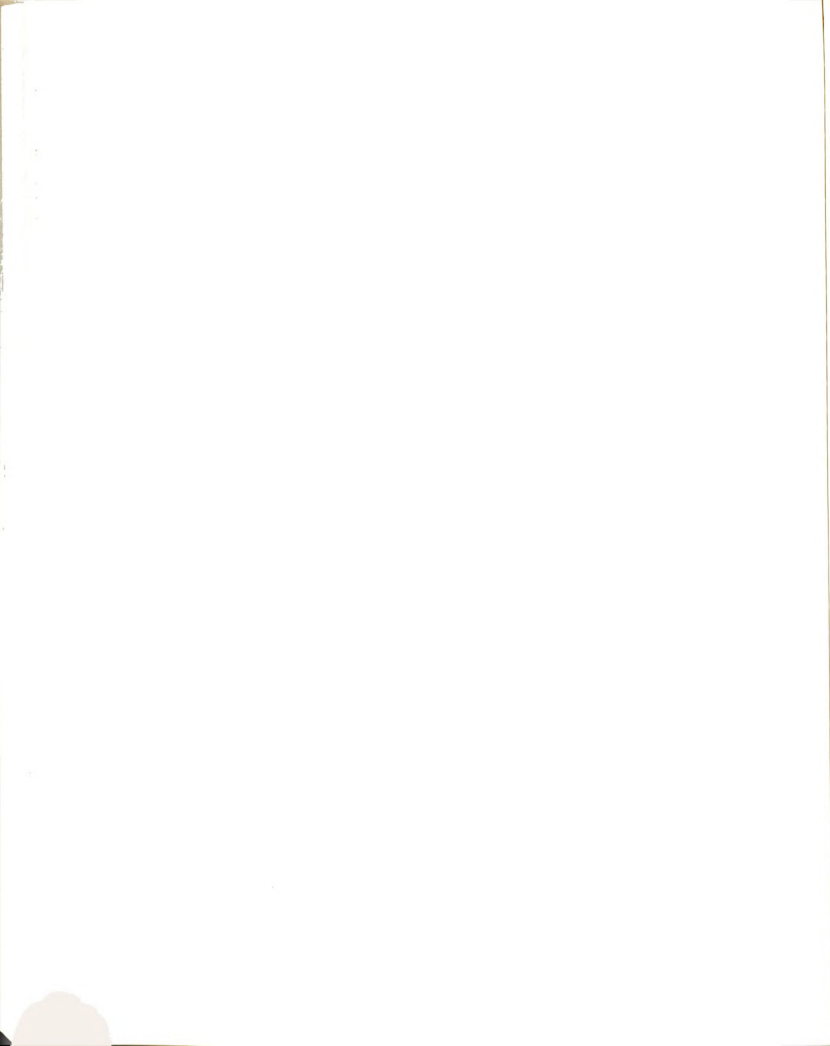
The first action the Network Configuration event performs calls for sorting the links into ascending destination facility numbers. The information regarding relative level is maintained with the links. Communication and transit parameters are also sorted in destination facility order. This sorting process aids in the development of an index table which provides link information. The indexing is important since link information is not tied directly to the facility number.

The second task of the Network Configuration activity is to check sources for all products on an echelon-by-echelon basis. This check is initiated at the lowest echelon number.



Thus, all manufacturers are checked first and those locations serving the customer are reviewed last. For each location, the products stocked at the facility are checked to establish the validity of the source. This checking, which is accomplished for both primary and alternate sources, reviews the following features of the network. First, are echelon levels of the sources less than the echelon level of the facility being checked? Second, does the source stock the product? Third, is there both a communication and a transit link between the facility in question and the potential source? When the source number is the same as the facility being checked, the product is automatically specified as being produced at that facility and no further checking is necessary. If one of the above checked conditions is not satisfied, the error flag is set and the product is deleted from the list of stocked products at that facility. Each of the facilities in the echelon level is checked in the above manner. The Network Configuration validation process is completed when all echelons have been checked.

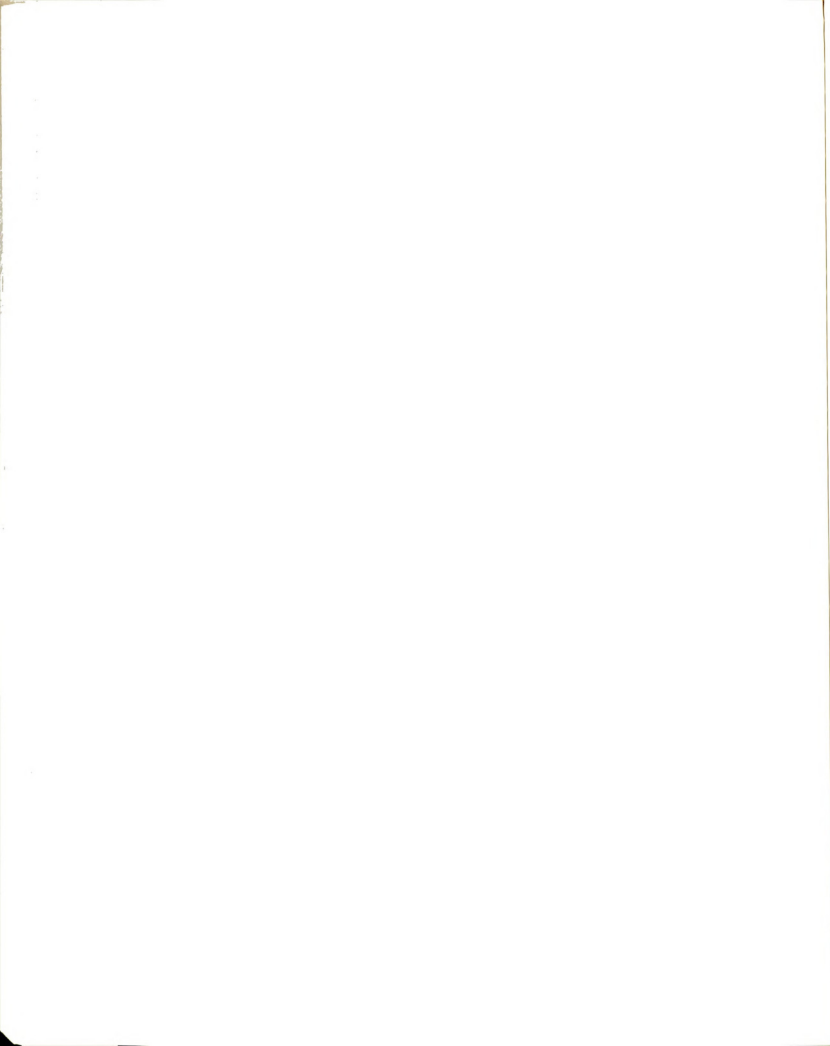
The final event task calculates the expected lead times for use in Demand Forecasting, which is also performed on an echelon-by-echelon basis. This forecast-related process begins at the facilities nearest the final product destination in terms of echelons. For each facility, the



expected value of each of the cycle time components is computed based on possible times and probabilities. Expected values for communication and processing times are a direct calculation since all orders use the same distribution function. For transit time, however, given the range of the existing model, up to six different probabilities and times may be applicable between a pair of source destination locations since alternate transportation modes are possible. Thus, to establish the required data, an expected time is computed for each mode and an overall expected transit time is then calculated on the basis of the probability of mode utilization. For example, suppose truckload has an expected transit time of 2 days, and less-than-truckload has an expected time of 4 days. If half of the orders have gone truckload historically, the expected transit time would be computed as 3 days $(.5 \times 2 + (1 - .5) \times 4)$. The three components are summed and stored in the array EXLDT to provide an estimate for the lag from each facility to final product disposition. This information is maintained by facility and by product. Figure 7 summarizes these tasks in a flow diagram.

Demand Forecasting

The Demand Forecasting event provides the interface between the forecast procedures and the operations simulator. The event is scheduled periodically during a model execution



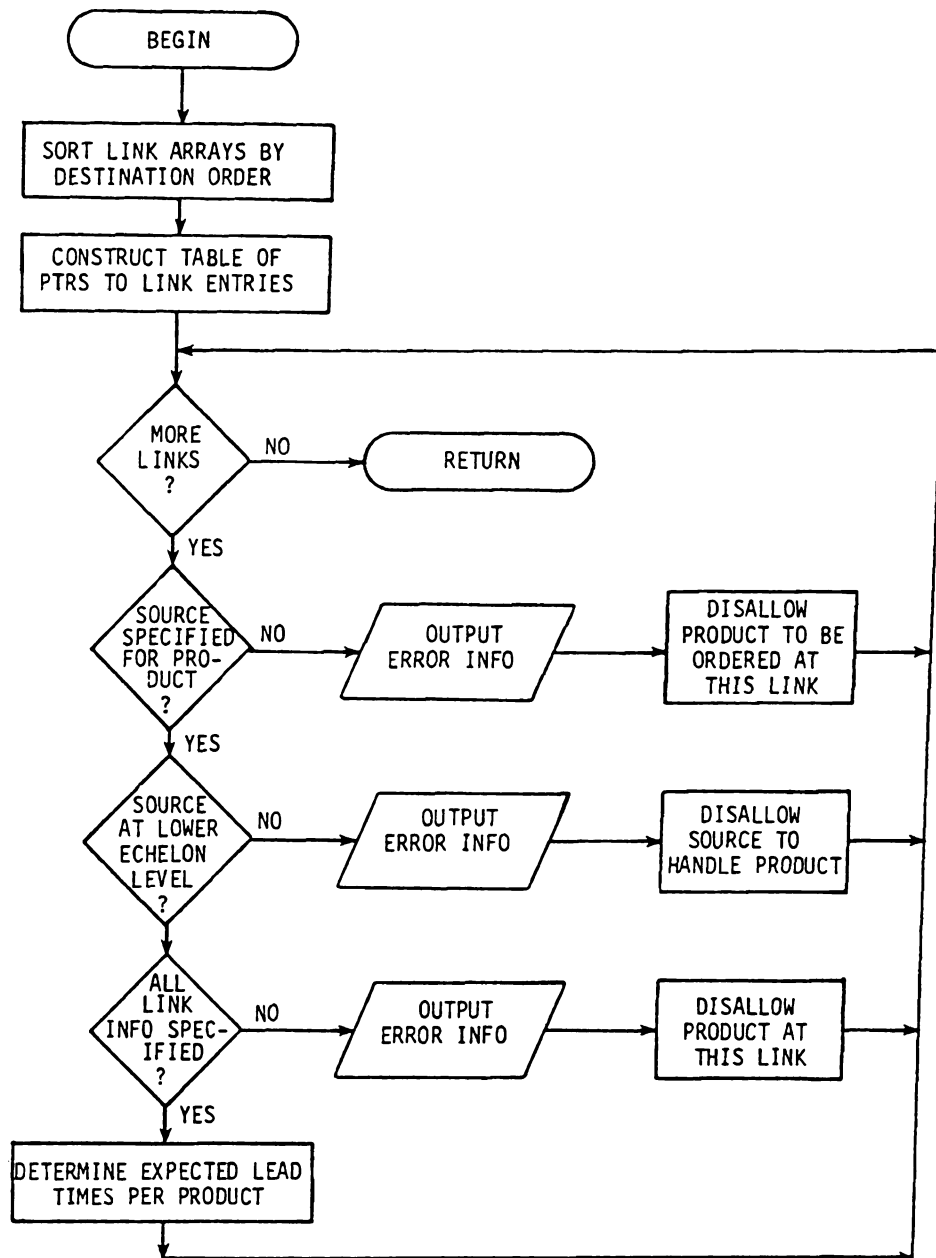
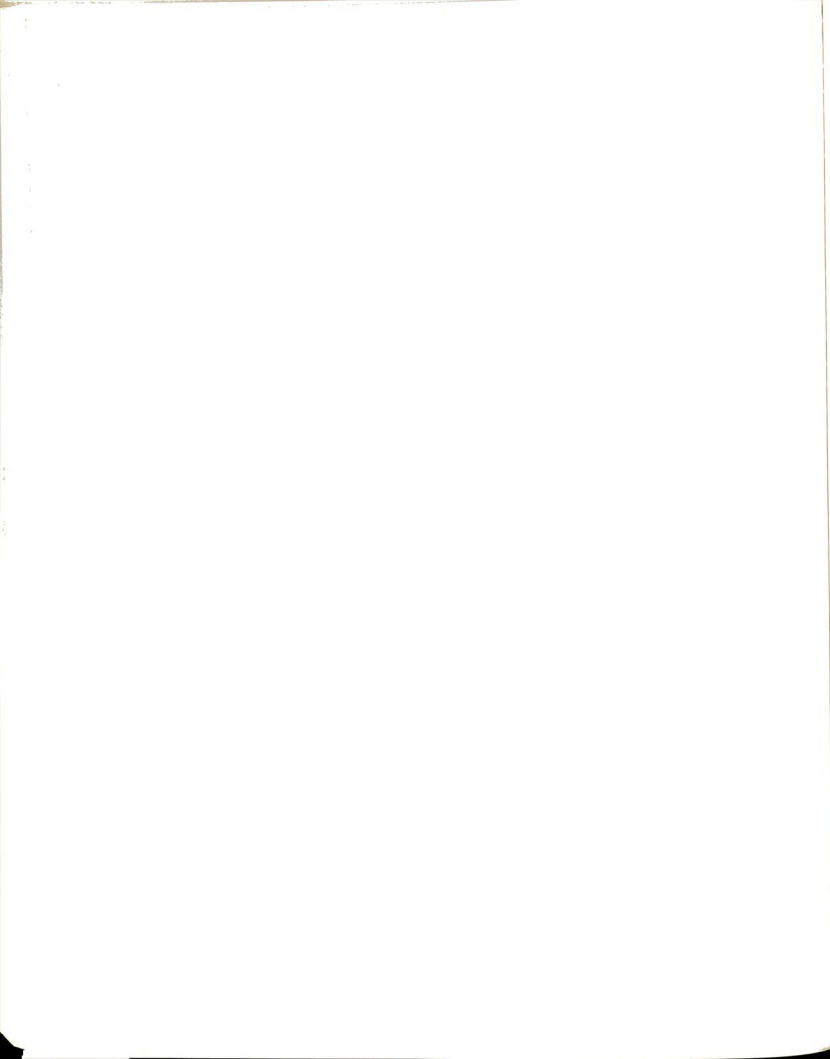


Fig. 7. Network Configuration Flow Diagram

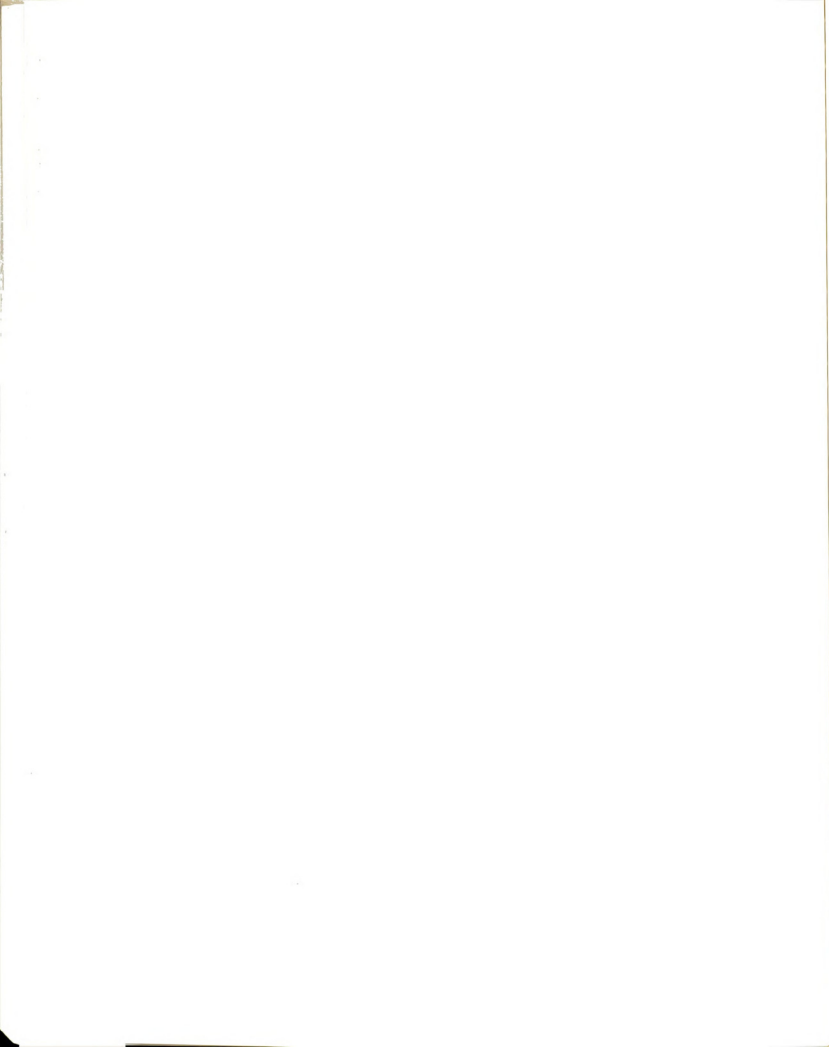


to provide the forecasts by facility and product for the time period desired. For example, distribution centers may use monthly forecasts while retailers may update weekly. The two tasks required for the Demand Forecasting process include forecast calculation and inventory level computation.

The forecast calculation uses one of the SPSF forecast techniques to generate a sales or shipment forecast. The inventory level computation then uses the forecast value to set operating inventory levels such as Reorder Points and Order Quantities. Use of this inventory level calculation is discussed more fully under the Inventory Management event. In situations where sales forecasting is not desired, the Demand Forecasting event is still necessary in order to establish inventory levels.

Two forecasting options are available for facilities intermediate to the product's final destination. The first option requires that the forecasting technique be scheduled and performed at each facility in the system. The forecasts are generated on the basis of facility sales during the last forecast period. This option must be used when the Demand Bleed-Off activity is used.

The second option generates forecasts only for facilities specified on the event parameter card. Instead of a single period forecast, this option is capable of generating forecasts for up to ten advance operational



periods (e.g., months). The multiple period forecasting option may be used with SPSF techniques that include trend and seasonality. Under the second alternative, forecasts from remote facilities are transmitted to and used at facilities further up the channel.

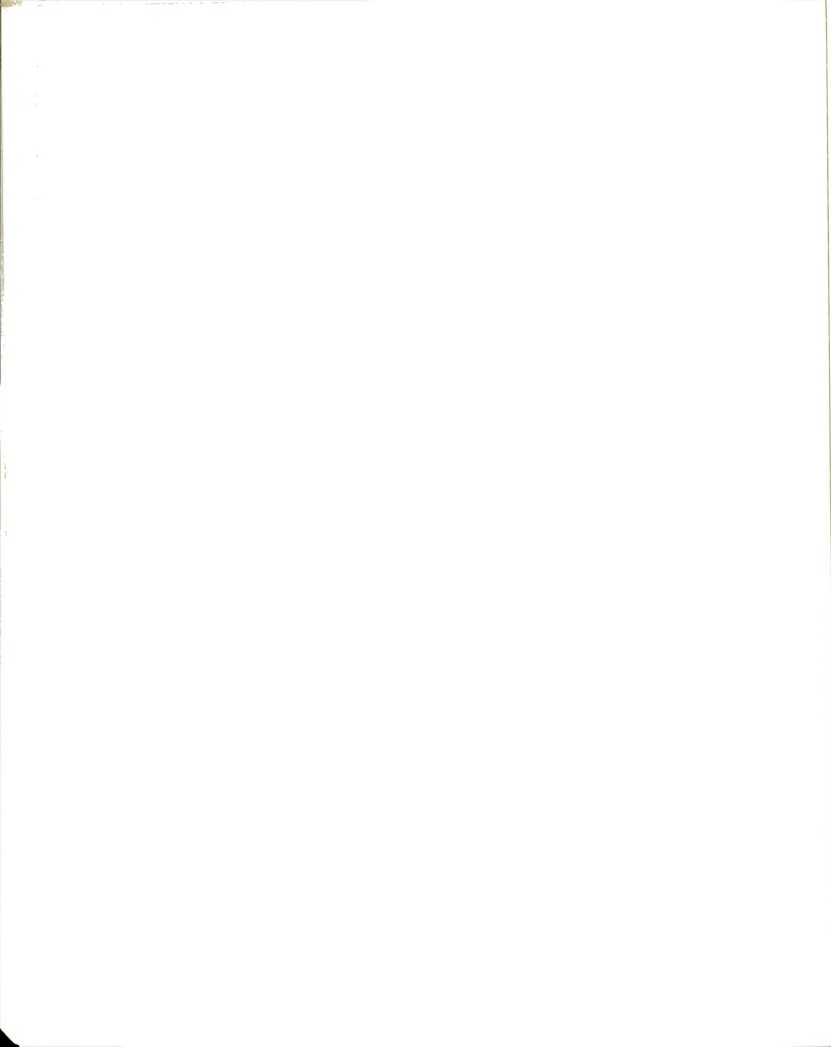
For upper echelons, the forecast value selected for use is based on the expected lead time from the market to the facility. The expected lead time, a summation of the total order cycle time between each echelon, was computed by the Network Configuration activity. Determination of the forecast value to use for a specified echelon or facility is based on the following procedure. When the total expected order cycle time is LT days and the length of the forecast period is FP days, the forecast desired for a facility that has a three-forecast period lag from the market is period $t + 3$, given that the base forecast is for period t . This is mathematically expressed in the following formula.

$$t = (LT/FP) + 1$$

Where:

t = time period whose forecast
is desired and LT and FP are
as previously defined.

The following discussion traces the logic of the event as it accomplished the above procedures.



The Demand Forecasting activity revolves around the facilities and product numbers defined on the parameter card. Two loops control the process: the major loop sets up the process for each facility while the second loop passes each product through the process.

The first loop uses the SELECT routine to identify the forecast technique to be used and to set up historical parameters and smoothing constants. This routine does not choose a forecast technique; it only identifies and sets up parameters for the technique specified by the user. The SELECT routine then issues a call to generate a forecast on the basis of the specified technique. Table 7 lists the forecast techniques and the specific call routines used by SELECT. Each technique generates the forecasts for the specified periods and modifies the historical parameters and the smoothing constants if the technique is adaptive. After the technique has generated the forecasts, control is returned to the SELECT routine which stores the modified parameters and ultimately returns to the FORECAST routine. The appropriate forecast is then stored in the current period forecast variable (CPFOR) for each facility and product.

At this point, the inventory parameters are computed. If the fixed reorder point-order system is being used, the replenishment parameters are set to the fixed quantities

TABLE 7
FORECAST TECHNIQUE ROUTINES

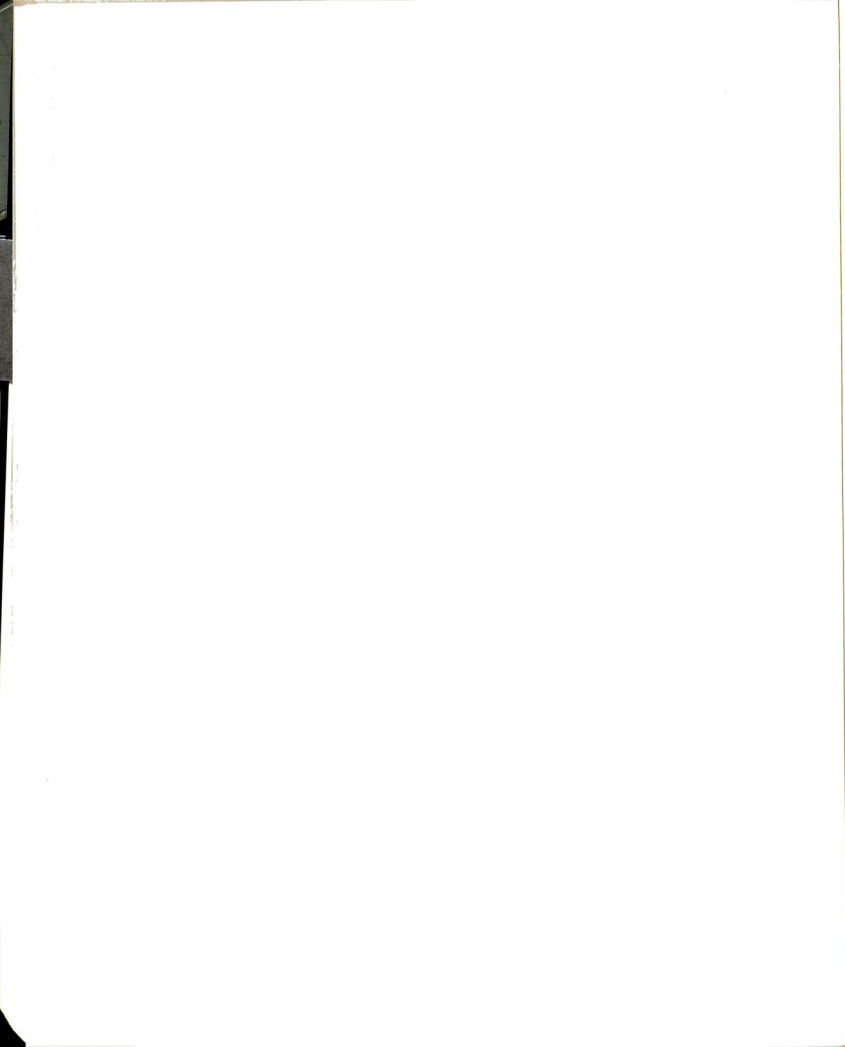
Forecast Technique	Routines Used in Forecast Generation
1. R. G. Brown Exponential Smoothing	BROWN
2. Trigg and Leach Adaptive Exponential Smoothing	TRILE
3. P. R. Winters Exponential Smoothing with Seasonality and Trend	BOTH
4. Roberts and Reed Self-Adaptive Forecasting Technique	BOTH, EVOP, TEST

and the procedure is complete for this product. When the variable quantity replenishment policies are used, the forecast is used to generate a quantity for actual replenishment. As an example, suppose the forecast for a given 30-day period was 1,500 units. If 10 days of stock is the desired reorder point level, the following calculation is performed to convert the daily stock level into units.

$$\begin{aligned}
 \text{ROP}(\text{DC}, \text{PR}) &= \text{CPFOR}(\text{DC}, \text{PR}) \times (\text{INVPD}(1, \text{DC}, \text{PR}) / \text{FP}) \\
 &= 1500 \times (10/30) \\
 &= 500 \text{ units}
 \end{aligned}$$

Where:

- ROP(DC,PR) = the reorder point or minimum level at DC for PR;
- CPFOR(DC,PR) = the following period's forecast at DC for PR;



INVPD(1,DC,PR) = the minimum or reorder point definition at DC for PR. This may be in absolute units or days of stock depending on the value of INVPOL(DC).

Once inventory levels have been established, the initial inventory allotment is calculated. Two alternatives exist for establishing the beginning inventory. The user may specify any non-zero initial inventory level, or the model may be used to set the initial level. The model uses the following formulation to calculate the level:

$$IOH(DC,PR) = MIN(DC,PR) + 1/2 \times MAX(DC,PR)$$

Where:

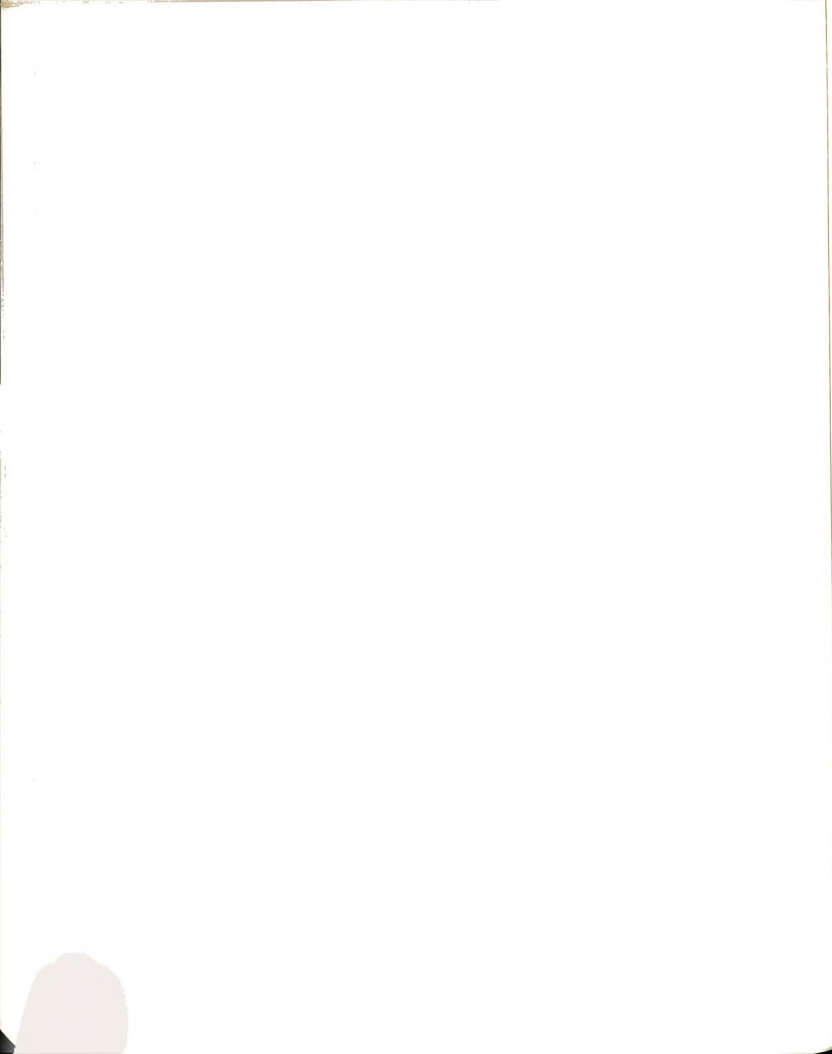
IOH(DC,PR) = the initial assigned inventory level at DC for PR;

MIN(DC,PR) = the minimum or reorder point level at DC for PR;

MAX(DC,PR) = the maximum or order quantity level at DC for PR.

When the forecast follow-through option is used, the appropriate forecast is transferred back to the sources and the initial inventory level is set. This follow-through is repeated until the final production source of the product is encountered.

Given the above routine, the forecast generation and inventory parameter setting process is completed for this facility-product combination. If additional facility-product



combinations are specified on the event parameter card, the process is repeated.

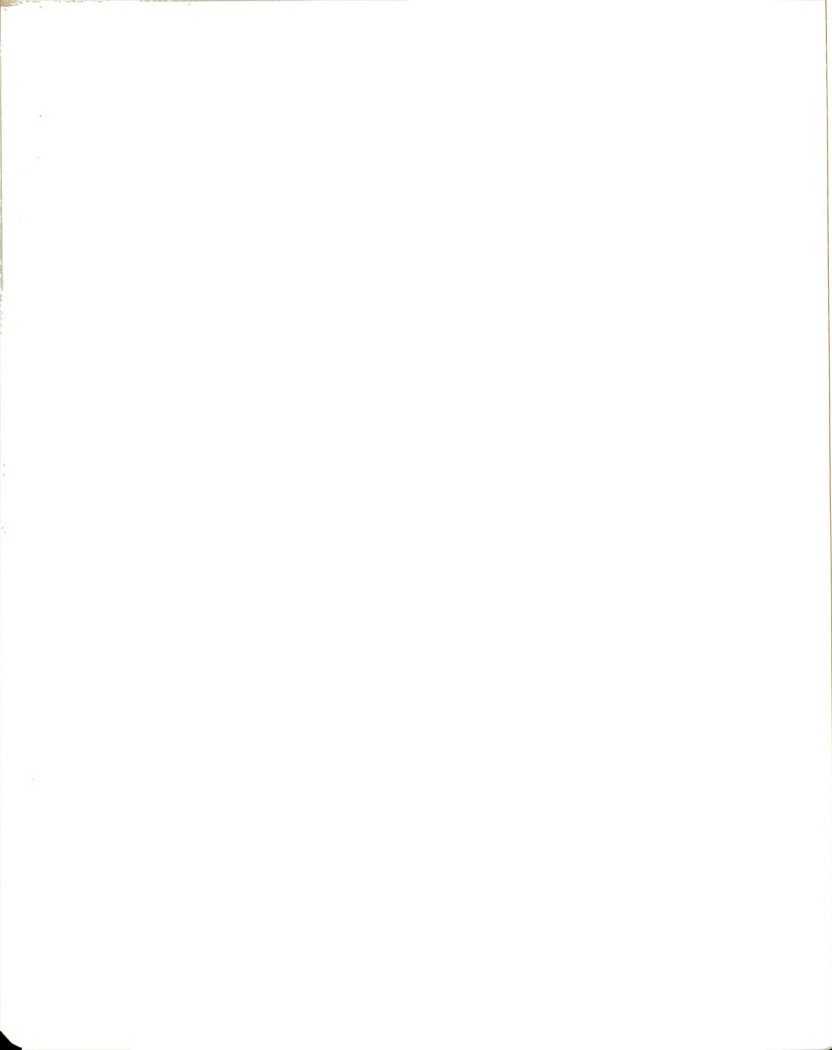
The last task performed by the Demand Forecasting activity reschedules the event for a future date if the user has specified a repeat period on the event parameter card. If no cycle time is provided, no further action is required. Figures 8 and 9 summarize the flows of the FORCST and SELECT routines.

Demand Generation

The Demand Generation activity models the firm's customer environment by creating orders which may reflect any type of environmental conditions. The actual activity objective is to deliver facsimile customer orders to the Customer Order Processing activity. Unlike all prior distribution models, the SPSF model includes four alternative demand generation options to allow for greater flexibility when creating environmental conditions. The alternative options include the following:

1. Externally created orders
2. Stochastic order generation
3. Regression generated firm sales
4. Regression generated industry sales utilizing the market share factor.

The first two alternatives are relatively easy to use although they do not provide as much flexibility when



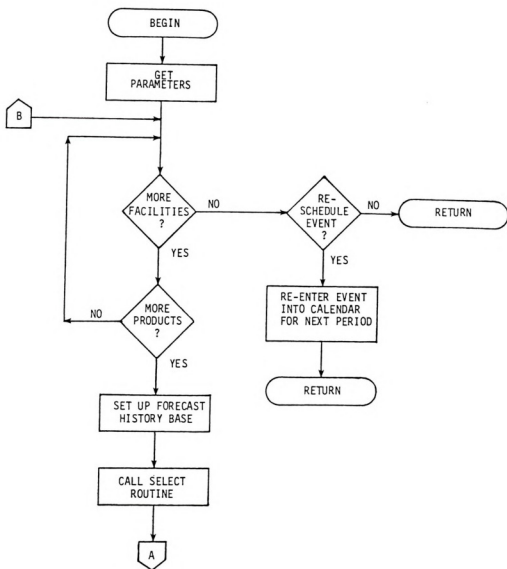
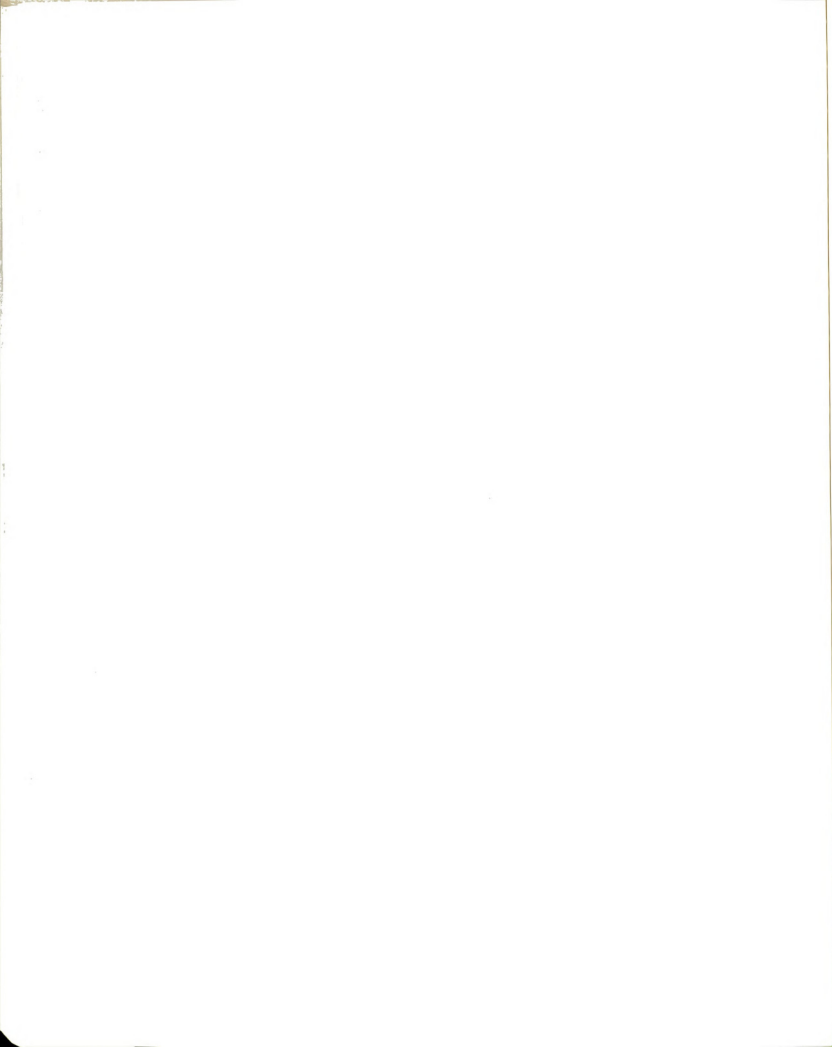


Fig. 8. Forecast Event Flow Diagram



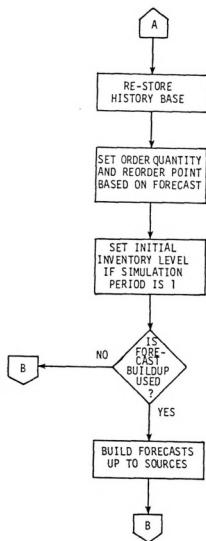
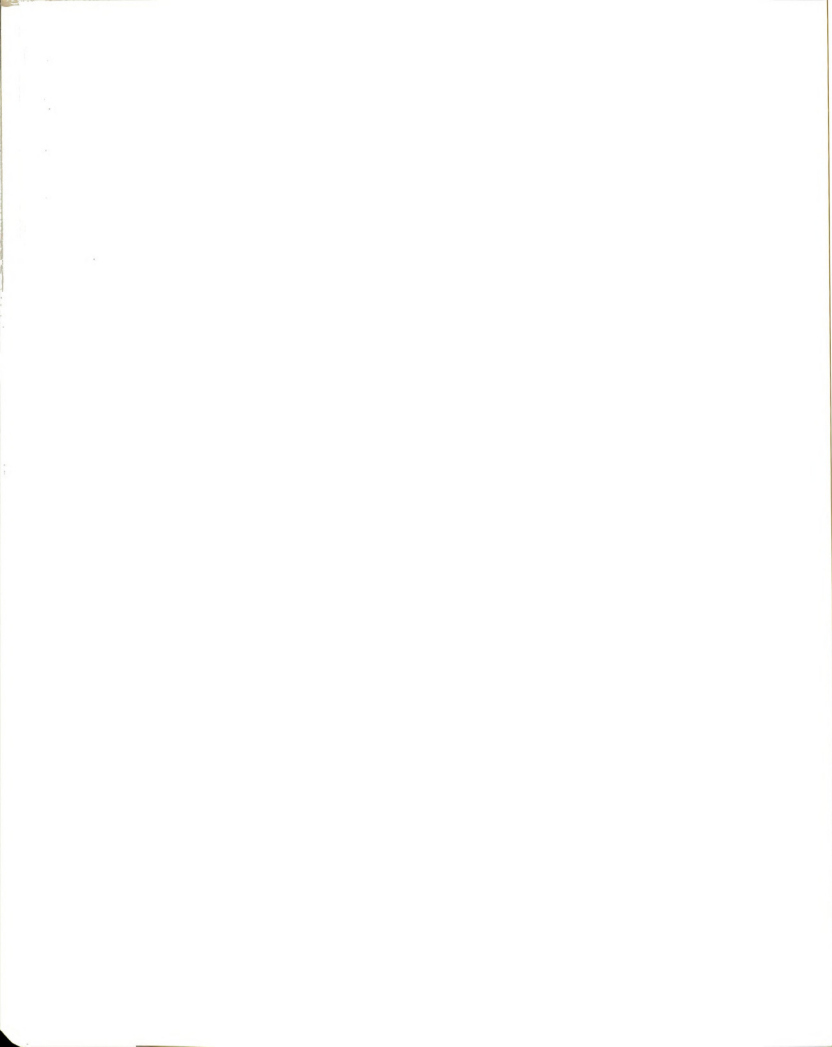


Fig. 8. (Cont'd.)



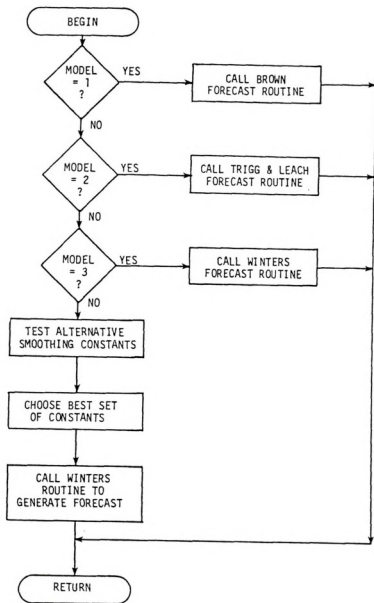
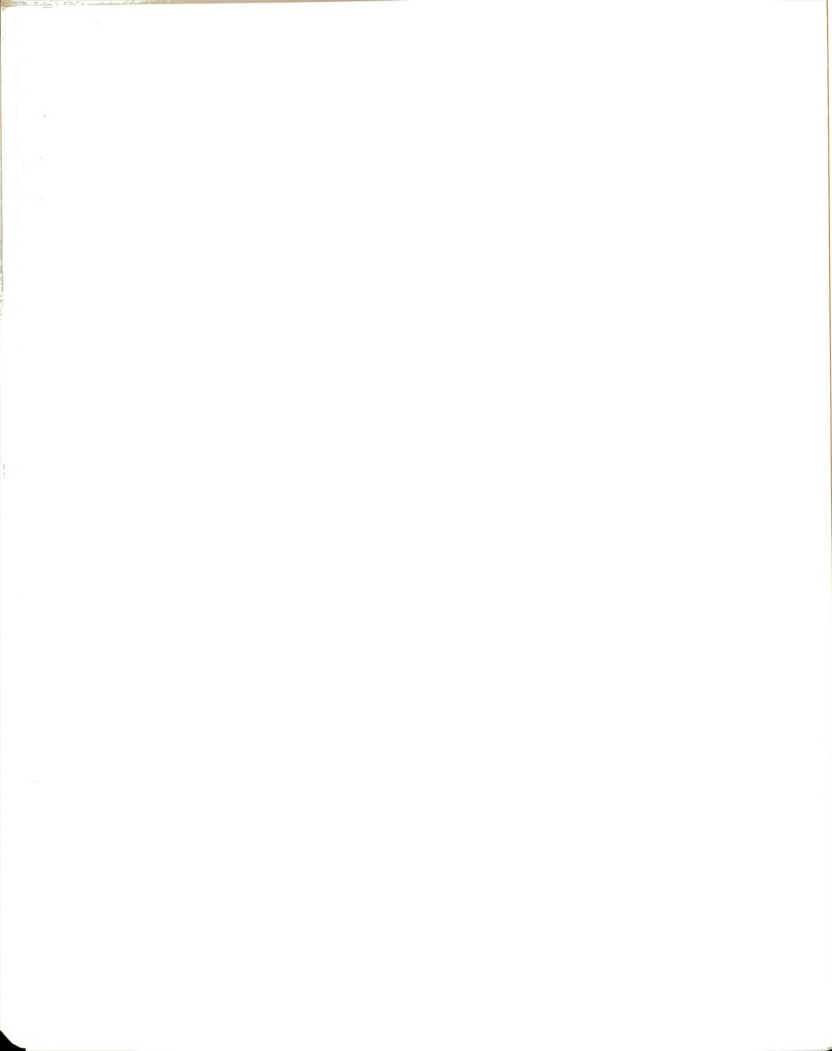


Fig. 9. Subroutine Select Flow Diagram

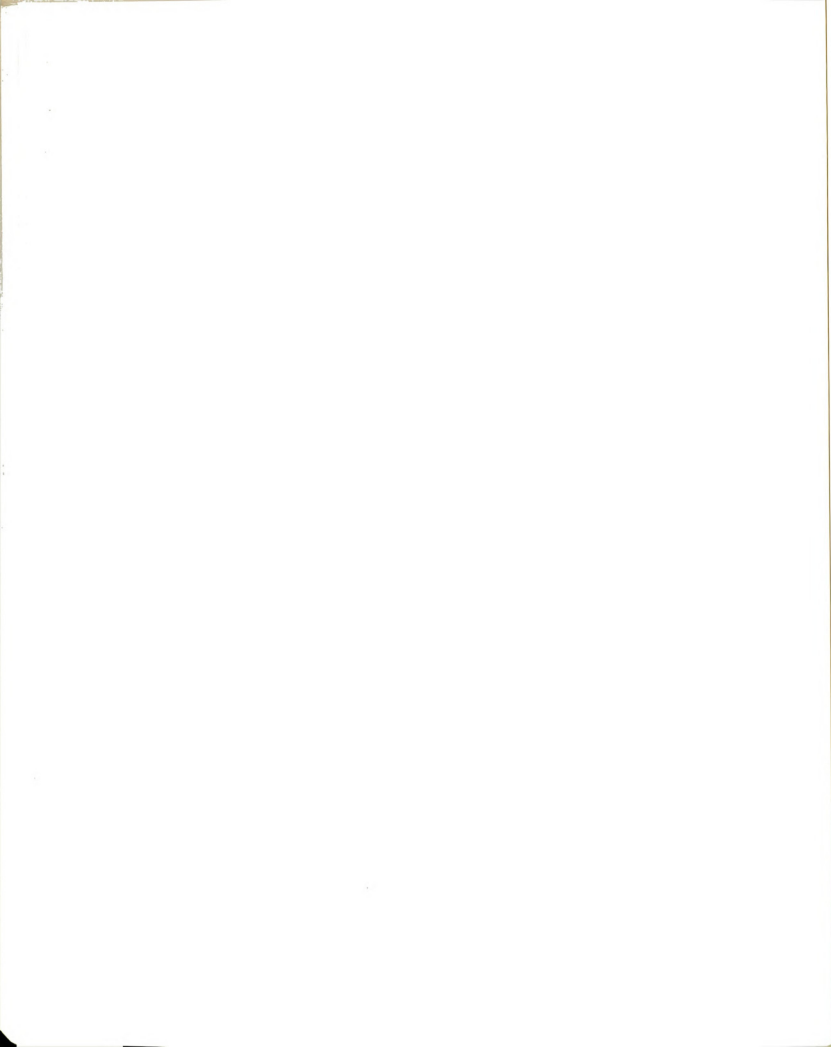


attempting to model non-historical environments. Although the second two alternatives require more pre-modeling data analysis, they allow more flexibility in creating alternative environments.

When the first alternative is used, actual orders are simply read from a file that has been created outside the model. The file may be a record of historical invoices or it may have been externally generated through some other process. In either case, the model processes only the number of orders that is provided to it. The model does not extrapolate the orders to create a larger population.

When any of the remaining Demand Generation alternatives are used, the analyst must supply the model with only a sample of orders. The sample is arranged into subsets to allow for introduction of product seasonality. Specific products may occur on orders only during particular times of the year. The remaining discussion outlines the logic used in the demand generation process.

The first step of the process is called routine PMONO to determine the appropriate order set to use. This usually corresponds to selecting the order subset appropriate for the simulation period. For example, for the first day of the simulation, the first month's orders are used, while for simulation day 31, the second month's orders may be appropriate. The correct set is found using the following formulation.



$$PMONO = MOD \left[\frac{TNOW}{SEASP} + SEASB, SEASP \right] + 1$$

Where:

PMONO = the order that will be used for the creation of orders;

TNOW = the simulation day;

SEASP = the length of the period that an order set will be used for;

SEASB = an adjustment factor so that the beginning of the order sets does not have to start at the beginning of the simulation;

MOD = a standard FORTRAN IV function which returns the integer remainder in a division operation.

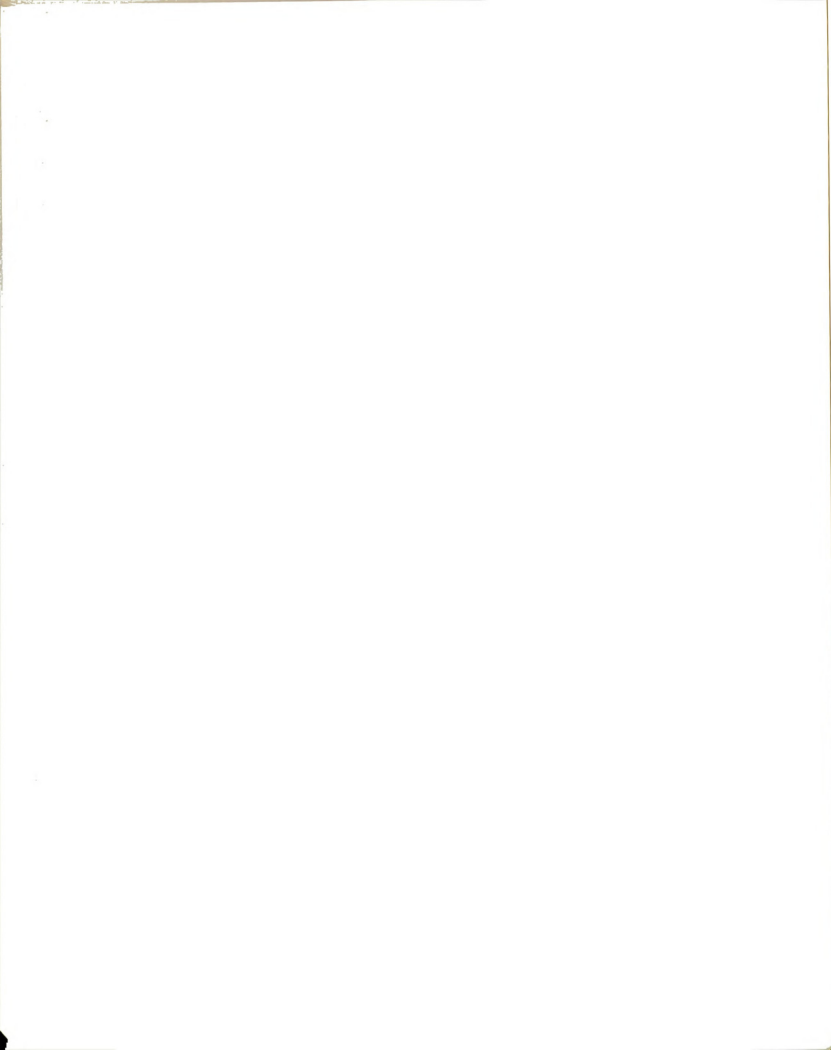
Following determination of the correct order set, the order set is accessed and made available to the routine. The next process faced by the routine is generation of a daily sales level. The details of this step depend on the Demand Generation option used.

Option 2 uses 12 uniformly distributed random numbers to approximate a standard normal distribution. The normalized distribution is adjusted using an expected value, a standard deviation, and a skew, each of which may be unique by customer. The mathematical formulation for this follows.

$$DAYSLS = EDSF(IDU) + R-SKEW(IDU)*SDDSF(IDU)$$

Where:

DAYSLS = the estimate for daily sales for customer IDU;



EDSF(IDU) = the expected level of daily sales for IDU;

R = the sum of 12 uniformly distributed random numbers which will have a mean of 6;

SKEW(IDU) = the skew factor for this customer; a value of 6 will provide no skew while a value of 0 will make the distribution skewed to the left;

SDDSF(IDU) = the standard daily deviation of sales around the mean.

For Demand Generation Option 3, a regression formula is used to calculate the expected monthly sales level. This procedure uses the following calculation:

$$\text{MSALES} = [\bar{A} + B(1)*X(1) + \dots + B(5)*X(5)] * \text{SEAS}(\text{MONO})$$

Where:

MSALES = the monthly sales level;

A = the fixed regression coefficient;

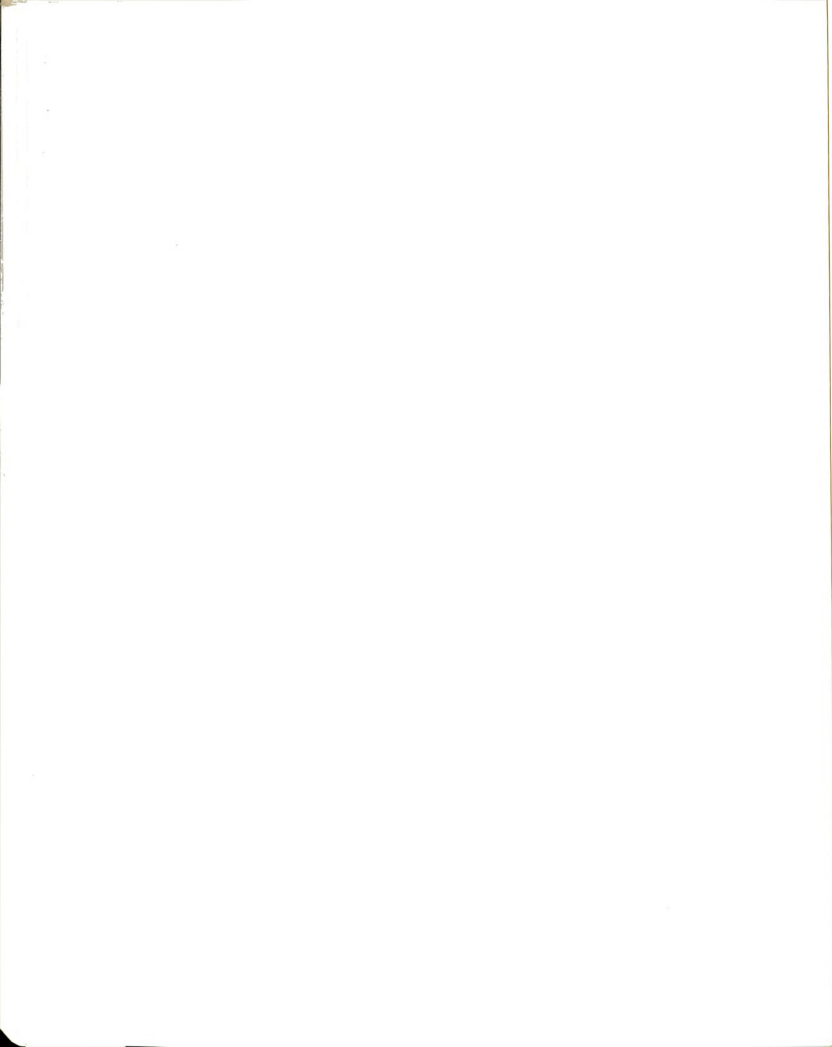
B(1)-B(5) = variable regression coefficients;

X(1)-X(5) = values of the independent variables;

SEAS(MONO) = the seasonality factor for this order set.

The monthly or periodic sales level is then decomposed into daily sales using a daily sales factor and the normal random number distribution generator.

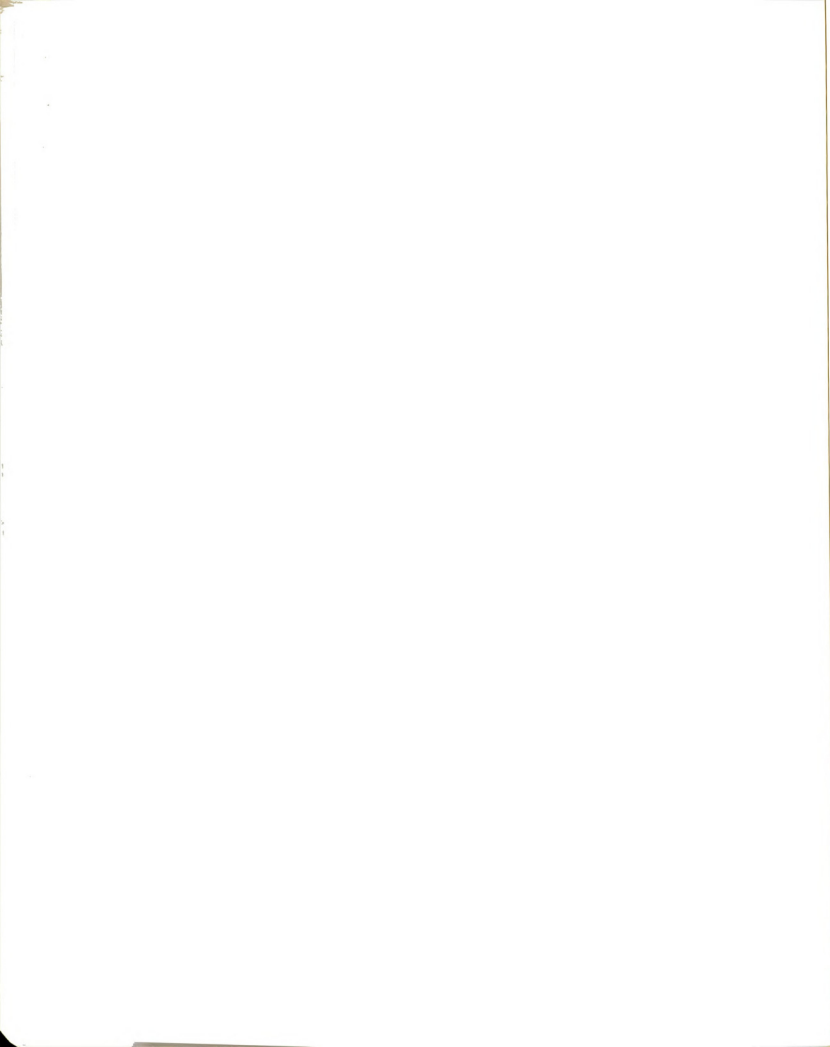
For Demand Generation Option 4, the regression equation is used to develop an estimate for industry period sales. The industry sales figure is then decomposed into firm sales using the market share model as discussed in



Chapter II. Subroutine SMS performs the actual development of the market share estimation. The last step under this option uses the normal random number generator and the daily sales factor to approximate the daily sales level.

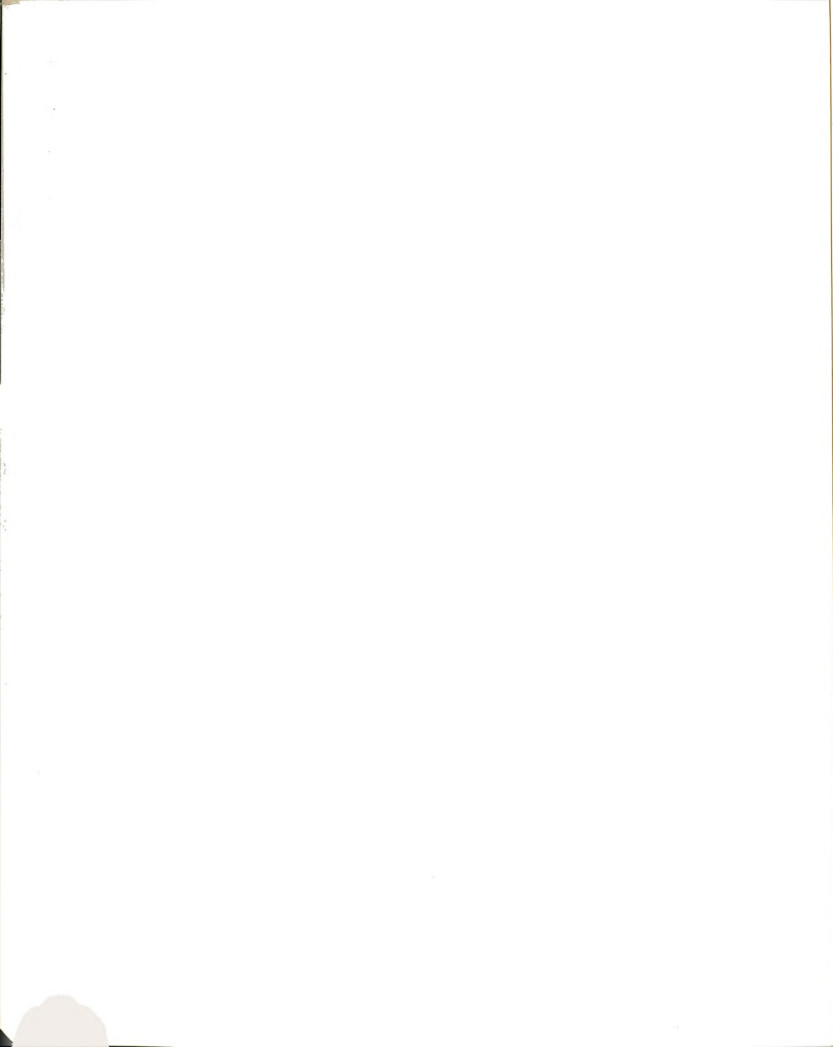
The final step for the internal order generation procedure for Options 2, 3, and 4 is the development of simulated customer orders to fulfill the daily sales estimate. Either the order sampling or the line sampling procedures may be used with any of the Demand Generation options.

The first alternative uses a sample of up to 100 complete orders for each set. When an order is desired, a uniformly distributed random number is selected. The range of the random number is adjusted to reflect the actual number of orders in the sample. The modified random number is then used as an index directly into the array containing the sample orders. The routine writes the sample order to the order file and decrements the order value from the cumulative daily sales count. When the cumulative sales level drops below zero, a decision rule is used to determine whether or not the last order should be kept. The detail of the rule is discussed later since the same algorithm is used when making the decision when line sampling is done. If more orders are required, the order sampling process is performed again until the daily quota is filled. The line sampling procedure provides a more suitable order generation



process when the composition of the orders is not homogeneous. Before using this option, the support program LINSAMP must be run to create the statistical base for the sampling process.

The line sampling process first uses the normal random number generator to determine the number of lines that the order to be constructed should have. This process uses ENLNS(IDU) and SDNLNS(IDU) as the expected value and standard deviation parameters, respectively. Once the number of lines has been determined, the selection process begins. For each line, a uniform random number is generated and compared against the entries of the product occurrence array (PRDPCT). PRDPCT contains the cumulative probabilities of the individual product occurrences from the original sample of orders. Once the product has been selected, another uniform random number is generated and adjusted so that it may be used as the index for selection of the quantity for that item. All the quantities for that item in the original sample are placed in the order array and are then selected on the basis of a uniform distribution. The same process is repeated for each of the lines of an order. The routine then writes the order to the temporary order file. It is possible that the same item may be selected more than once since this is an uninhibited stochastic process.



When the value of the actual daily sales orders exceeds the original approximation, a decision must be made to eliminate the built-in bias for higher than average sales. If the last order would cause the actual to be above the expected, a ratio is computed using the value of the last order and the available sales prior to the last order. Mathematically, this is:

$$R = \text{SUM}/\text{SLSREM}$$

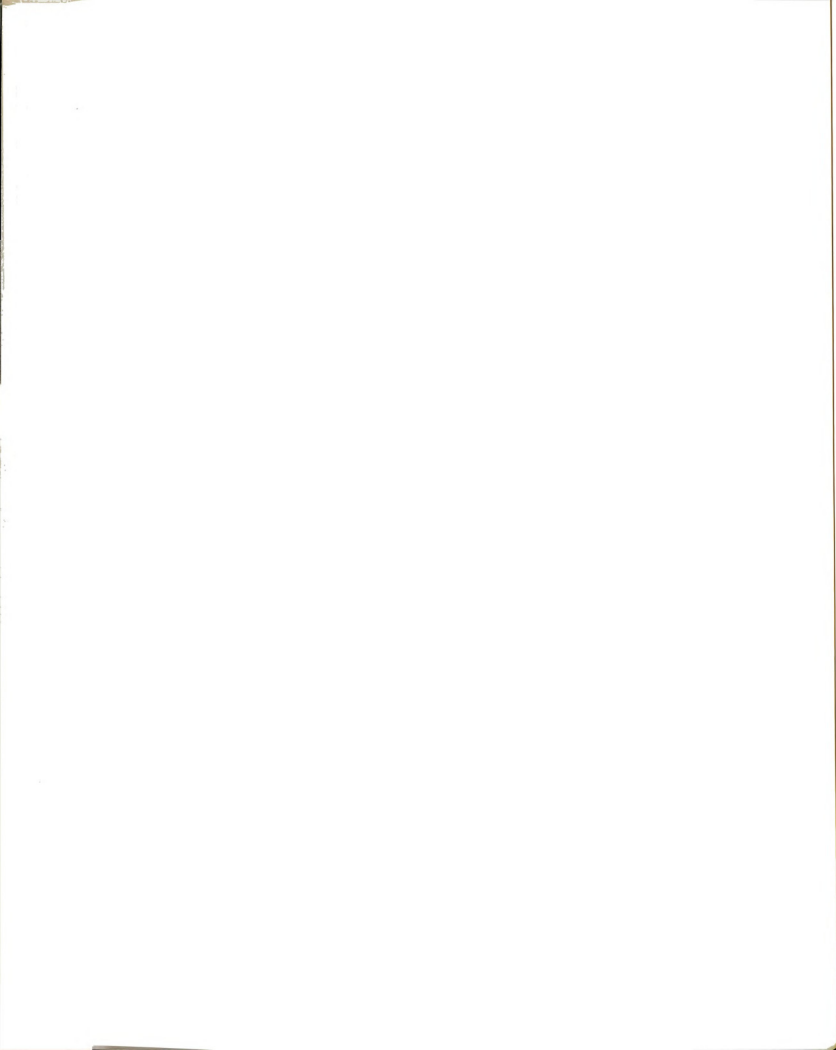
Where:

R = the test ratio;

SUM = the value of the order
in question;

SLSREM = the daily sales value that
remains to be filled before
the computed value is
reached.

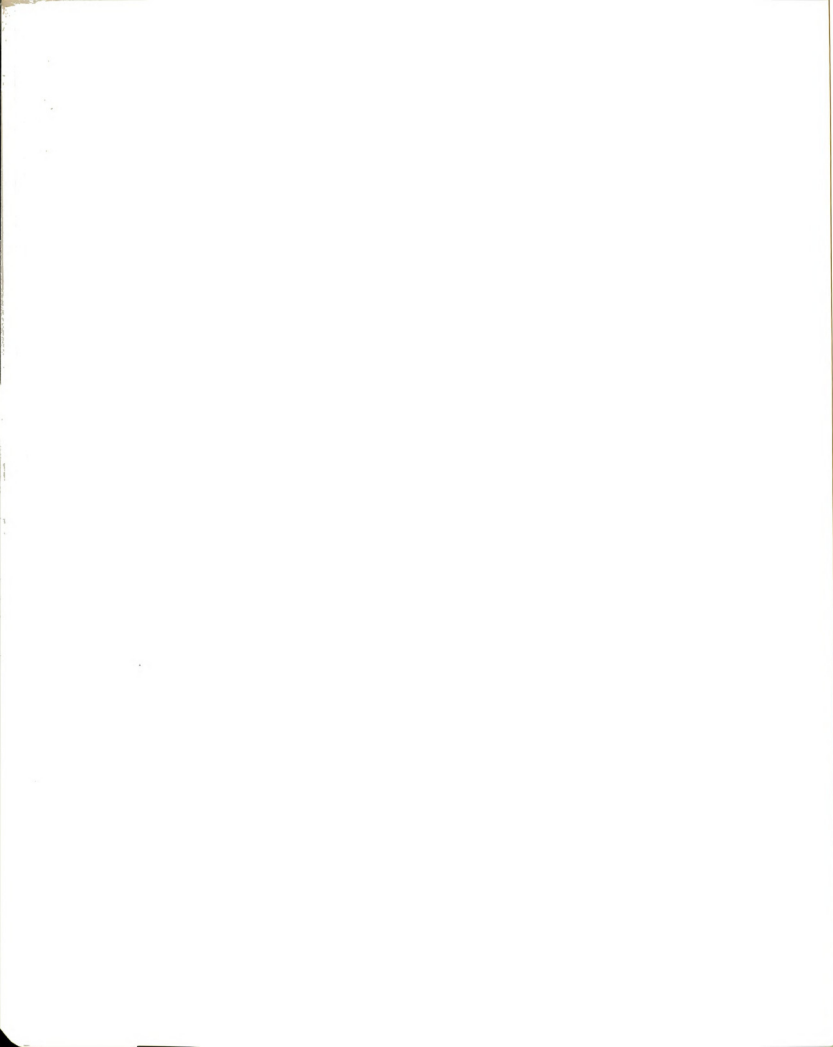
When R is greater than 1.33, the order is arbitrarily thrown out as too large. When this happens, the order generation process is complete for this customer. If R is less than 1.33, a uniformly distributed random number is used to decide whether or not the last order is to be kept. A random number of less than .5 implies that the last order is to be kept while a value of not less than .5 will cause the last order to be ignored. In either case, the order generation process is then completed for this customer.



At this point, the process is completed for a single customer. When there is more than one customer, the entire process is begun again. When there are no more customers, program flow returns to the main ORDER routine. Figure 10 presents a summary of flow for the Demand Generation routine.

Customer Order Processing

The interface between the Demand Generation Module and the Operations Module is provided by the Customer Order Processing event (ORDER). The ORDER event processes the externally input or internally generated customer orders which provide the driving mechanism for the SPSF Testing Environment. In either case, the order processing function usually occurs during each simulation period. Since the event is repetitive, it is rescheduled internally by the model once it is initially scheduled by the analyst. The primary functions of ORDER include reading orders, checking the demand quantities specified on the orders against the available inventory, and accumulating the sales and service information. When not enough inventory is available to fill the entire quantity, the unfilled quantity is either forgotten and recorded as a stockout or it is saved as a back order to be filled when inventory becomes available. It should be noted that once an order has been saved as a back order, it is not removed from the back-order queue until



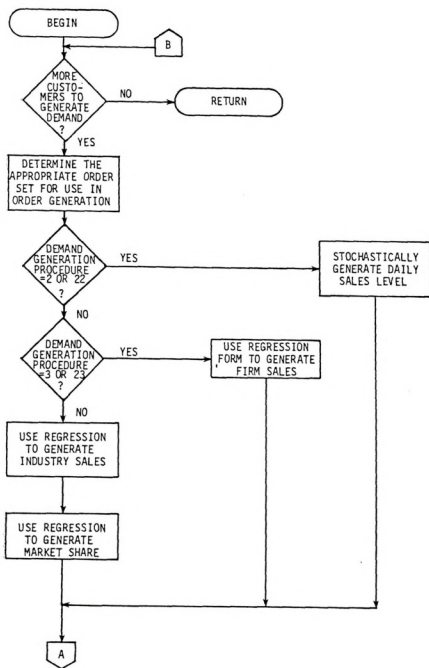


Fig. 10. Demand Generation Flow Diagram

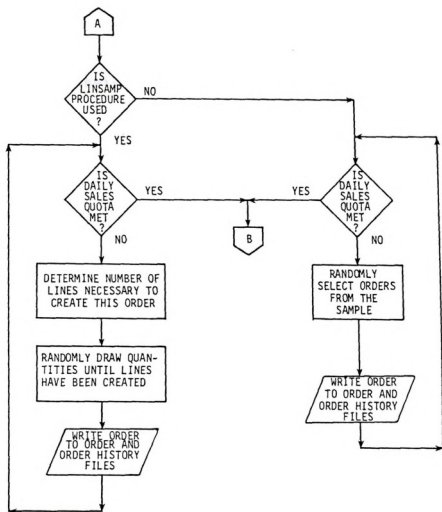
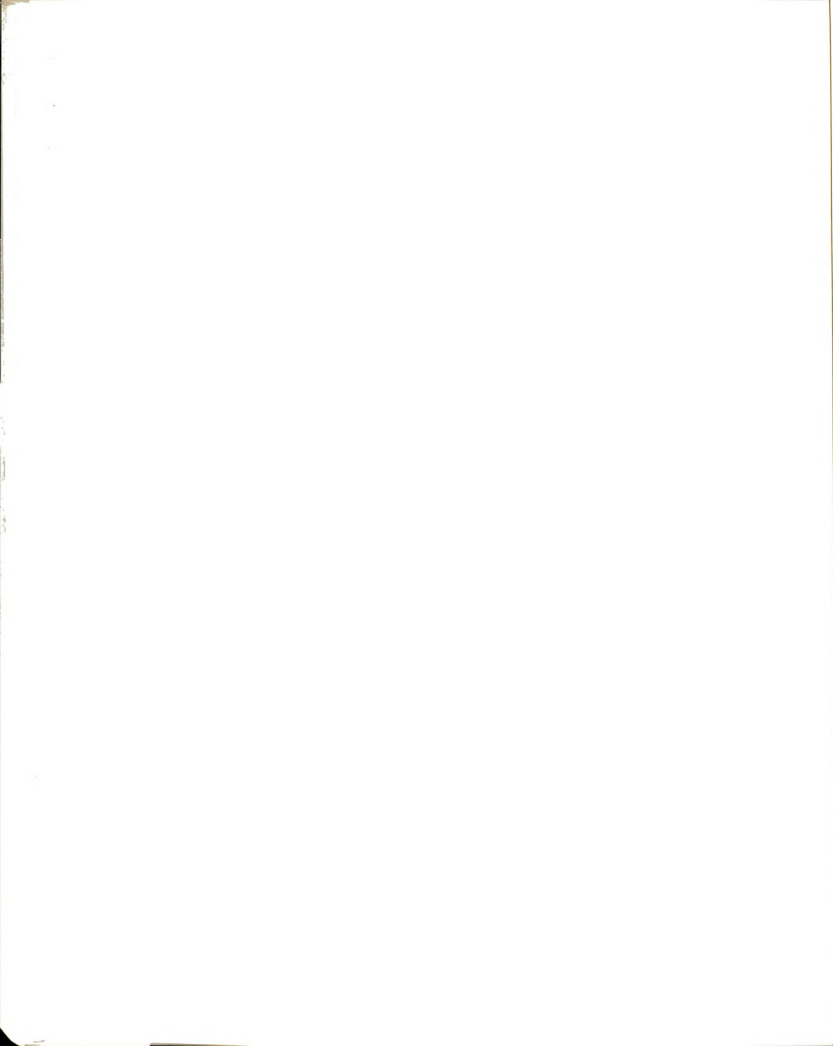


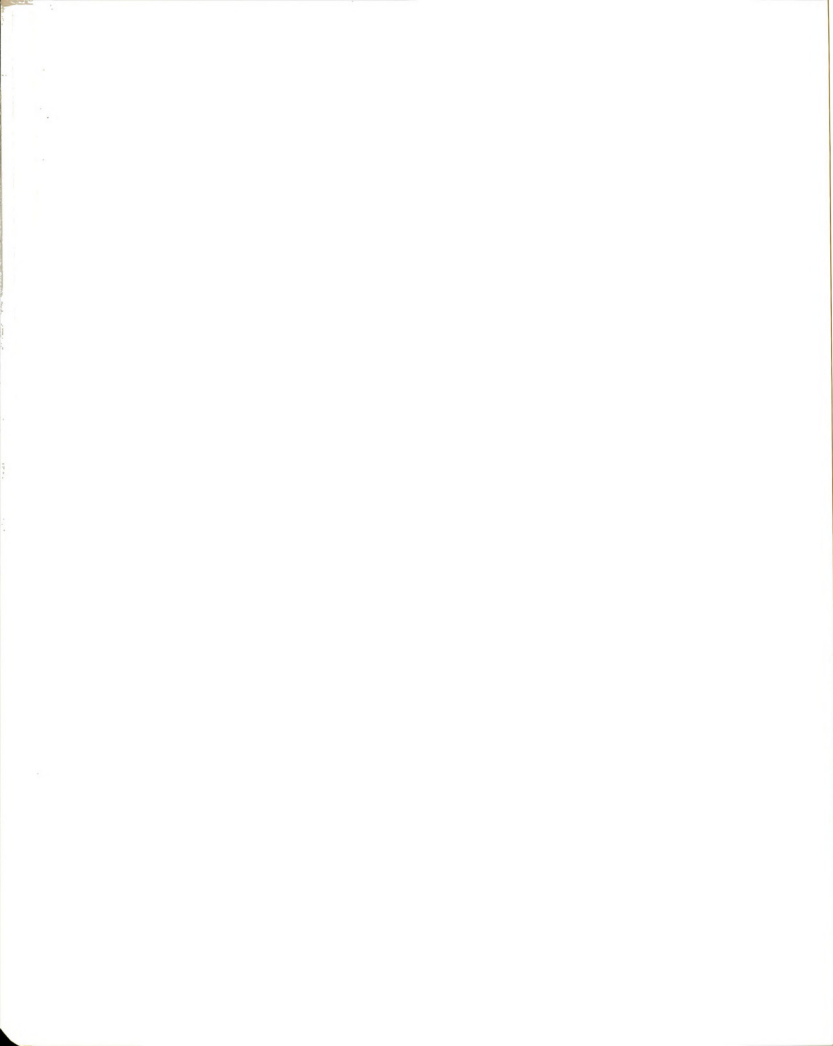
Fig. 10. (Cont'd.)



the entire back order is filled, which implies that if two separate products are back-ordered from the same original order, the order will not be released from the back-order queue until both products can be filled completely.

When the orders are generated internally, the Customer Order Processing routine calls the Demand Generation routine (PGMADS). Once the orders are created, program control returns to the ORDER event itself where these orders are actually processed.

ORDER processes all simulated customer orders for a simulation day with a single execution of the routine. Therefore, all customers, all products, and all facilities are treated at the same time. The first decision faced by the routine is the choice between external or internal order input. If the orders are to be generated internally, a call is made to the Demand Generation subroutine. (The details of the order generation process were presented in the previous discussion.) Using either option, the next step calls for reading the simulated customer orders from the order file. The simulation date on the order is then checked against the date of the simulator. If the dates do not match, Customer Order Processing is complete for that date and the ORDER event is finished. If that was not the last order on the file, then the ORDER event is rescheduled for the future simulation period automatically.



ORDER now checks the order itself to determine whether or not it is consistent with the remainder of the simulation. At this point, it checks that the customer number, facility number, and product numbers are acceptable. It also checks that the products are available at the specified facility. If any of these conditions are not met, an informative message is printed out and the order is disregarded. Although this is relatively minimal order checking, it aids in identifying some rather obvious mistakes.

The ORDER routine now begins the actual processing of the simulated orders. On an item-by-item basis, the quantity on the order is compared against the quantity on hand. When sufficient inventory is available, the full quantity is recorded as sold, and the appropriate amount is deducted from inventory on hand. The model accomplishes this mathematically through the following transformations on the status and flow variables.

$$\text{INVCUS}(\text{DC}, \text{PR}) = \text{INVCUS}(\text{DC}, \text{PR}) + \text{QTY}(\text{PR})$$

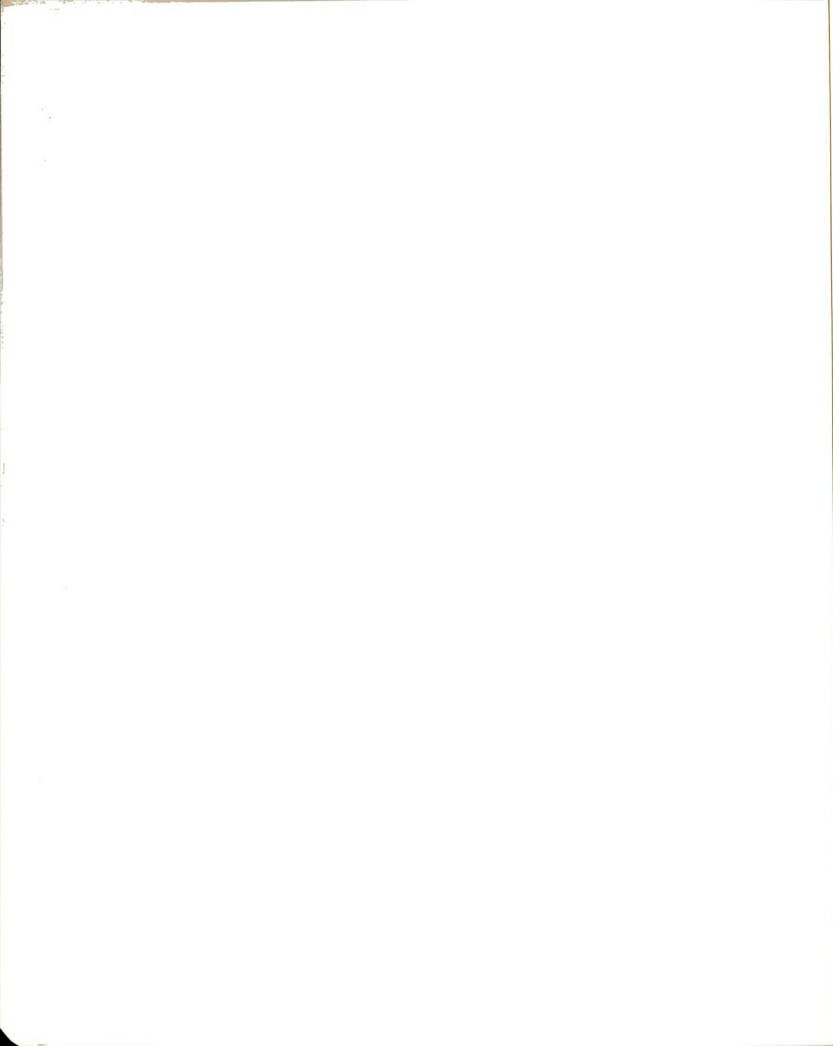
$$\text{IOH}(\text{DC}, \text{PR}) = \text{IOH}(\text{DC}, \text{PR}) - \text{QTY}(\text{PR})$$

Where:

$\text{INVCUS}(\text{DC}, \text{PR})$ = the accumulator of customer sales, in units, at DC for PR;

$\text{QTY}(\text{PR})$ = the quantity ordered for PR;

$\text{IOH}(\text{DC}, \text{PR})$ = the state variable representing inventory on hand at DC for PR.



In addition, the service measures are updated to reflect that an additional line has been filled entirely.

On the other hand, if the quantity is not available to fill the order, a different process is used to fill whatever is possible. The amount that cannot be met is recorded as a lost sale (CSTLST) or a back order depending on the alternative selected. The following transformations accomplish this process mathematically.

$$\text{INVCUS}(\text{DC}, \text{PR}) = \text{INVCUS}(\text{DC}, \text{PR}) + \text{IOH}(\text{DC}, \text{PR})$$

$$\text{BCKQTY}(\text{PR}) = \text{QTY}(\text{PR}) - \text{IOH}(\text{DC}, \text{PR})$$

$$\text{IOH}(\text{DC}, \text{PR}) = 0$$

Where:

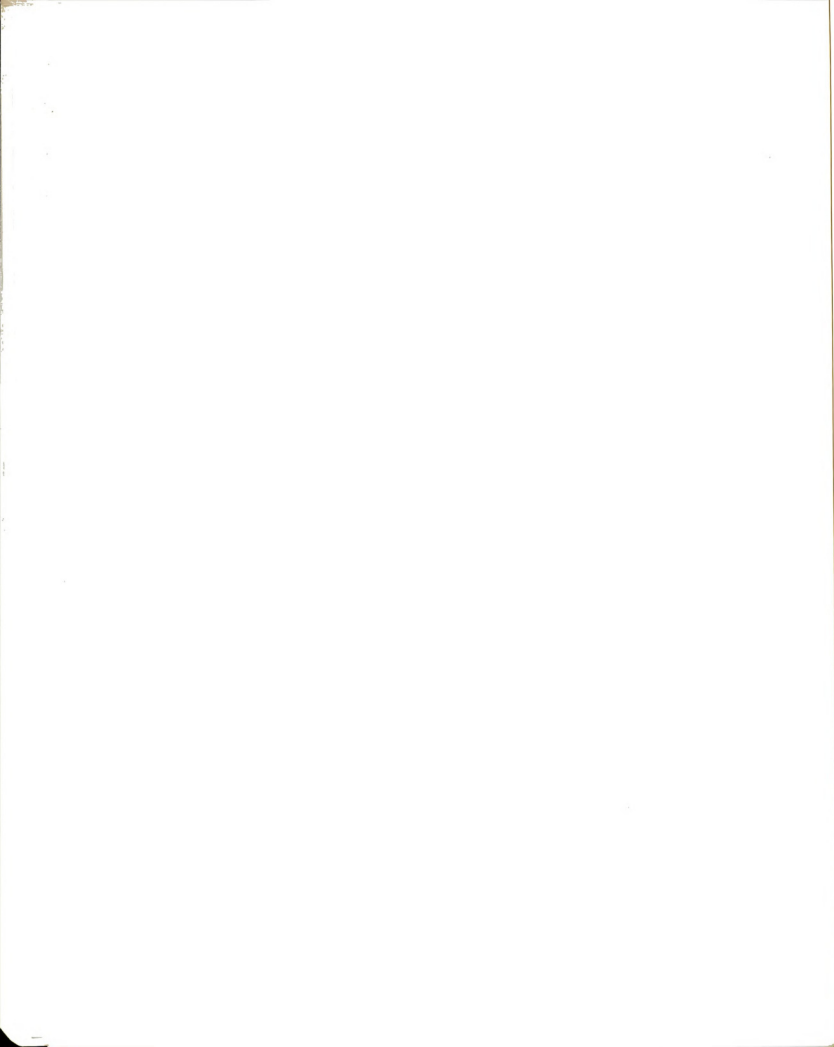
$\text{INVCUS}(\text{DC}, \text{PR})$ = the accumulator of customer sales at DC for PR;

$\text{BCKQTY}(\text{PR})$ = the quantity to be back ordered or stocked out for PR;

$\text{IOH}(\text{DC}, \text{PR})$ = the state variable representing inventory on hand at DC for PR.

The service accumulators are also updated to reflect partial fulfillment of a line.

When all items on an order have been processed, a check is made to determine whether or not a back order must be generated. If not, the processing advances to the summary processing functions. When a back order is necessary, the individual items are assembled into a complete back order which is then stored in the parameter storage array via the



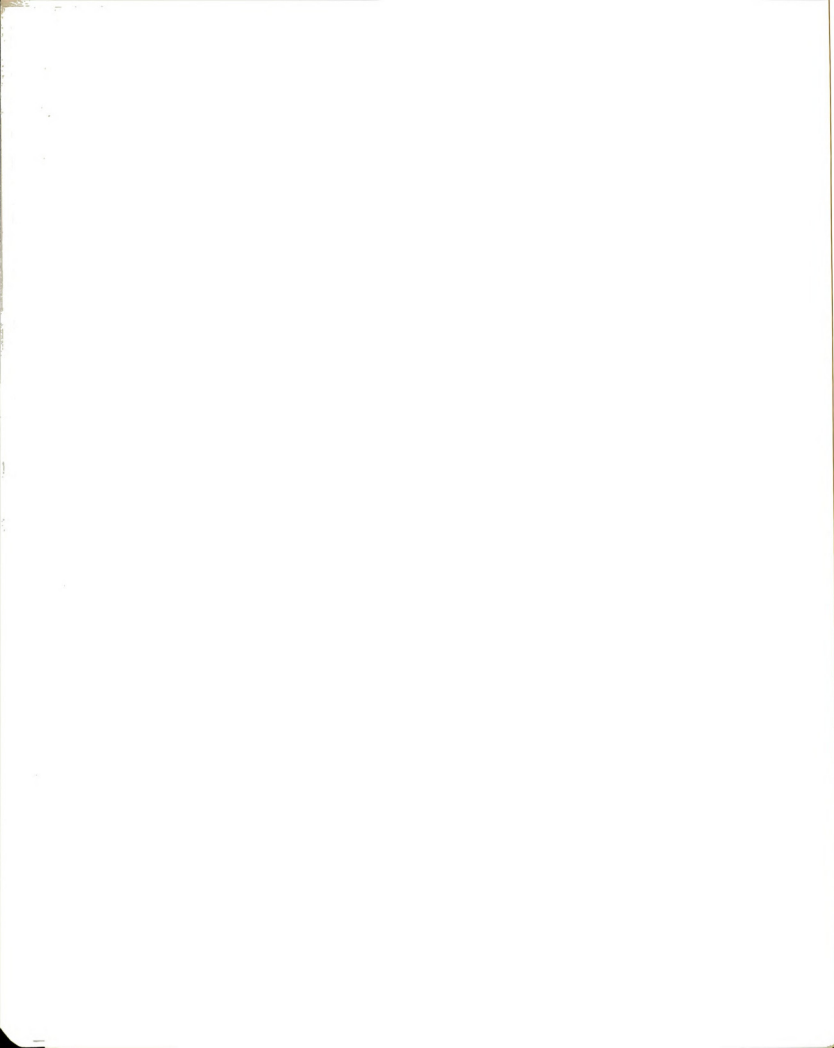
FILLIT routine. The address for the back order is stored in a First-In, First-Out (FIFO) linked list at the appropriate facility.

The summary processing functions accumulate and record the measurements of sales and service based on the order as a whole rather than by the individual lines. The measures include a record of the ability to fill the entire order as well as the aggregate sales statistics such as total dollars, weight, and cases sold. Following this step, the routine returns to the beginning to start the process again for another simulated order. Figure 11 summarizes the procedure.

Bleed-Off Event

The Bleed-Off event provides the mechanism to create and approximate the demand of customers that are not the subject of detailed analysis. This event may be scheduled at any facility to draw off the inventory from the facility so that the actual volume of the location may be modeled realistically.

Demand Bleed-Off is used in conjunction with the Customer Order Processing event to provide the demand for the simulator. The primary difference between the two mechanisms lies in the fact that the Bleed-Off event uses and maintains much less detail. In this case, only a series



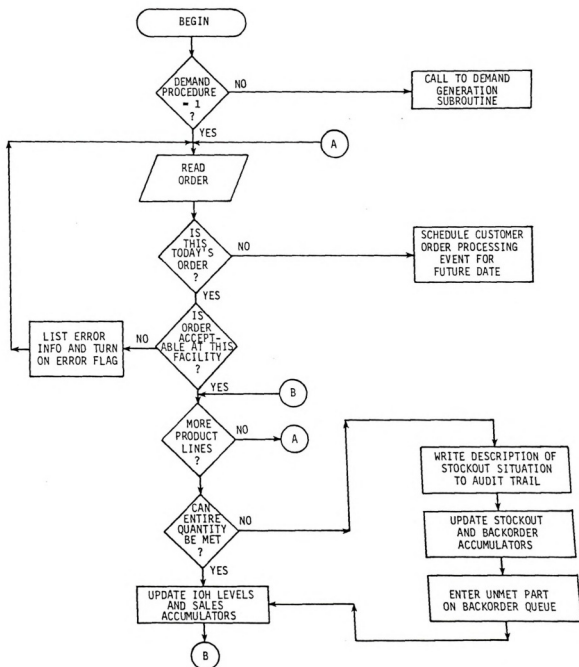
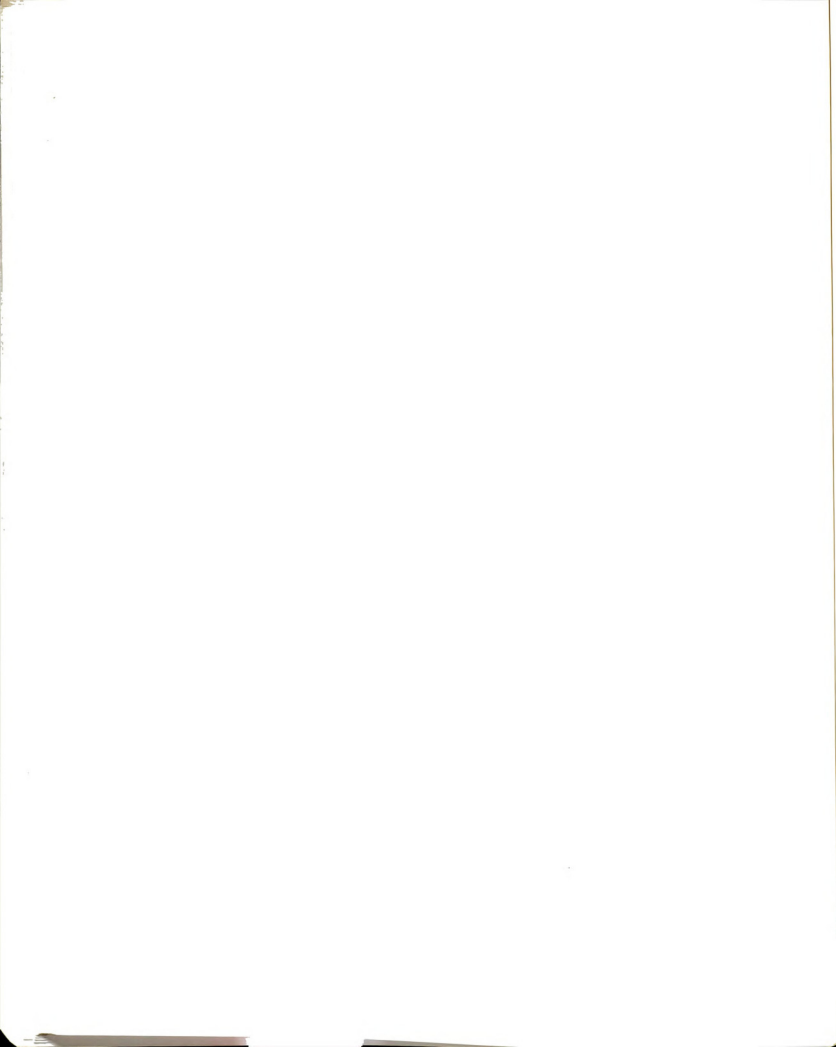


Fig. 11. Customer Order Processing Event Flow Diagram



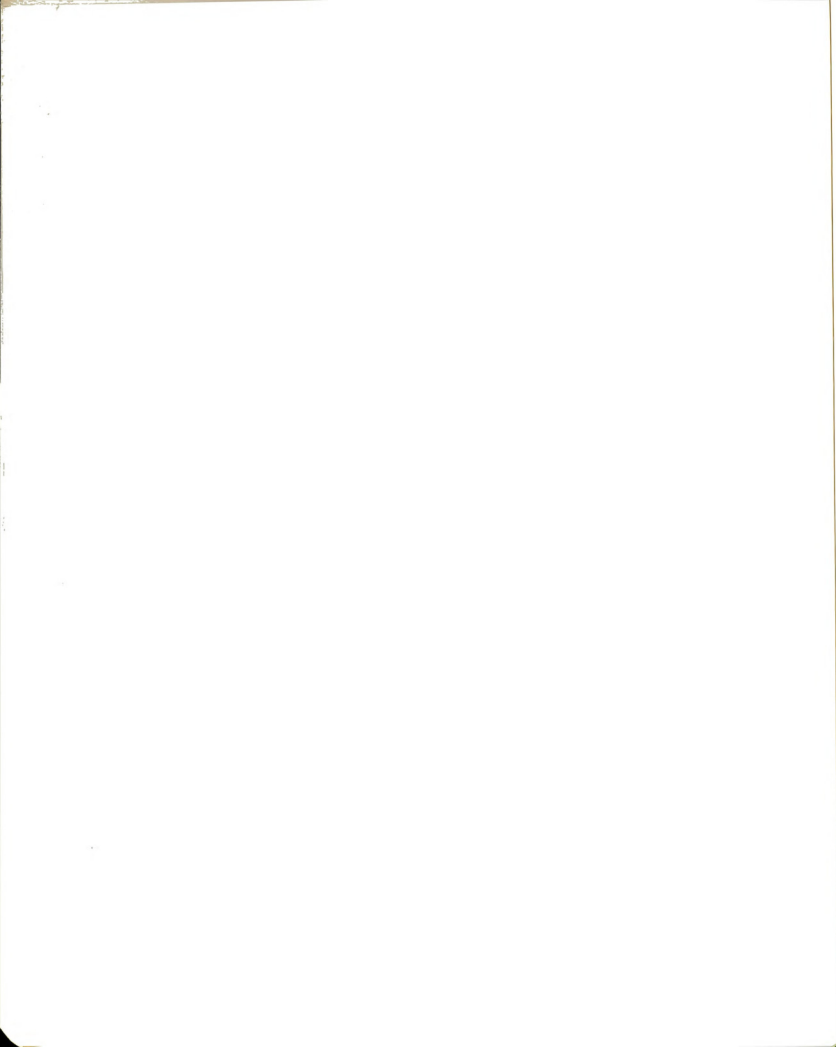
of aggregate volumes are placed against the facility with no attempt being made to assemble them into orders.

The demand that is faced due to the Bleed-Off event is also processed differently in the sense that it is accounted for using separate accumulators. Both sales and out-of-stocks are identified. No back orders are maintained for Bleed-Off demand. However, the event does allow partial order fills.

The event logic provides for Bleed-Off demand to be created for only one facility-product combination during each performance of the event. This implies that the event must be scheduled many times to approximate demand for more than one facility and product.

The first step of the Demand Bleed-Off process determines the number of lines or simulated single-line "orders" that will be generated during the period. This uses the normal random number generator with mean, standard deviation, and skew parameters. Once the line count has been established, the routine initiates a loop which is executed once for each simulated line. A simulated quantity is developed using the normal random number generator with a different set of mean, standard deviation, and skew parameters.

Once the quantity is stochastically generated, it is compared against the current inventory level. If enough



inventory is available, the entire quantity is met and recorded as bleed-off sales. The count in units is maintained by product as well as by facility but the dollar, weight, and cube accumulators are maintained only by facility. The quantity sold is then subtracted from available inventory. The following computations demonstrate these concepts mathematically.

$$\text{INVDEM}(\text{DC}, \text{PR}) = \text{INVDEM}(\text{DC}, \text{PR}) + \text{QTY}(\text{PR})$$

$$\text{IOH}(\text{DC}, \text{PR}) = \text{IOH}(\text{DC}, \text{PR}) - \text{QTY}(\text{PR})$$

Where:

$\text{INVDEM}(\text{DC}, \text{PR})$ = the unit sales through the
Bleed-Off event at DC for PR;

$\text{QTY}(\text{PR})$ = the quantity demanded for
this line;

$\text{IOH}(\text{DC}, \text{PR})$ = the current inventory on hand
at DC for PR.

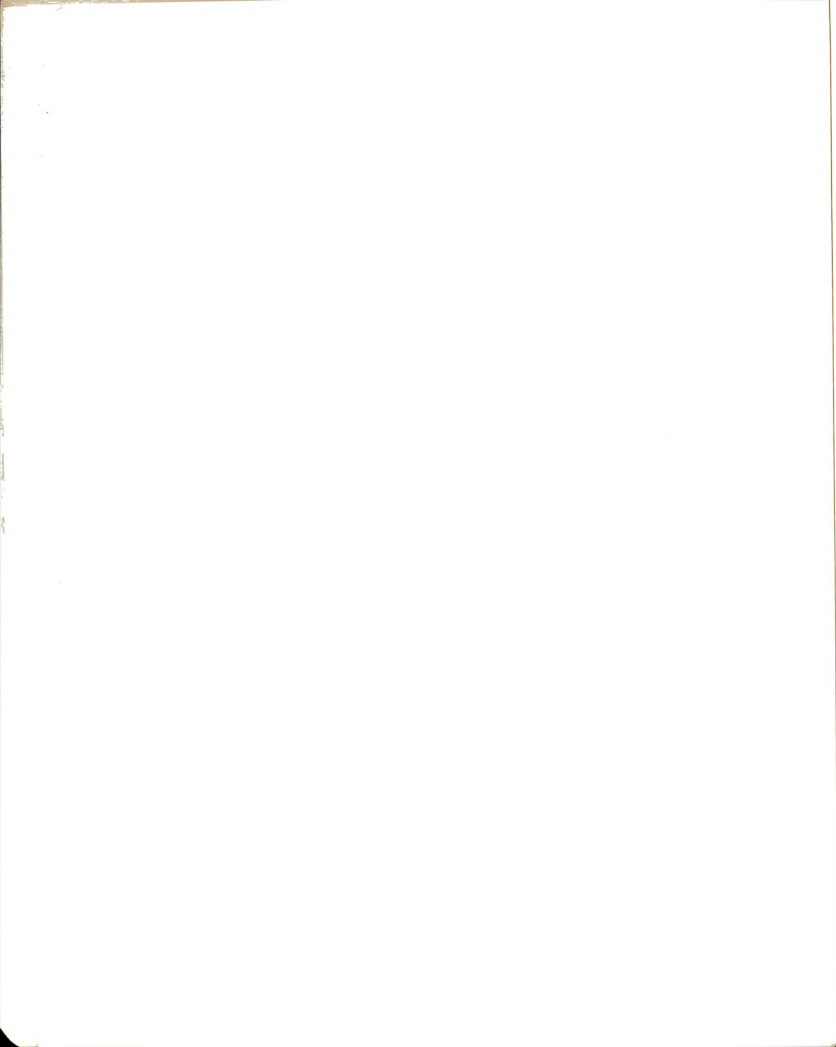
When the demand cannot be met completely, the available inventory is used to fill as much as possible, with the remainder counted as out-of-stock. The following formulations are used to approximate this process.

$$\text{QTY}(\text{PR}) = \text{QTY}(\text{PR}) - \text{IOH}(\text{DC}, \text{PR})$$

$$\text{STKOTD}(\text{DC}, \text{PR}) = \text{STKOTD}(\text{DC}, \text{PR}) + \text{QTY}(\text{PR})$$

$$\text{INVDEM}(\text{DC}, \text{PR}) = \text{INVDEM}(\text{DC}, \text{PR}) + \text{IOH}(\text{DC}, \text{PR})$$

$$\text{IOH}(\text{DC}, \text{PR}) = 0$$



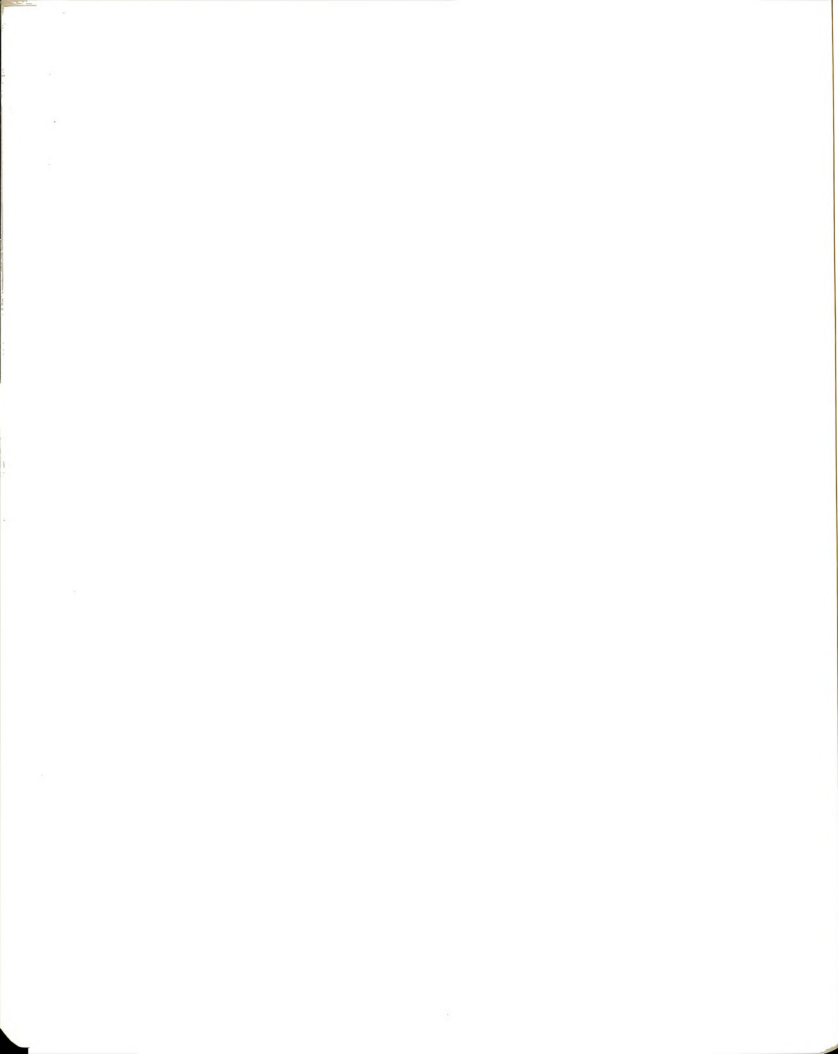
Where:

- QTY(PR) = the quantity demanded for PR;
- IOH(DC,PR) = the quantity of currently
available inventory at DC for PR;
- STKOTD(DC,PR) = the accumulator for Bleed-Off
Demand stockouts at DC for PR;
- INVDEM(DC,PR) = the unit sales through the
Bleed-Off event at DC for PR.

Once the quantity generation and processing is completed for one simulated line, the procedure is repeated for the remaining lines. When all lines have been generated and processed, the event may be rescheduled to occur at some future time. Figure 12 presents the flow of the Bleed-Off event.

Inventory Management

The Inventory Management event, INVMGT, performs the measurement accumulations for the simulator and initiates replenishment order processing. INVMGT might be termed the housekeeping event since it accomplishes many of the necessary daily data maintenance tasks. The event must be scheduled initially by the user for the first simulation period. INVMGT then automatically reschedules itself for as long as the simulation is to run. The event is designed so the operations occur at each of the facilities for every product during each simulation period. Thus, only one INVMGT scheduling card is required for each run.



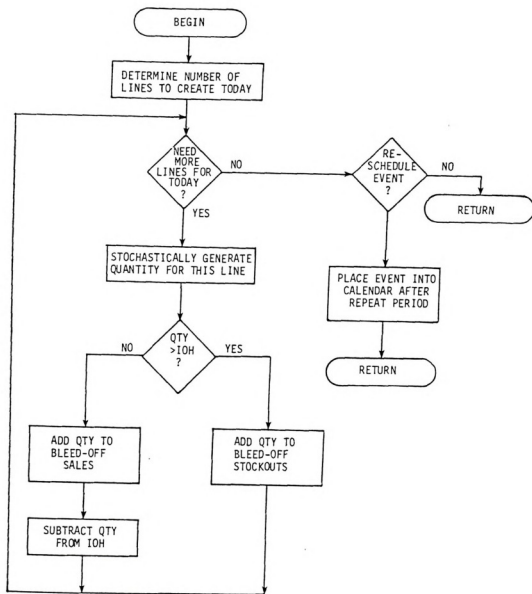
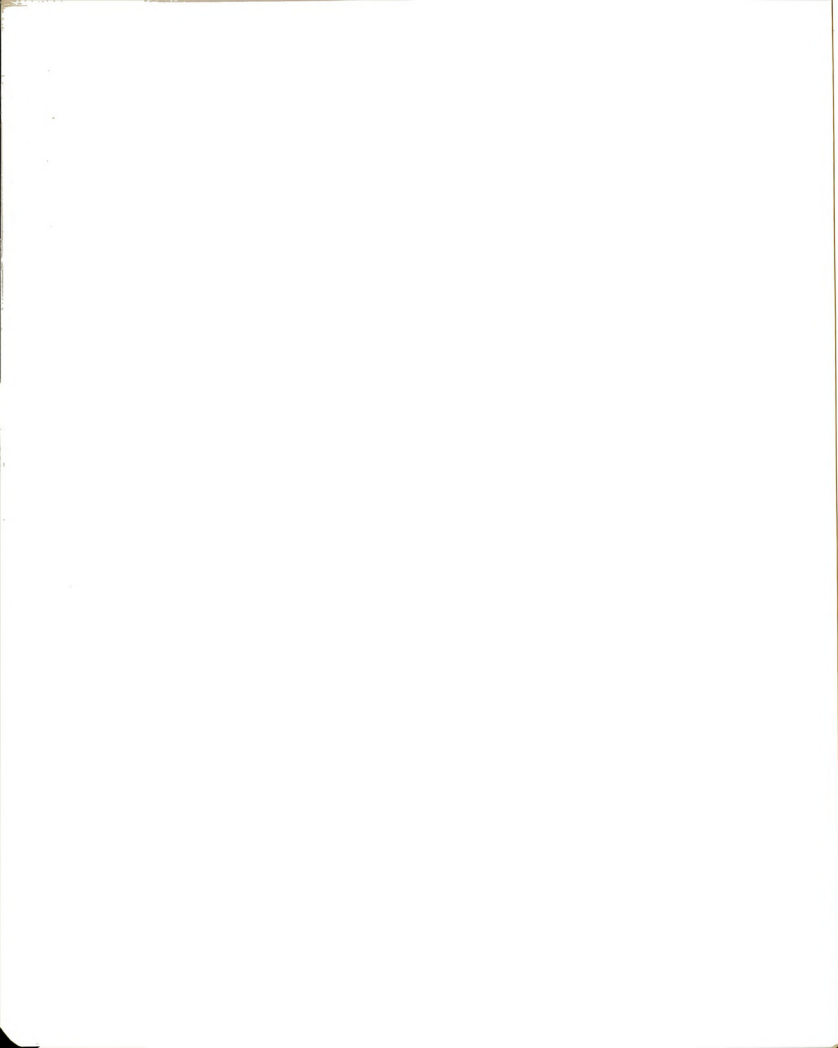


Fig. 12. Bleed-Off Event Flow Diagram

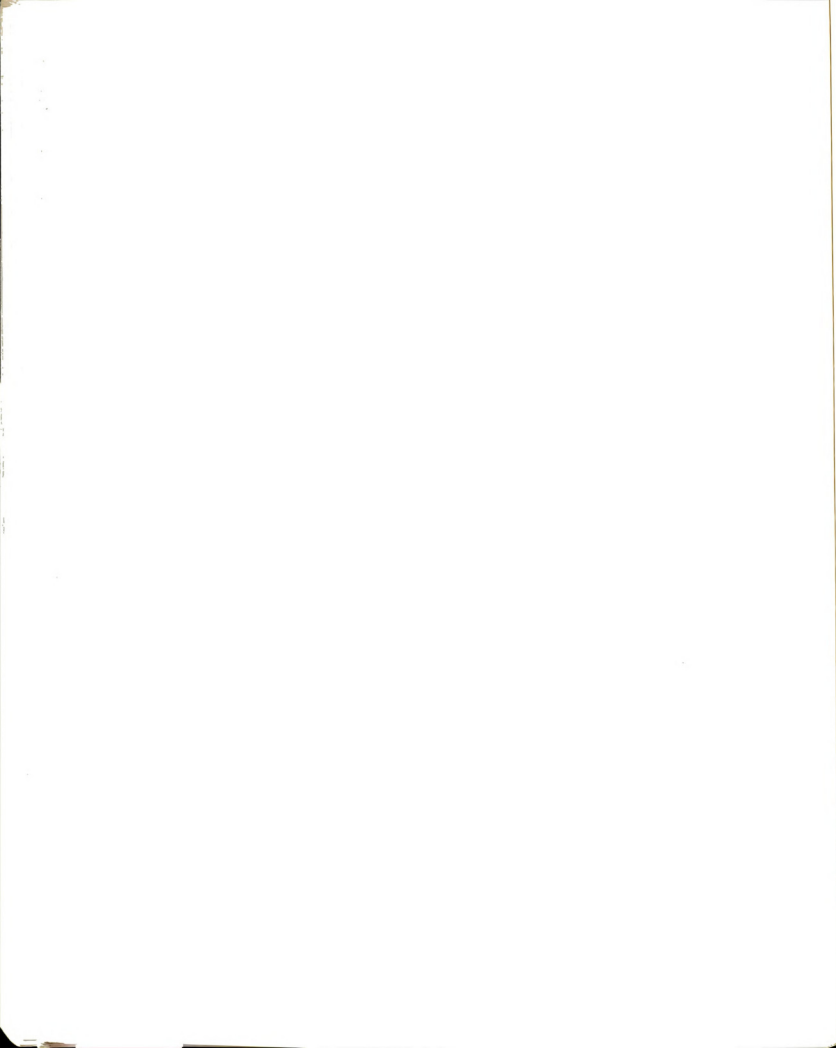


The first function performed by the event is the accumulation of daily inventory on hand so that time integration may be used to provide an accurate estimate of average inventory. The second function of the event, performed on a periodic basis only, is inventory review for replenishment order initiation. The user must specify a review period for each facility. A one-day review period corresponds to a perpetual review system while a longer review period corresponds to a periodic review system. When the review period is specified as longer than a single day, the inventory review function of the event is executed only every "review" simulation days.

As part of the review process, replenishment quantities are computed when necessary. These quantities are then grouped together to form orders which can then be communicated to the appropriate source. A replenishment order is "sent" when INVMGT schedules the Replenishment Order Processing event to occur at the supplier.

INVMGT uses two loops to accomplish its functions. The primary loop evaluates the facilities while the secondary one checks the individual products at each facility. In both cases, a check is performed initially to determine whether or not the facility or facility-product combination is active.

The first segment of the routine flow performs the inventory accumulation process. The process for average



inventory computation is demonstrated through the following formulations.

$$\text{IOHOT}(\text{DC}, \text{PR}) = \text{IOHOT}(\text{DC}, \text{PR}) + \text{IOH}(\text{DC}, \text{PR})$$

Where:

$\text{IOHOT}(\text{DC}, \text{PR})$ = the summation of inventory on hand over time for the DC, PR combination;

$\text{IOH}(\text{DC}, \text{PR})$ = the current inventory on hand at DC for PR.

At the same time, the number of periods must be accumulated for use when computing the averages. This is accomplished as follows:

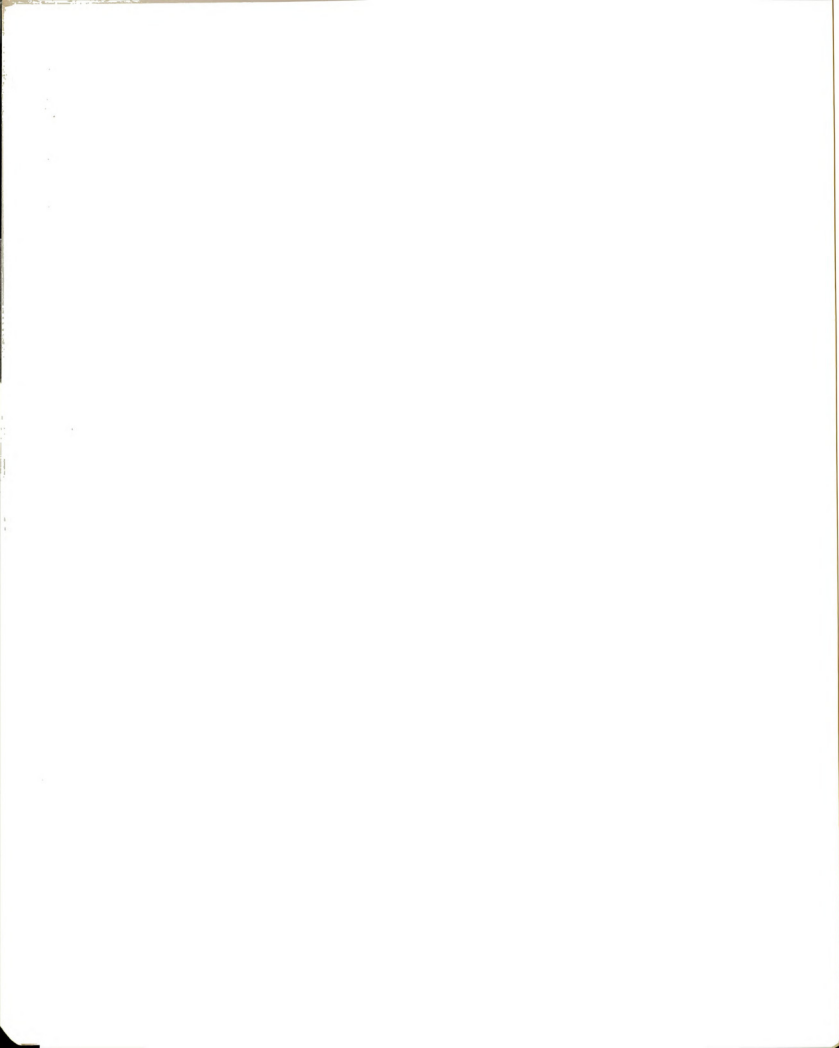
$$\text{NPD} = \text{NPD} + 1$$

Where:

NPD = the accumulation of the number of periods.

Although the next step does not occur within the INVMGT routine, logically it should be presented here for continuity. The actual computations are performed by the Report event; however, the computations are based on the accumulations performed in this routine. The following computation develops the time integrated measure of average inventory.

$$\text{AVGINV}(\text{DC}, \text{PR}) = \text{IOHOT}(\text{DC}, \text{PR}) / \text{NPD}$$



Where:

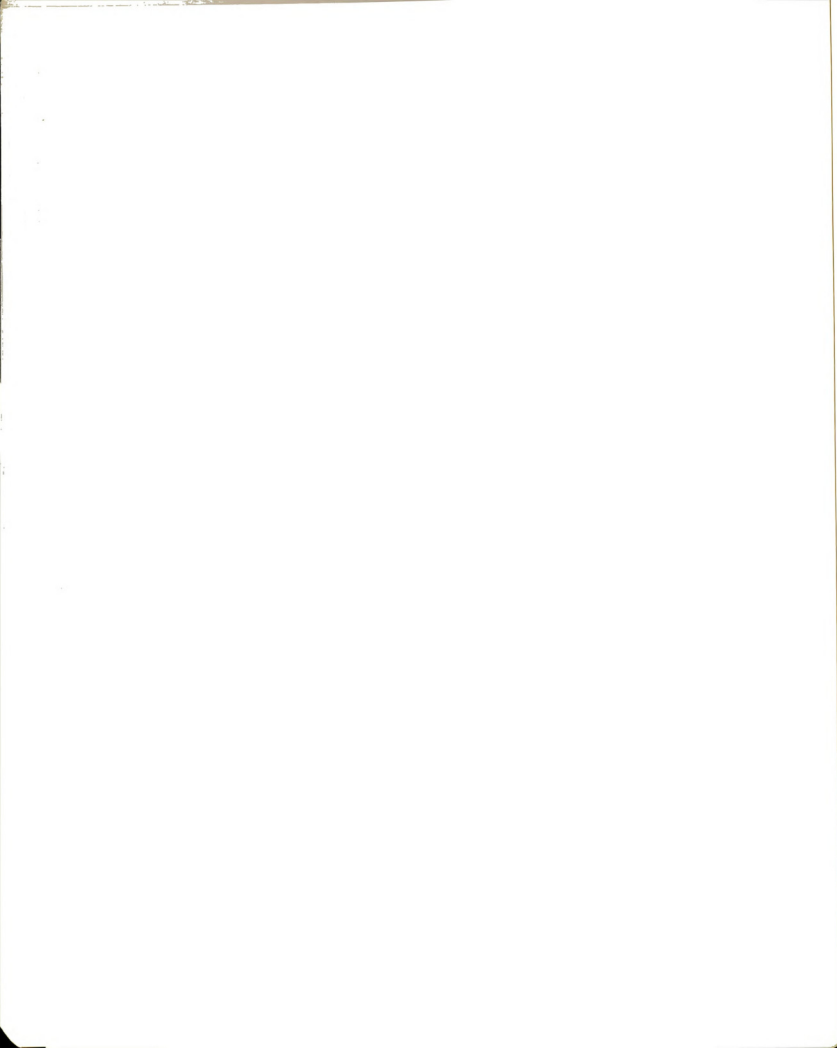
AVGINV(DC,PR) = the average level of inventory over the past accumulation period for the DC,PR combination;

IOHOT(DC,PR) = the summation of inventory on hand over time for the DC,PR combination;

NPD = the accumulation of the number of operating periods.

The next phase of the INVMGT event checks inventory levels and initiates replenishment orders from predefined sources. The first step in this process determines whether or not this simulation day is a review period by dividing the simulation time variable TNOW by the length of the review period. If the remainder is non-zero, then no review process is performed. If the current day is accepted as a review day, the routine initiates a loop to review each product.

For each product, the current inventory level is compared against the reorder point (ROP) or minimum level. The inventory level reflects the current inventory situation incorporating inventory on hand, back-order quantities, and replenishment order quantities. Whenever the level is below minimum, a reorder quantity is determined and a replenishment order generated. Two options are available for determining the quantities: a fixed reorder quantity or a variable quantity. When the fixed quantity is desired, the



Order Quantity (OQ) is specified on the input parameters as a set number of units or days of stock. If days of stock are specified, the Demand Forecasting event converts the value into units based on current forecasted sales. The mathematical formulation for the fixed order quantity option is as follows:

If: $IOH(DC,PR) - BO(DC,PR) + ROQ(DC,PR) < ROP(DC,PR)$

Then: $OQ(DC,PR) = EOQ(DC,PR)$

Where:

$IOH(DC,PR)$ = the current inventory on hand
at DC for PR;

$BO(DC,PR)$ = the quantity that is currently
on back order at DC for PR;

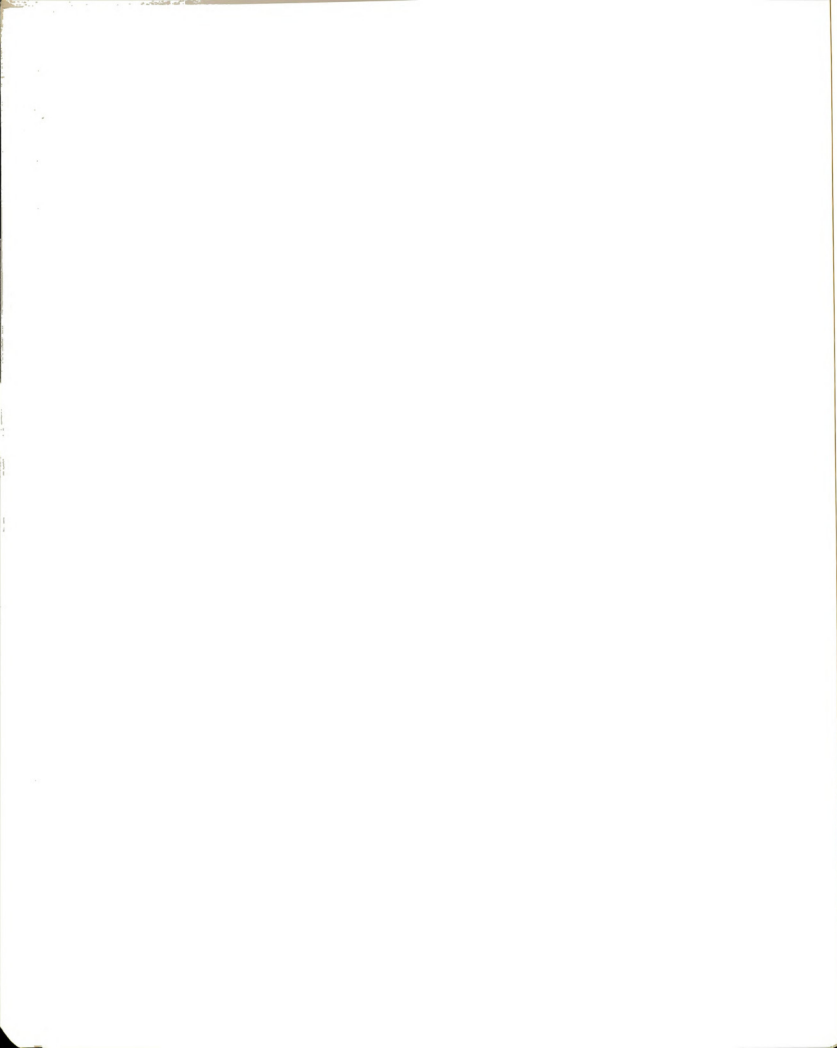
$ROQ(DC,PR)$ = any quantity that is currently
on order but has not yet arrived;

$ROP(DC,PR)$ = the reorder point or minimum
level at DC for PR;

$OQ(DC,PR)$ = the quantity to be reordered for
the DC and PR combination;

$EOQ(DC,PR)$ = the fixed order quantity that may
be based on the forecast for this
DC and PR combination.

When the other inventory option using a variable order quantity is desired, the maximum must also be specified via the inventory parameters. This level may be specified as either an absolute quantity or as the number of days of stock, which can then be converted to units via the Demand



Forecasting event. When a replenishment order is required, the difference between the current inventory level and the maximum is used as the order quantity. Note that the current inventory level reflects the back-order and on-order quantities as well as the inventory on hand. The mathematical formulation for this process follows.

If: $IOH(DC,PR) - BO(DC,PR) + ROQ(DC,PR) < ROP(DC,PR)$

Then: $OQ(DC,PR) = EOQ(DC,PR) + BO(DC,PR) - IOH(DC,PR)$
 $- ROQ(DC,PR)$

Where:

$IOH(DC,PR)$ = the current inventory on hand at DC for PR;

$BO(DC,PR)$ = the quantity that is currently on back order at DC for PR;

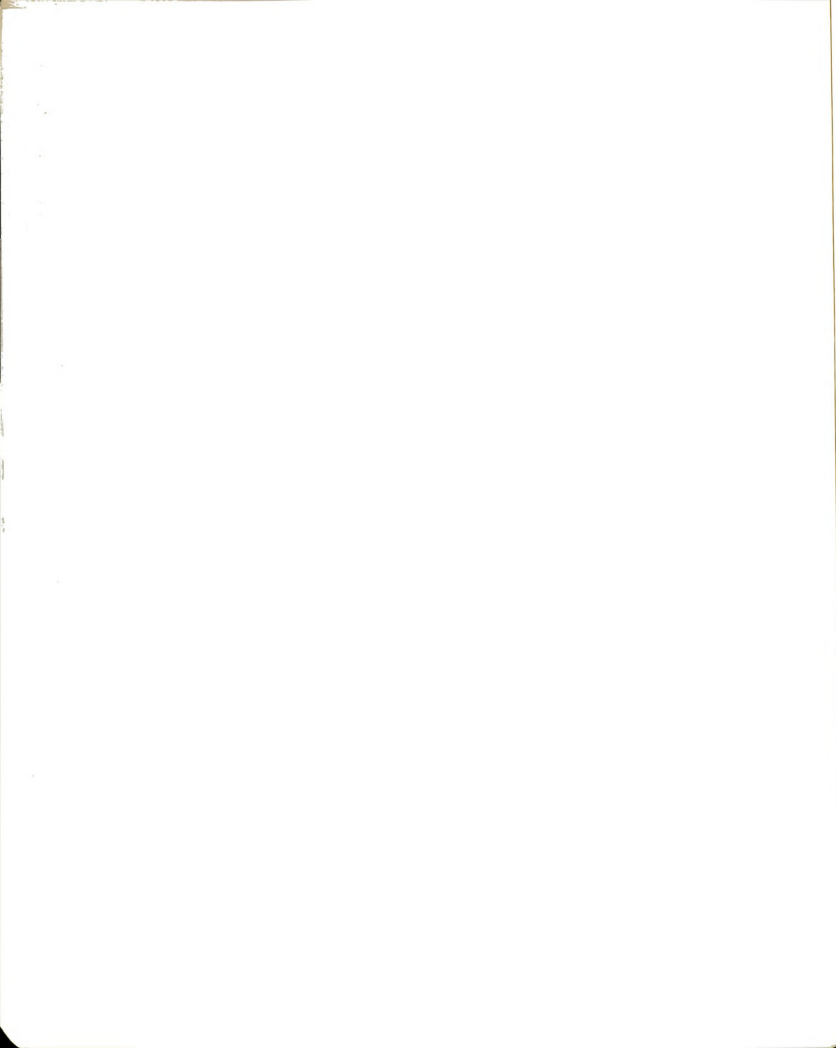
$ROQ(DC,PR)$ = any quantity that is currently on order but has not yet arrived;

$ROP(DC,PR)$ = the minimum level to reorder at DC for PR;

$OQ(DC,PR)$ = the quantity to be reordered for the DC and PR combination;

$EOQ(DC,PR)$ = the maximum level to be used in generating the order quantity.

Once the replenishment quantity has been determined for each product, the individual products are assembled into orders which can then be submitted to the appropriate sourcing location. Following the assembling of orders, a replenishment order communication time is generated. The

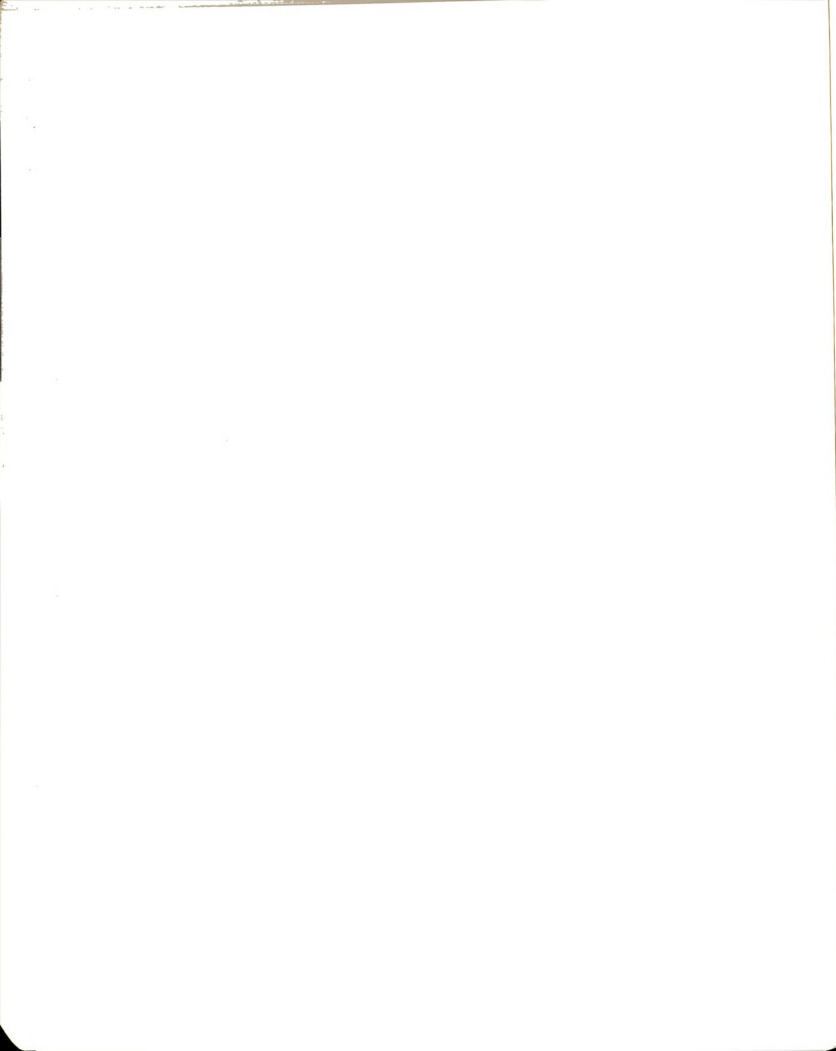


model uses a Monte Carlo simulation technique for stochastic time generation. This method uses a five-point cumulative probability density function along with a corresponding list of possible communication times. The cumulative probability function is defined as follows:

$$0 \leq P(1) \leq P(2) \leq P(3) \leq P(4) \leq P(5) = 1.$$

The list of communication times can be any list of times which reflects the same temporal increments used for the remainder of the simulation. In other words, if the simulation is being run in daily increments, then the communication times should be in daily increments also. To select a stochastic communication time for a particular order, a random number R is generated using a uniform random number generator. The value of R is compared against the value of P_i for $i = 1, 5$. When $R \leq P_i$, the time t_i is used as the communication time for this order.

The final step of the order initiation process is scheduling the receipt of the order at the product source facility. This is accomplished by placing the order parameters in the storage array while scheduling a Replenishment Order Processing event to occur after the communication time has elapsed. The same process is followed for other orders initiated by the location under process.

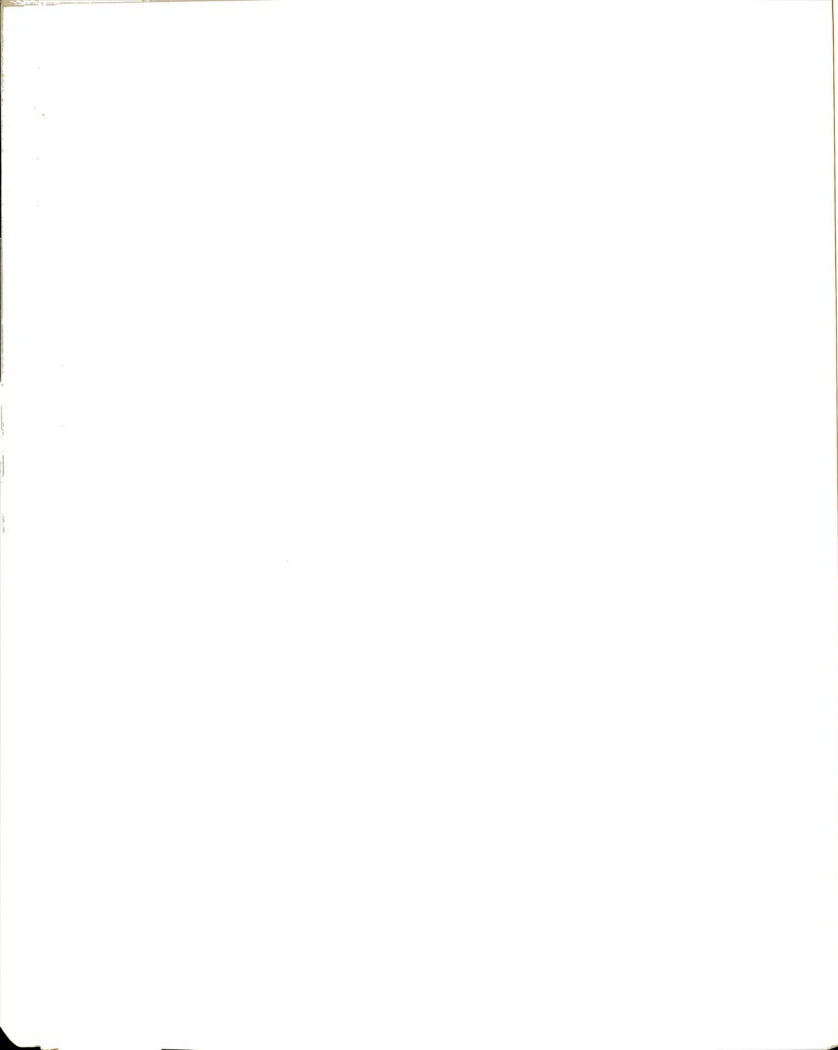


Once the individual location has been processed, the event goes to the next facility sequentially and performs the inventory accumulation and order initiation process again. When this procedure has been completed at all active facilities, the Inventory Management event is automatically rescheduled for the following simulation day. This process is shown in Figure 13.

Production

The Production event (PROD) provides the mechanism to replace or build up stock within the system. This must be done to maintain the material balance of the system.

Two mechanisms are available for introducing new stock into the system. The first utilizes the "infinite inventory" option which is available only at production facilities. With this option, quantities are "instantly" produced at this facility whenever they are demanded so that the stock level at these facilities never changes. This also implies that no stockouts or back orders can ever occur for items using the "infinite inventory" option. Non-produced items at the facility, however, may experience stockouts. The "infinite inventory" option is appropriate when it is not necessary or desirable to simulate the production process, and assumes that the physical distribution component of the system is independent of the production

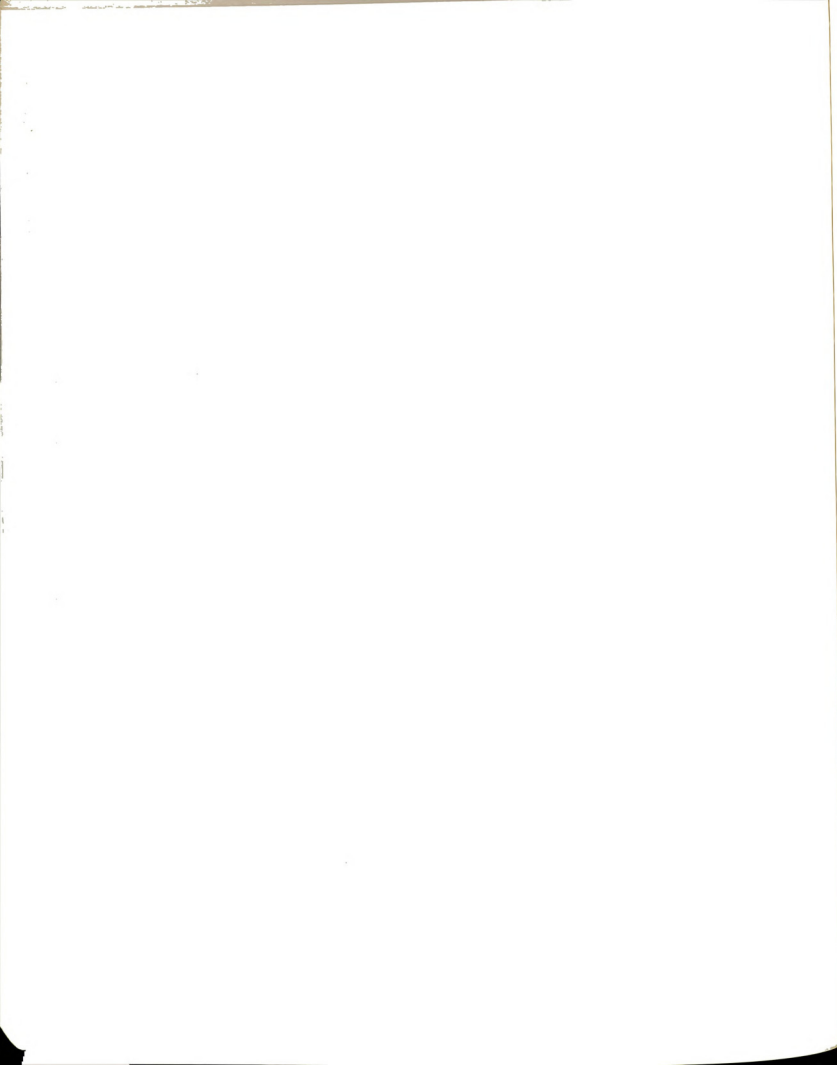


component. Although this may not be very realistic, it simplifies the modeling process since it is not necessary to synchronize the patterns of production with those of a lagged demand. When the "infinite inventory" option is desired, no Production event is required.

When the assumptions necessary for use of the "infinite inventory" are not acceptable, the model allows the use of the Production event which can simulate the actual production process. A list of products may be specified each time the event is scheduled along with the production option to be used for each product. The available options include: (1) produce to an externally specified fixed quantity, (2) produce to fill back orders, (3) produce to a fixed quantity which is dependent on the forecast, and (4) produce to a variable quantity which is dependent on the forecast and the current inventory position. Options three and four correspond to the two Inventory Management options. For example, the order quantity variables become the fixed or "build up to" production levels when the item is produced at the facility. Keeping dual utilization of variables in mind, the four production options can be stated mathematically as follows.

OPTION 1: Externally Specified Fixed Quantity

$$QTY = INQTY(PR)$$



Where:

QTY = the amount that the event
will cause to be produced
today;

INQTY(PR) = the quantity that is specified
on the event parameter card
for PR.

OPTION 2: Build to Order

QTY = BCKORQ(DC,PR)

Where:

QTY = the amount that the event will
cause to be produced today;

BCKORQ(DC,PR) = the quantity that is currently
on back order at DC for PR.

OPTION 3: Fixed Quantity Based on Forecast

QTY = OQ(DC,PR)

Where:

QTY = the amount that the event
will cause to be produced
today;

OQ(DC,PR) = the level in units that is
the fixed production quantity.

OPTION 4: Variable Production Quantity

QTY = OQ(DC,PR) - IOH(DC,PR) - ROQ(DC,PR) + BCKORQ(DC,PR)

Where:

QTY = the amount that the event
will cause to be produced
today;

OQ(DC,PR) = the maximum level to produce
up to;

$IOH(DC,PR)$ = the current level of inventory on hand at DC for PR;

$ROQ(DC,PR)$ = the amount that may be on order in addition to the production at DC for PR;

$BCKORQ(DC,PR)$ = the amount of PR that is currently on back order at DC.

The Production event may be scheduled initially at any time during the simulation. In addition, a repetition cycle may be specified to cause the event to occur weekly, monthly, or at any other appropriate cyclic period. If a zero cycle is specified, the event is not rescheduled. The Production event checks the back-order queue and schedules a Check Back Orders event if it is necessary. Figure 14 presents a complete diagram of the production process.

Replenishment Order Processing

Replenishment Order Processing (REORD) simulates the receipt and initial processing which occurs at the source for replenishment shipments. The primary functions of this event include generation of stochastic order processing times and the accumulation of order communication (T1) and order processing (T2) times. Unlike all prior events, the REORD event is not scheduled by the modeler. This event is scheduled only by the INVMGT event.

Generation of the order processing time is accomplished via the same Monte Carlo simulation process used in

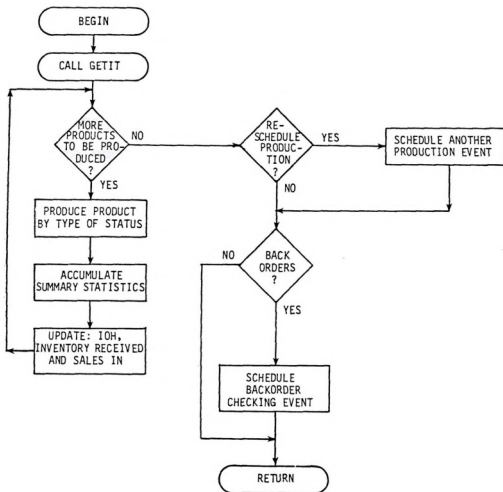
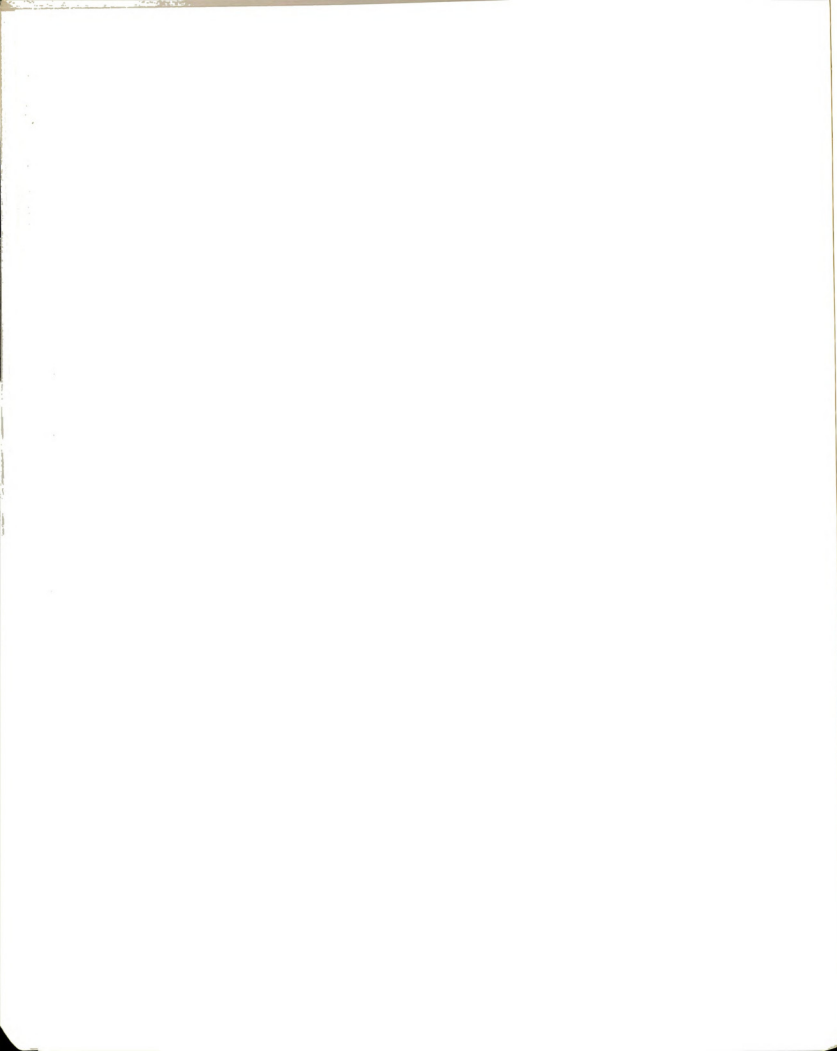
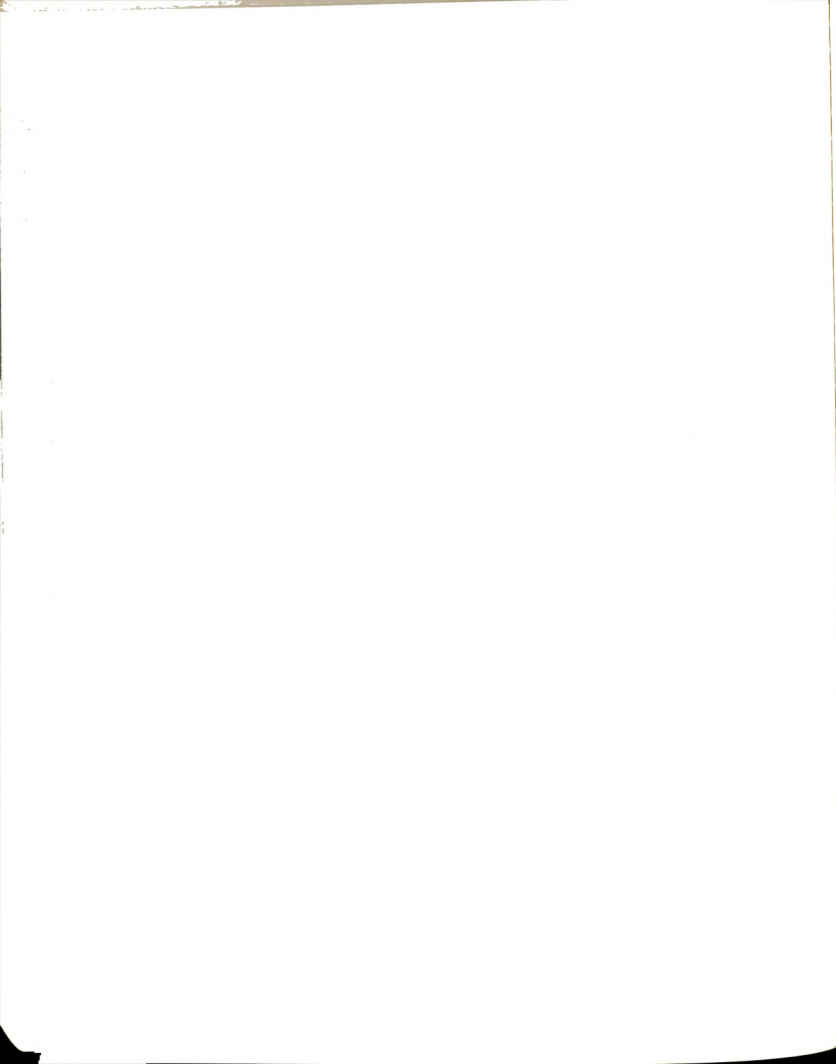


Fig. 14. Production Event Flow Diagram



creating the communication time. Once the processing time has been generated, the sums and sum-of-squares are accumulated for the communication and processing times. A count of the number of orders that have been processed is also maintained. These data are used to compute the mean and standard deviations for the individual cycle time components in the Report event.

The Replenishment Order Processing event initiates processing for a single order. The event flow follows from beginning to end with no loops for products, facilities, orders. The first action taken by the event calls for retrieval of order parameters from the storage array. Once this is accomplished, these appropriate processing parameters, along with a Monte Carlo process, generate the order processing time that will be used for this order. The next segment of the event accumulates the statistics for reporting the average and standard deviation of order communication and order processing times. The final process of the REORD event schedules the Replenishment Order Picking to occur after the assigned order processing time has elapsed. This phase includes storage of the parameters and entry of the event attributes into the schedule. This concludes the processing of a single order and control of the simulation is returned to the executive routines. Figure 15 presents a flow diagram of the Replenishment Order Processing event.



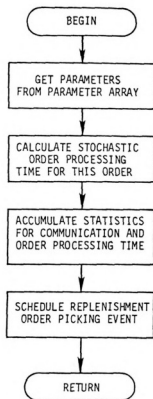
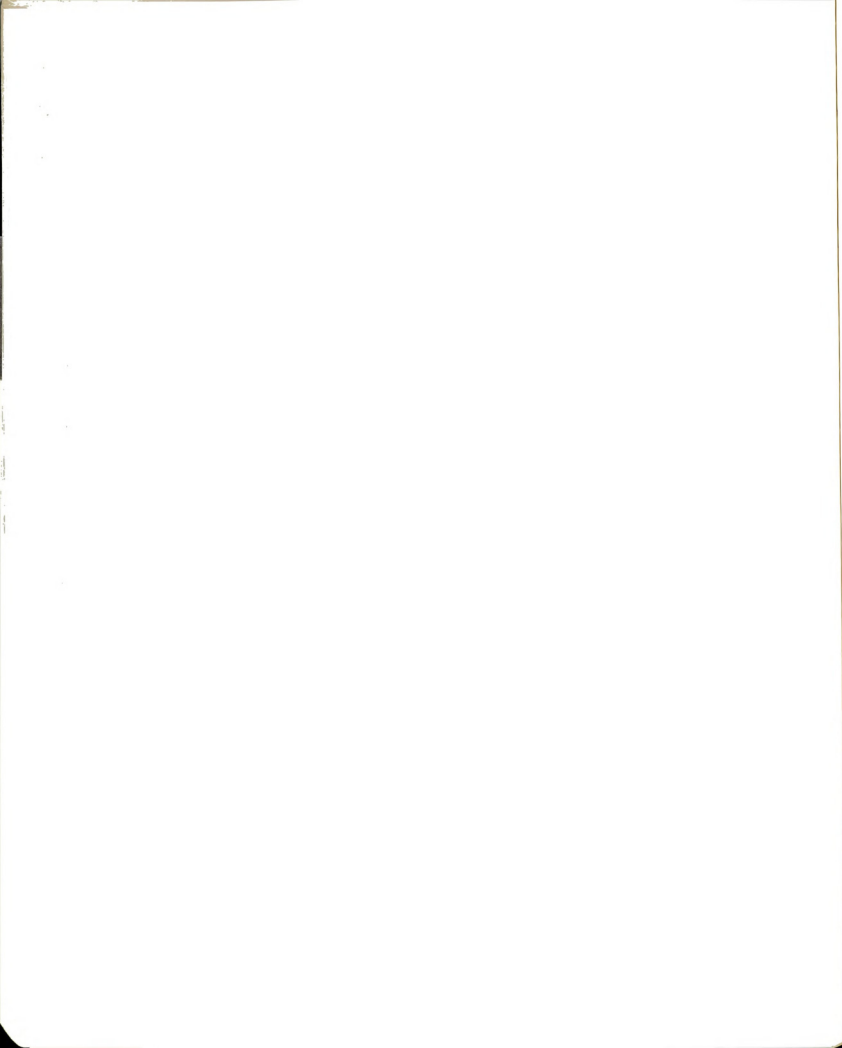


Fig. 15. Replenishment Order Processing Event Flow Diagram



Replenishment Order Picking

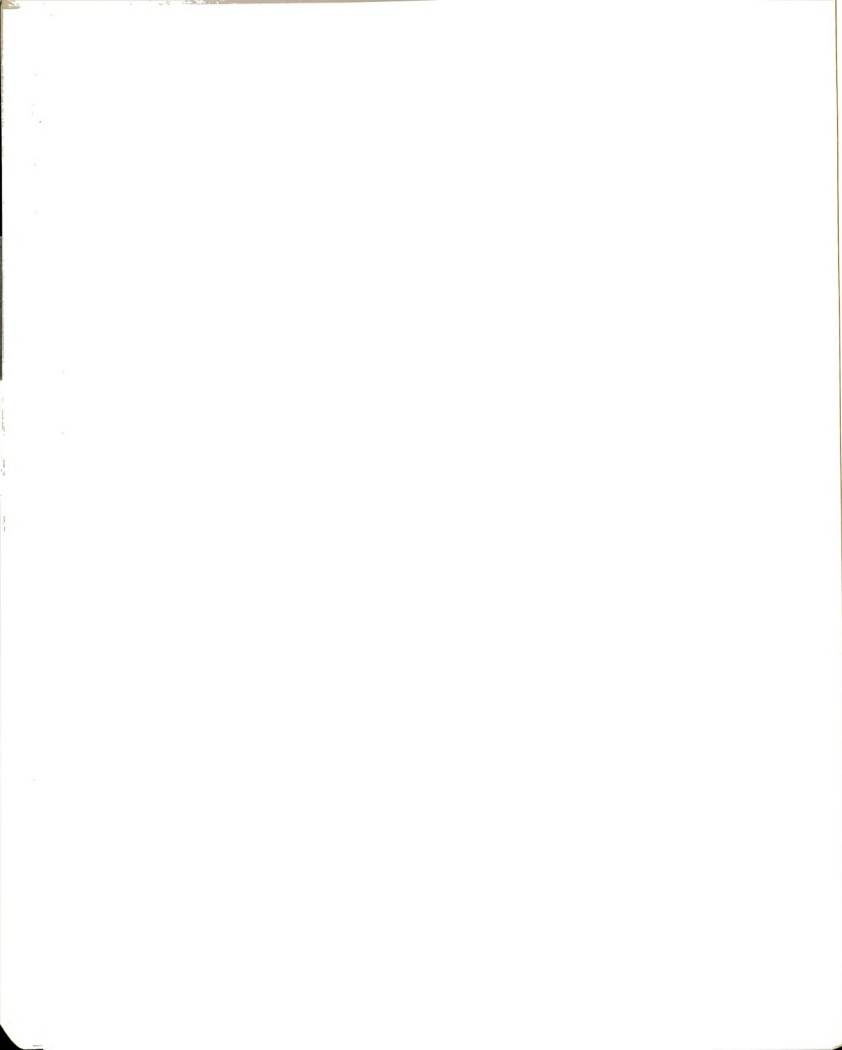
The Replenishment Order Picking event (ORDPR) simulates actual picking and shipping of replenishment orders from suppliers. After the elapsed time allocated for replenishment order processing has elapsed, ORDPR compares the order quantities against available inventory, deducts shipments from inventory, creates back orders, and initiates shipments. This entire process is performed for a single order with each occurrence of the event. The order is examined on a line-by-line basis to determine whether or not enough stock is available to meet order needs. When the quantity can be met, the order segment is filled and processing continues with the next line. If the entire quantity cannot be met, the amount available is picked while the remainder is back-ordered. Replenishment orders are never stocked out; they are always back-ordered. The mathematical formulation of this process is identical to that of the Customer Order Processing event, with the exception that stockouts are not allowed.

Once the order has been picked, the shipping weight of the order is computed. On the basis of the weight, the shipment is assigned to a weight break. Once the correct weight break is established, a transit time (T4) is generated stochastically for application to the order. Once the transit time has been assigned to the order, the entire

order cycle time, by component, can be identified and recorded. This includes the total order cycle time and the back-order delay time. Similar to the previous time elements, the individual elements and the total cycle time are reported in terms of their averages and standard deviations. All time components are recorded and reported by source-destination pair rather than by either source or destination. The shipment weight is also accumulated for reporting cost and volume across a specific link.

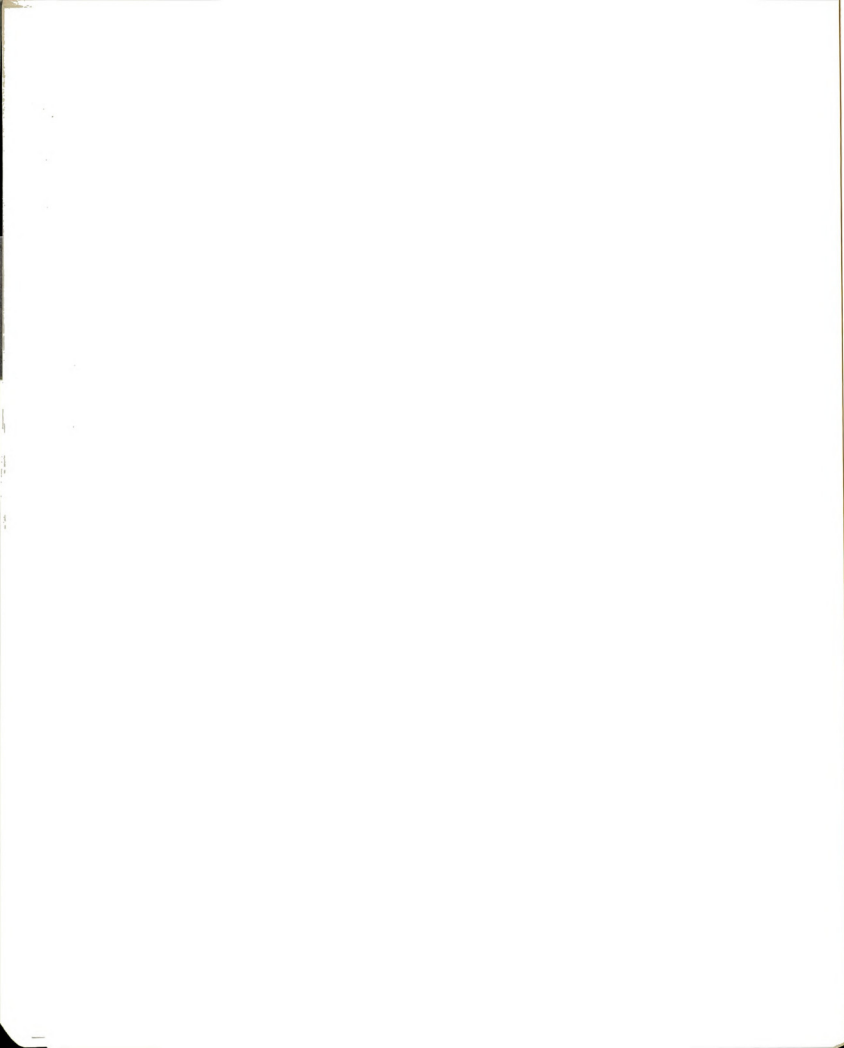
ORDPR also accumulates the service measures for model reporting. These include the proportion of lines and quantity that were satisfied when first presented. These two measures provide an insight into how the system satisfies all orders. The percentage fill-rate of each individual order by quantity is also accumulated by fill-rate category to demonstrate the range of fill-rates for all orders experienced at a facility.

The final tasks of the Replenishment Order Processing event include simulated shipment of the order and queueing of the back order. The order is "shipped" by scheduling the Shipment Arrival event to occur at the appropriate destination after the assigned transit time has elapsed. The items which require back-ordering are placed in the storage array and are linked to the back-order queue. The following description presents a more detailed review of the event flow.



After the event is initially called and the parameters have been retrieved from the storage array, processing begins on the individual products requested on the order. The quantity on order for each item is examined to determine whether or not a stockout is necessary. If not, inventory levels and sales are updated to reflect a complete sale. If the entire quantity cannot be met, the unfilled portion is placed in a temporary array to be later combined into a back order. A record of this out-of-stock situation is made on the simulator audit trail. The audit trail provides the information for analysis of system discrepancies. Since the model knows the quantity that ought to be on hand, it can determine whether the source is operating or forecasting discrepancy. For the portion of the quantity that can be filled, the normal processing is performed. Once all the products on the order have been processed, the summary information from the order is recorded at the shipping facility so that aggregate replenishment statistics can be reported. The statistics include the total value, weight, cube, and units, as well as the number of products on the order. The same aggregate information is also accumulated by source-destination pairs to report activity through a particular channel.

The time generation and temporal aspects are treated next in the event. A transit time is stochastically



generated based on the weight break used for the shipment. Then, the routine calculates and records the transit time along with the other temporal components. The order parameters are then returned to the storage array while the event attributes are placed in the schedule to occur after the transit time has elapsed.

When the entire order quantity cannot be met, the unmet quantities are placed in the storage array. When the back order has been queued, processing is completed for the ORDPR event. Figure 16 illustrates this flow.

Shipment Arrival

The Shipment Arrival (SHPARR) event completes processing of the replenishment orders. This event simulates the arrival of the order at the destination facility and placement of the order quantities into available inventory. In addition to incrementing the inventory on hand (IOH) variable by the appropriate order quantity, SHPARR also records the summary statistics describing the replenishment order so that aggregate receipt statistics can be reported. Since the Shipment Arrival event can alleviate an out-of-stock situation, the event also checks the back-order queue to determine whether or not the Check Back Order (CKBKO) event should be scheduled. If necessary, the CKBKO event is scheduled.

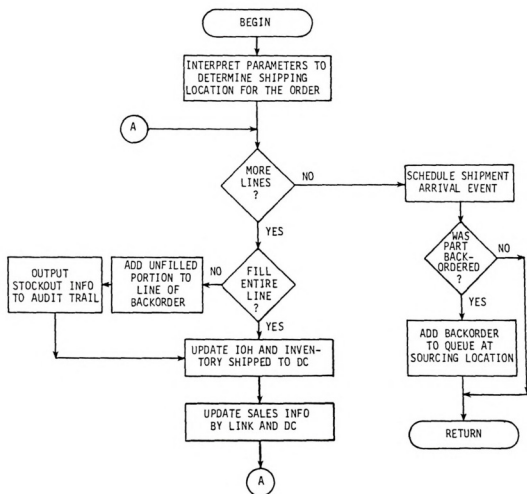


Fig. 16. Order Processing Flow Diagram

Since SHPARR requires that the two previous replenishment order initiation and processing events occur in sequence, it can only be scheduled by a Replenishment Order Processing event.

The following formulations summarize the effects that SHPARR has upon the status of various simulator components.

$$IOH(DC, PR) = IOH(DC, PR) + OQ(PR)$$

$$ROQ(DC, PR) = ROQ(DC, PR) - OQ(PR)$$

$$INVREC(DC, PR) = INVREC(DC, PR) + OQ(PR)$$

Where:

$IOH(DC, PR)$ = the status of on-hand inventory at DC for PR;

$OQ(PR)$ = the quantity that is on the order for PR;

$ROQ(DC, PR)$ = the status variable reflecting the amount that is currently on order at DC for PR;

$INVREC(DC, PR)$ = the level variable reflecting the amount of inventory received at DC for PR.

The Shipment Arrival event processes a single replenishment order each time it is executed. It begins by retrieving the order parameters from the storage array. Following this, a loop is initiated to process individual product entries on the replenishment order. For each product, the inventory on hand, receipts, and current

replenishment order quantity variables are updated. When the list of products is completed, summary order statistics such as dollar value, weight, and cube are added to the summary accumulators for the receiving facility. Finally, the event checks the back-order queue for scheduling the CKBKO event, if necessary. Once this is accomplished, the simulator control returns to the executive routines.

Figure 17 illustrates this flow.

Check Back Orders

The Check Back Order (CKBKO) event reviews the back-order queue whenever it is scheduled. It processes and ships orders when the previously out-of-stock inventory becomes available. Once part of a replenishment or customer order has been placed on the back-order queue, the only time that it can be filled is after additional inventory is received from either a Production or a Shipment Arrival event. Thus, CKBKO is only scheduled through one of these events.

The back-order queue is a First-In, First-Out (FIFO) linked list which contains the parameters for the individual back orders. The parameters include the location which ordered the shipment, the simulation date that the back order was saved, and the product numbers and quantities that were back-ordered. The location number is simply the facility number for replenishment orders or the customer number for customer or market area back orders.

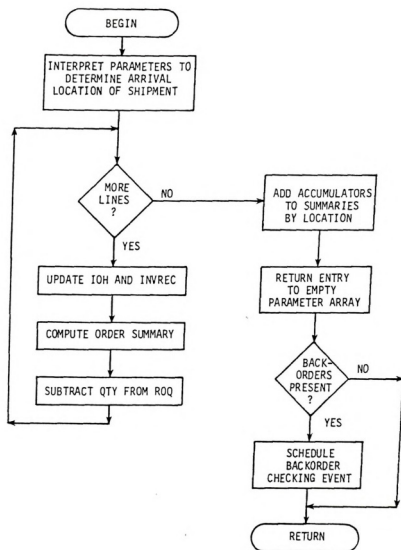


Fig. 17. Shipment Arrival Flow Diagram

Once part of an order is placed on the back-order queue, no part of the order is shipped until the entire order can be met. This means that an order is not removed from the back-order queue until it is filled entirely. However, each quantity is picked and saved for a specific order as it becomes available. Therefore, if the CKBKO event discovers that one product on an order is in-stock while another remains out-of-stock, the in-stock product is deducted from inventory and saved for the order but the entire back order is placed back in the queue. Other than its inability to re-back-order items, CKBKO processes orders identical to either the ORDER or ORDPR event depending on the type of order involved.

The appropriate status and flow variables are updated and the aggregate order summaries are recorded. For replenishment orders, the temporal components are generated and recorded so that the order cycle statistics are available. In addition to the standard order cycle statistics such as communication time, processing time, transit time, and total time, the back-order time is also recorded.

The two parameters required for the execution of CKBKO are immediately retrieved from the parameter storage array after the routine has been called. These parameters include the facility number where the back orders are to be processed and the pointer to the list of back orders.

The routine initiates a loop which processes each back order individually. The first step in this phase retrieves the parameters for the individual back orders from the storage array. Within the individual back-order loop, the routine initiates another loop which processes each line-item entry on the back-order. If the quantity is available to meet the request, the inventory is picked and added to the order. This is denoted by a change in the status of the individual line from STATUS = 1 (unmet) to STATUS = 2 (met). The use of this STATUS variable allows filled and unfilled quantities to coexist without confusion. When the quantity is filled, the inventory on hand and sales accumulators are updated by facility and by link. If the entire product quantity on a back order cannot be met, a flag is set to designate that all lines were not filled and processing continues to the next product.

When processing of an individual back order has been completed, the routine checks the flag to determine whether or not all lines were filled. If they were not, the back order is returned to the queue and processing begins for another back order. When the entire back order has been filled, aggregate order summaries are computed and recorded at the shipping facility. Following this, the various time elements are computed and recorded so that cycle time summaries may be generated. This phase of the routine includes

determination of shipping weight and selection of a weight break. The final step schedules the Shipment Arrival event to simulate receipt of the order at the destination. When processing is completed on this back order, the major loop is begun again to process another back order. When the end of the back-order list is reached, the back-order queue is tied to the facility and the process control returns to the executive routines. This flow is summarized in Figure 18.

Report File Generation

The REPORT routine produces the output file which can then be input to the cost and report modules for generation of SPSF management reports. Report File Generation organizes and writes the various status and flow variables to an intermediate file which provides a data base for the management reports. This intermediate file is not useful in itself because it contains only data with no labels.

The REPORT routine writes all records in the same format, identifying them only by the keys MATYPE (major type) and MITYPE (minor type). The combination of these keys provides specific definition of the contents of the record. Each record contains information concerning a single facility or a single facility-product combination. The locations and/or products are identified through the MAKEY (major key), MIKEY (minor key), and TERKEY (third key) fields.

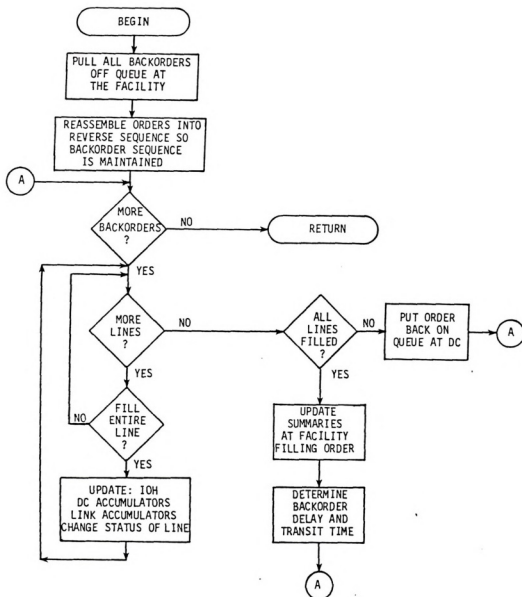


Fig. 18. Back Order Checking Flow Diagram

The REPORT event writes all endogenous status and flow variables at any time desired within the simulation. The reports are written to a continuous file with different report periods denoted by the variable ICYCLE. For the initial report ICYCLE has a value of 0, for the second ICYCLE = 1, and so on. After each report, the event offers the option of having the following report be either cumulative or non-cumulative. In either case, the status variables are not affected. However, for cumulative reporting, the simulator's flow variables are not changed; for non-cumulative reports, these variables are all reset to zero. The desired option is defined by the analyst on the event parameter card.

The final option provided by the REPORT event allows repetitive scheduling of the event. By specification of a non-zero REPEAT cycle, the event is rescheduled after the REPEAT cycle has elapsed. Figure 19 summarizes the REPORT event flow.

CONCLUSION

Chapter IV has addressed the problems encountered during the conceptualization and implementation process of the research. For the general process of model building, the problem was primarily one of identifying the alternatives and selecting the most appropriate with respect to the needs of the research. This analysis has concluded that for an

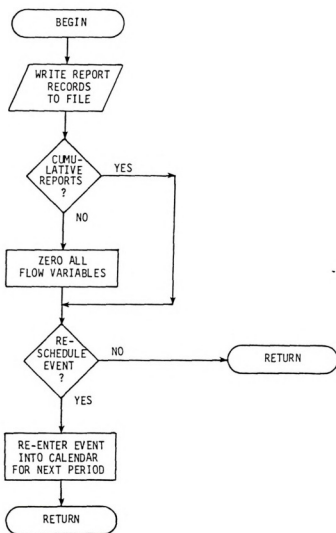


Fig. 19. Report Event Flow Diagram

integrated distribution planning model, a dynamic simulation model incorporating a discrete time increment, stochastic time delays, and detailed analysis and reporting capability is appropriate. It is felt that these characteristics are important for any model attempting to analyze the integrated distribution process. The model also ought to be event or functionally oriented since that corresponds with the process being modeled and also reflects the decision maker's point of view. Finally, for this research, the use of a language that is both portable and flexible is deemed important, thus the selection of the GASP alternative. Other research may desire a language that is more user oriented; however, the experience of the researchers in this situation overcame that deficiency of GASP.

Through an analysis of the questions described here and subsequent action by the researcher, the concept is converted to a working but, as yet, unvalidated model. The next phase of the research addresses the problems of building initial model credibility.

CHAPTER IV--FOOTNOTES

¹James R. Emshoff and Roger L. Sisson, Design and Use of Computer Simulation Models (New York: Macmillan Publishing Co., 1970), p. 65.

²Ibid., pp. 66-8.

³Ibid., p. 69.

⁴Ibid., p. 68.

⁵Donald J. Bowersox, et al., Dynamic Simulation of Physical Distribution Systems (East Lansing, Mich.: Bureau of Business Research, Michigan State University, 1973), pp. 73-7.

⁶Ronald H. Ballou, Business Logistics Management (Englewood Cliffs, N.J.: Prentice-Hall, Inc., 1973).

⁷Donald J. Bowersox, Logistical Management, 2nd ed. (New York: Macmillan Publishing Co., Inc., 1978).

⁸J. L. Heskett, N. A. Glaskowsky, Jr., and R. M. Ivie, Business Logistics (New York: Ronald Press, 1973).

⁹D. G. Luenberger, Introduction to Linear and Non-linear Programming (Reading, Mass.: Addison-Wesley Publishing Co., Inc., 1973), pp. 168-78.

¹⁰R. E. Markland, "Analyzing Geographically Discrete Warehouse Networks by Computer Simulation," Decision Sciences (April 1973):1405-16.

¹¹T. W. Speh, "The Performance of a Physical Distribution Channel System Under Various Conditions of Demand Uncertainty: A Simulation Experiment" (Ph.D. dissertation, Michigan State University, 1974), Chapter 6.

¹²G. D. Wagenheim, "The Performance of a Physical Distribution Channel System Under Various Conditions of Lead Time Uncertainty: A Simulation Experiment" (Ph.D. dissertation, Michigan State University, 1974), Chapter 6.

¹³R. E. Shannon, Systems Simulation: The Art and Science (Englewood Cliffs, N.J.: Prentice-Hall, Inc., 1975), p. 120.

¹⁴Ibid.

¹⁵Ibid., p. 131.

¹⁶Bowersox, Logistical Management, p. 155.

CHAPTER V

VALIDATION METHODOLOGY

Chapter V discusses the problems and procedures involved in establishing the operational validity of the model. Operational validity is concerned with the computer program's ability to produce theoretically accurate results. It does not necessarily imply that the model would operate accurately with "live" data.

The fundamental question addressed by this chapter is:

What methodology is required for building the validity of the integrated distribution model?

The question is one that has never been discussed in detail for existing distribution models. Although the problem of managerial validity has received some attention, existing physical distribution models have not been subjected to tests for operational validity as detailed by general simulation texts.

The broad question of operational validity can be segmented into four specific sub-questions. The four areas address the first set of potential problems as outlined by Emshoff and Sisson.¹ The specific questions are:

1. Do the basic programming techniques used to implement the model operate correctly?
2. Do the physical distribution activities, as implemented in the model, operate as intended and are the activities satisfactory to analysts and decision makers?
3. Does the model converge to a steady-state condition and remain there over time? In particular, do the initial starting conditions or different random number streams have any significant effect on model performance?
4. Do the values of the target variables respond logically to changes in parameters and exogenous factors?

The above questions provide a specific framework for establishing the operational validity of the SPSF Testing Environment. At the same time, the guidelines and the resulting methodology are sufficiently general to provide a basis for evaluating other distribution models. In fact, except for specific measures, the methodology can be used on non-distribution models as well. The specific questions are organized in a building block fashion with the first questions serving as a basis for the latter ones. Thus, even though the initial questions are quite basic, it is only after testing them that one can proceed to the others. Skipping the initial areas may allow errors to remain undetected in the model, thereby clouding further analysis.

For each question listed above, the remainder of the chapter discussed each one's specific problem(s), a methodology to address it, and the results obtained while

working with the SPSF Testing Environment. In general, the evaluation of each question requires an analysis utilizing multiple test procedures.

PROGRAMMING TECHNIQUES

The first area addresses the problems in evaluating the program itself. In a sense, this question formalizes the basic debugging process since it must truly be a part of the validation procedure. The first issue concerns the programming itself, while the second issue concerns the testing of the random variate generators.

PROGRAM EVALUATION

The program evaluation component reviews model input and corresponding output under contrived conditions to establish that the model operates according to design specifications. The problem addressed by this analysis concerns whether the program performs correctly.

The first step for this analysis stage requires the development of test data. Although Emshoff and Sisson suggest actual data, this researcher suggests utilization of contrived data for this stage since such data can provide a more robust test of model performance. The data should be contrived so that it tests as many model components as possible while providing enough standardization to allow for statistical analysis. The complexity of the contrived system

must be restricted since consideration of too many alternatives could make the number of runs necessary for analysis very large. Admittedly, failure to test all alternatives could leave some doubt about model credibility. However, the level of doubt must be traded off against the increased cost of testing as the number of alternatives increases exponentially. This research suggests a level of analysis that is appropriate.

Two data sets were contrived to validate the SPSF Testing Environment. The first, and simpler, data set was used to perform rigorous statistical model testing while the other data set was used to test more complex model conditions. Only the first is presented and discussed here since the second set was used primarily to demonstrate managerial validity. For a description and discussion of the output from the more complex data set, see the research monograph describing the SPSF research.²

The specific structure of the first data set is a three-echelon distribution system consisting of a manufacturer, a distribution center, and a retailer. Figure 3 illustrates this structure. Tables 8 through 14 summarize the policies and operating assumptions that were used in the first data set. The alternatives and relationships used were selected arbitrarily, although they are realistic in terms of how an actual distribution system might be

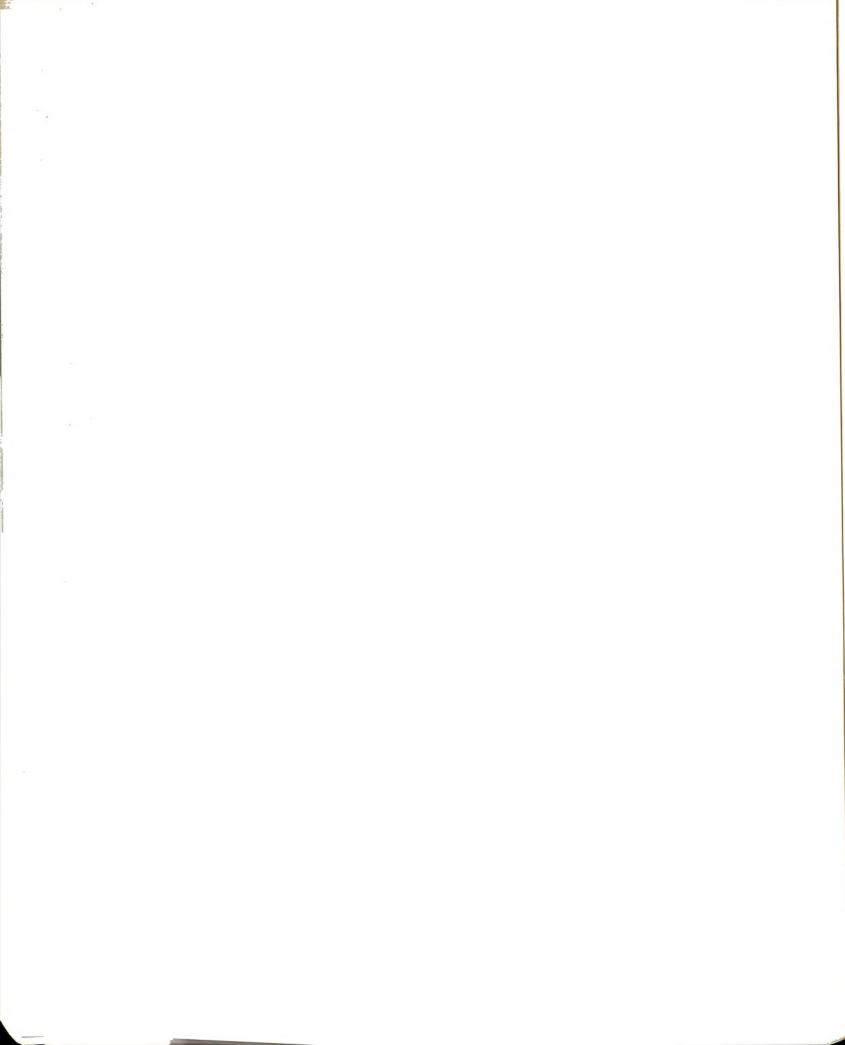


TABLE 8
SIMPLE DATA SET MANUFACTURER POLICIES

Production Policy:	Supply is immediately added to inventory as needed ("infinite inventory").	
Inventory Policy:	No stock is maintained at the production facility. All products produced at single facility.	
Order Processing Time:	Zero days	
Costs:	Fixed	\$50,000 per year
	Handling	\$.25 per hundred-weight
	Storage	\$.50 per cubic foot per month
	Inventory	20 percent of the sales value of average inventory
	Order Processing	\$10 per order

TABLE 9

SIMPLE DATA SET DISTRIBUTION CENTER POLICIES

Forecasting Methodology:	Simple exponential smoothing repeated every 30 simulation days.	
Inventory and Stocking Policies:	All products processed through single facility.	
	Reorder point--250 units	
	Order quantity--250 units	
Order Processing Time:	Zero days	
Review Period:	Stock level is reviewed every day for replenishment order generation.	
Demand Bleed-Off Functions:	None used	
Replenishment Order Forecasting Methods:	None used	
Source of Supply:	All products are obtained from the manufacturer.	
Costs:	Fixed	\$5,000 per year
	Handling	\$.75 per hundred-weight
	Storage	\$.75 per cubic foot per month
	Inventory	35 percent of the sales value of average inventory
	Order Processing	\$10 per order

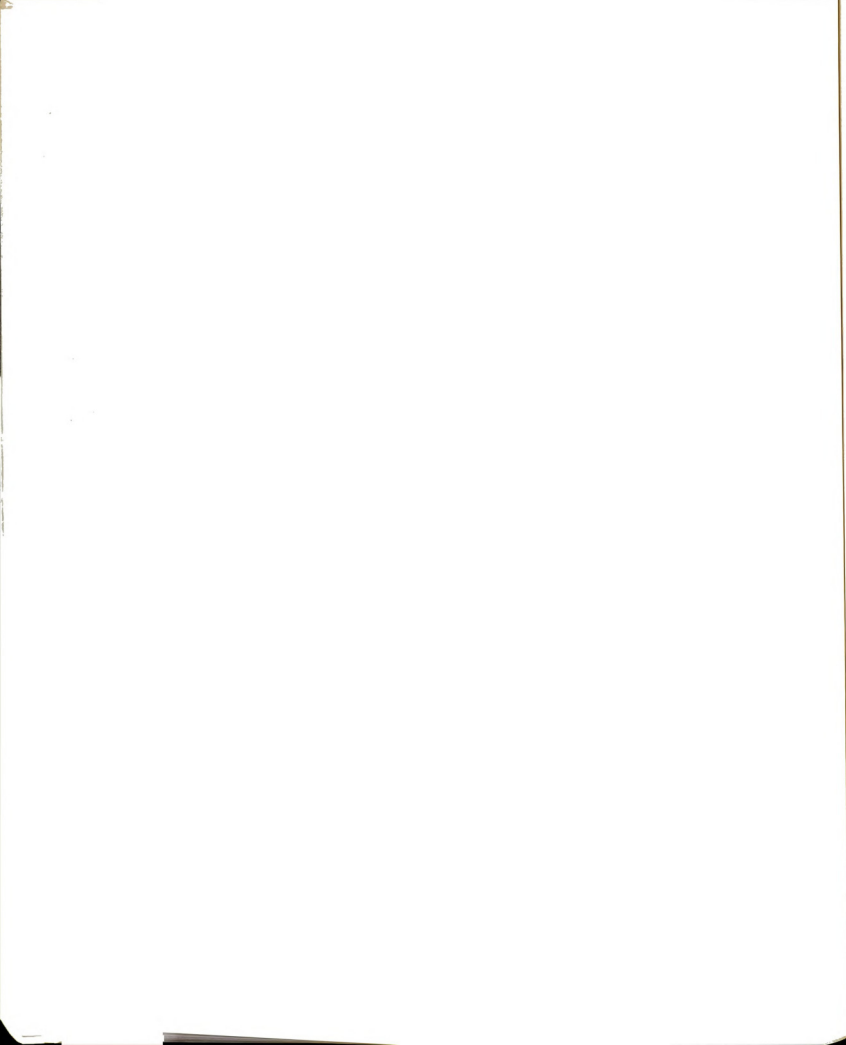


TABLE 10
SIMPLE DATA SET RETAILER POLICIES

Forecasting Methodology:	None used
Inventory and Stocking Policies:	All products are processed through each facility. The re-order point approximates 2 days of average sales. The replenishment order quantity is also set to 2 days of average sales.
Order Processing Time:	Zero days
Review Period:	Stock level is reviewed every day for replenishment order generation.
Demand Bleed-Off Functions:	None used
Replenishment Order Factoring Methods:	None used
Source of Supply:	All products are obtained from the distribution center.
Costs:	None

TABLE 11

SIMPLE DATA SET CUSTOMER CHARACTERISTICS

Number of Orders:	One order per simulation period with each of the 5 products on all orders.
Demand Level:	Expected value of 50 units per day for each product.
Demand Variation:	Control variable used in the research design.

TABLE 12

SIMPLE DATA SET LINK CHARACTERISTICS:
MANUFACTURER-DISTRIBUTION CENTER

Communication Times:	Average:	Zero days	
	Variation:	None	
Transit Characteristics:			
<u>Mode</u>	<u>Weight Break</u>	<u>Average Time</u>	<u>Cost</u>
LTL1	0-15,000 lbs.	8 days	\$4.30 per hundred weight
LTL2	15,000-30,000 lbs.	7 days	\$4.00
TL	30,000-up	5 days	\$2.50

Variation of the transit time is a control variable used in the research design.

TABLE 13

SIMPLE DATA SET LINK CHARACTERISTICS:
DISTRIBUTION CENTER-RETAILER

Communication Times:	Average:	Zero days
	Variation:	None

Transit Characteristics:

<u>Mode</u>	<u>Weight Break</u>	<u>Average Time</u>	<u>Cost</u>
All	0-up	2 days	0

There is no variance in this transit time.

TABLE 14

SIMPLE DATA SET PHYSICAL PRODUCT CHARACTERISTICS

<u>Product</u>	<u>Price</u>	<u>Cost</u>	<u>Weight</u>	<u>Cube</u>
A	\$300	\$200	150 pounds	7.5 cubic feet
B	300	200	150 pounds	7.5 cubic feet
C	300	200	150 pounds	7.5 cubic feet
D	300	200	150 pounds	7.5 cubic feet
E	300	200	150 pounds	7.5 cubic feet

represented. The elements that were treated stochastically include demand and replenishment order cycle time. The reorder points and order quantities for the distribution center were set to 250 units each (50 units/day sales x 5-day average cycle time), therefore the system did not include safety stock. Five identical and independent products were simulated to increase the number of observations obtained from each run. Although the average daily demand for the products never changed, three alternative levels of demand variance were tested in the system. In particular, the coefficients of variation σ/μ were 0, .30, and .60.

The average cycle time was five days for all tests although different levels of variance were introduced using coefficients of variation of 0, .15, and .30.

Once the basic data base had been outlined, the next step evaluated the performance of the program processes. Beginning with the described system using the no variance parameters, the model was run in a mode where the movement of all orders is traced. The trace output was then reviewed manually to isolate problems with the orders or the individual processing functions. The processing of each function was reviewed to establish that, given the input stimulus to the function, the correct transformations were performed and the correct output was produced. As an example, the Customer Order Processing routine was analyzed as follows. For a

small sample of orders that were processed, the analyst's logic of how the orders should have been processed given current inventory availability was manually compared against the results of the model. In particular, the changes in inventory and sales levels were reviewed to determine if correct adjustments had been made. The same process was used for each event identified in Chapter IV.

The second phase of the program logic introduced the maximum amount of uncertainty into the system and performed the same manual analysis again. In this case, the demand per product could range from 0 to 140 units per day and the cycle time from one to thirteen days. While the previous situation did not push the model's capabilities to a great extent, the latter phase did so since it forced numerous out-of-stocks and back-order situations. In both cases, after some minor program adjustments, the model was found to process as expected. Once the basic model functions were found to operate as expected, at least on the surface, the algorithm generating stochastic variates had to be tested to assure accuracy of those program segments. The second phase of the procedure used statistical rather than manual analysis since errors in the statistical routines might be difficult to isolate manually.

BASIC STATISTICAL ANALYSES

Simulation generally utilizes a number of random variate generating functions to inject the uncertainty component into the model. The random variate source may be either: (1) a "system" routine (e.g., uniform random number generator); (2) a routine supplied by the simulation language (e.g., the statistical routines provided by GASP); or (3) a routine that is developed or at least implemented as part of the modeling project. Under conditions (1) and (2), it is probably not necessary to test the routines since it could be assumed that the functions can generate random variates as documented. On the other hand, under condition (3), some analysis should be done to test the algorithm. In cases where the algorithm is developed internally, one should be certain that the algorithm has the required degree of theoretical foundation. Necessary conditions for the acceptance of such algorithms include fit to the desired distribution and non-existence of autocorrelation. Shannon suggests statistical tests for establishing these conditions.³ Whether the algorithm has been developed through prior research or as a part of the current research, some testing is required before the quality of the random variates can be accepted.

One suggested procedure to evaluate the match between the observed and expected number of occurrences for

the random variates is the Chi-square test.⁴ Table 15 illustrates the form of the appropriate table. Another alternative uses the Z-test to compare the observed statistics against the specified parameters. At the specified confidence level, the analyst should be able to accept the hypothesis that there is no statistical difference between the expected and the observed distributions.

For the SPSF Testing Environment, the Chi-square test was used for each of the random variate generation methodologies. In particular, the demand quantity generator, the daily sales generator, the lines per order generator, and the order cycle time generators were tested. The first three generators use transformation algorithms to approximate a normal distribution while the order cycle time generator uses the rectangular approximation method, which can produce any distribution form with a limited number of integral entries. The following paragraphs illustrate the procedures used to test both the transformation method and the rectangular approximation method.

When the transformation approach was used, the Z-test provides an easier test of fit. To establish the fit of the demand quantity generation procedure, a random sample of thirty days was selected from the 150 day validation runs. To build credibility, four different test conditions were tested. The test conditions, as outlined in Table 16,

TABLE 15
CHI-SQUARE TEST SAMPLE TABLE

	Observed Occurrences	Expected Occurrences
Functional value 1		
2		
3		
4		
.		
.		
.		
N		

TABLE 16
DEMAND TEST CONDITIONS

Test Condition	Mean Sales (M_{ds})	Standard Deviation (σ_{ds})
I	50	15
II	50	30
III	150	45
IV	150	90

provided different mean sales and standard deviation levels. To test the desired relationships, the sample mean (X_{ds}) was compared to the expected distribution of the sample mean around the population mean (M_{ds}) using the Z-test. The upper (CV_2) and lower (CV_1) critical values were established using a .05 confidence level. Table 17 shows the results obtained from the analysis of fit. Since the sample mean falls within the critical values established around the hypothesized mean, it can be concluded that the distribution produced by the demand generation program yields a mean that is statistically identical to the input parameters.

The same type of procedure was used to test the fit of the variance parameter. However, for testing the equality of variance, the F statistic, which is obtained by dividing the larger of the variance factors (either observed or expected) by the other, is used. If the calculated F is less than the critical F value, based on the degrees of freedom, the null hypothesis can be accepted. For Test Condition I, the F statistic is computed as follows:

$$\begin{aligned}
 F &= \frac{\hat{\sigma}^2}{\sigma^2} \\
 &= \frac{289}{225} \\
 &= 1.28.
 \end{aligned}$$

TABLE 17
DEMAND GENERATION FIT VALIDATION

Test Condition	Mean Fit					Variance Fit			
	M_{ds}	$\hat{\sigma}_{\bar{x}_{ds}}$	CV_1	CV_2	$\bar{x}_{ds}$	$\hat{\sigma}_{ds}^2$	σ_{ds}^2	F_{CALC}	F_{CRIT}
I	50	3.10	43.92	68.08	55.8	289.0	225	1.28	1.46
II	50	4.85	40.5	59.5	56.0	706.5	900	1.27	1.46
III	150	9.29	131.79	168.21	168.0	2590.8	2025	1.30	1.46
IV	150	15.24	120.13	179.87	174.1	6963.9	8100	1.16	1.62

Since thirty observations were used, df_1 equals twenty-nine while df_2 equals infinity since it is a defined population parameter. The resultant critical F value is 1.46 using an F table with $\alpha = .05$. Since the computed F statistic is less than the critical value ($1.28 < 1.46$), it can be concluded that the variance of the generated daily sales was equal in fit to the input variance. As illustrated in Table 17, the statistics for the remaining Test Conditions were within the critical region also. Therefore, it was concluded that the observed variances were also statistically identical to the input parameters. Similar tests were performed for the daily dollar sales generator, daily quantity sales by product, and the order per day generator. In all cases, both the observed mean and the observed variance were found to be within the established limits with an α equal to .05. Thus, it was concluded that the transformation algorithms used to provide these distributions were statistically accurate.

For the algorithms using the rectangular approximation method, such as the order cycle time components, a more thorough Chi-square analysis is appropriate. Although this analysis may appear unnecessary, it proved particularly useful in SPSF validation as it pointed out a problem with the Testing Environment. Specifically, when testing the order cycle time generation functions with the Chi-square test

explained earlier, initially the distributions did not match. Investigation uncovered an error in the algorithm which had allowed non-acceptable values to be generated. Although the problem was not noticed during the initial manual analysis, the more rigorous statistical methods uncovered it.

The two components of order cycle time--communication time and transit time--were analyzed individually. For each of the components, two test conditions were tested, one for both high and low variance. Tables 18 and 19 summarize the results for communication and transit linkages, respectively. On the basis of the output from more than twenty runs, each of which provided more than 130 observations, Table 20 provides the calculated and critical Chi-square values for all four test conditions. Since the calculated Chi-square values were less than the critical values in all cases, it was concluded that the generated distributions were statistically identical to the hypothetical distributions at the .05 level.

With the series of manual and statistical tests outlined above, the first question concerning operational validity has been answered. The complete analysis is not presented here since it is discussed in detail in the research monograph.⁵

This section's objective has been to define the problems faced during the initial tests of a model, describe

TABLE 18
COMMUNICATION LINKAGES

Low Variance Test Condition

Mean = 2 days

Standard Deviation = 1 day

<u>Time (days)</u>	<u>Probability</u>
1	.150
2	.700
3	.150

High Variance Test Condition

Mean = 2 days

Standard Deviation = 1.71 days

<u>Time (days)</u>	<u>Probability</u>
0	.100
1	.200
2	.400
3	.200
4	.100

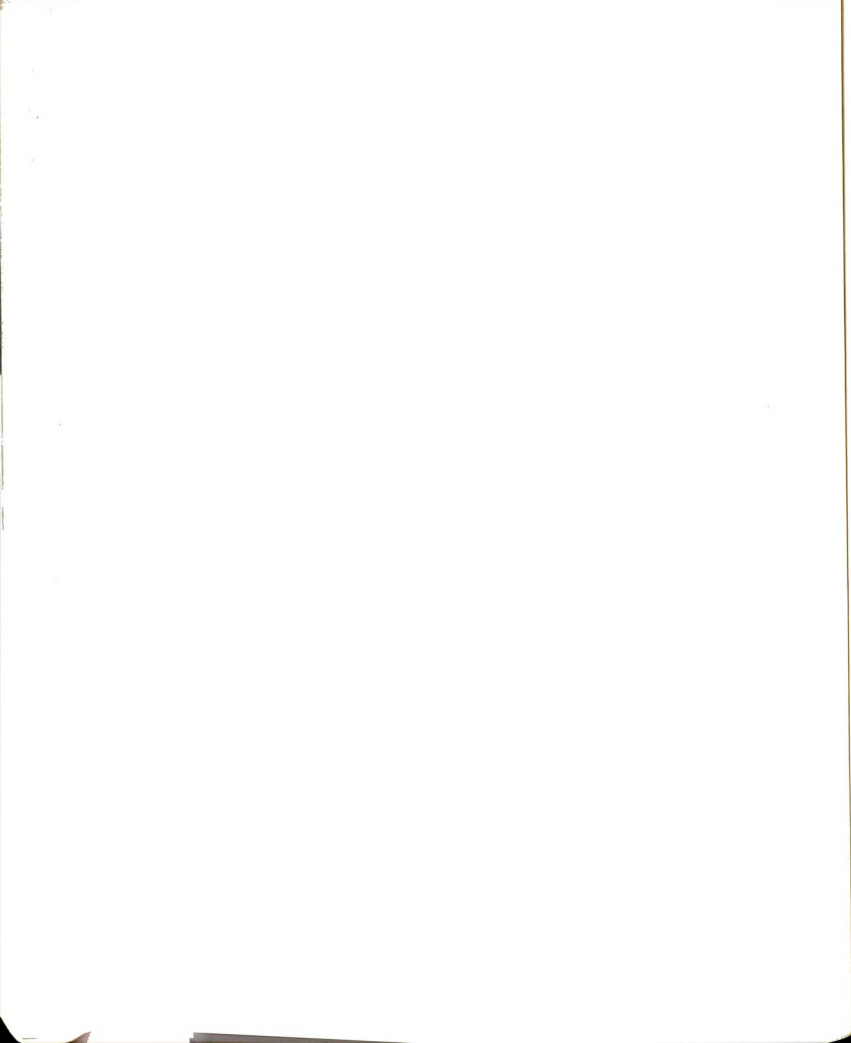


TABLE 19
TRANSIT LINKAGES

Low Variance Test Condition

Mean = 5 days Standard Deviation = 1 day

<u>Time (days)</u>	<u>Probability</u>
4	.407
5	.292
6	.243
7	.058

High Variance Test Condition

Mean = 5 days Standard Deviation = 1.71 days

<u>Time (days)</u>	<u>Probability</u>
3	.190
4	.217
5	.217
6	.181
7	.129
8	.066

TABLE 20

OPERATIONS MODULE LINKAGE FIT VALIDATION

Test Condition	χ^2_{CALC}	χ^2_{CRIT}
Communication time		
Low variance	1.62	3.84
High variance	1.03	7.81
Transit time		
Low variance	1.50	5.99
High variance	9.12	9.49

a methodology, and illustrate it with examples from the SPSF research. The analysis outlined above, although conceptually basic, is a necessary foundation on which to build and an often overlooked stage in model development.

FACE VALIDITY

The second question that must be addressed in establishing operational validity concerns the model's face validity as judged by model users. According to Emshoff and Sisson, this is not, strictly speaking, a test of validity; it only serves to demonstrate model reasonableness and to increase credibility. Nevertheless, this is an extremely important test since it provides a setting for the decision makers to study the model concept as implemented and to review the results. In fact, one consultant on the validation procedure for the model suggested that the face

validity test is the only one that is really needed.⁶ He suggested that all problems will be found by the decision makers during their analysis.

The basic problem in this area is to solicit input from the decision makers and analysts prior to completing the model's operational validity tests. The review may serve to spot obvious problems which the researcher has overlooked because of his closeness to the research. More importantly, however, the review should serve to highlight problems or potential problems related to model design and usage. In particular, items such as detailed data requirements, event processing, and report formats should be scrutinized. Once the users feel comfortable with the model processes as well as the input and output requirements, the basic operational model can be accepted as face valid. This test is performed prior to the remainder of the operational validity tests since changes resulting from this step may require a repetition of earlier steps.

The suggested procedure for this phase begins with the selection of a series of runs, using the contrived data from the prior phase, to demonstrate model performance and some of the model's capabilities. The next step requires scheduling a model review meeting for all users. The format should include a detailed presentation describing the data requirements, functional processes, and report formats. The

assumptions required for model implementation ought to be reviewed also. Questions that might be asked of the users include the following:

1. Are the assumptions required for model implementation consistent with business operations?
2. Can the model accomplish everything you thought it could?
3. Are the report formats informative and understandable?
4. Are there any specific situations within your firm's operation that you believe the model cannot treat?

Once the initial model has been presented, and questions such as the above have been resolved, the model can be accepted as face valid.

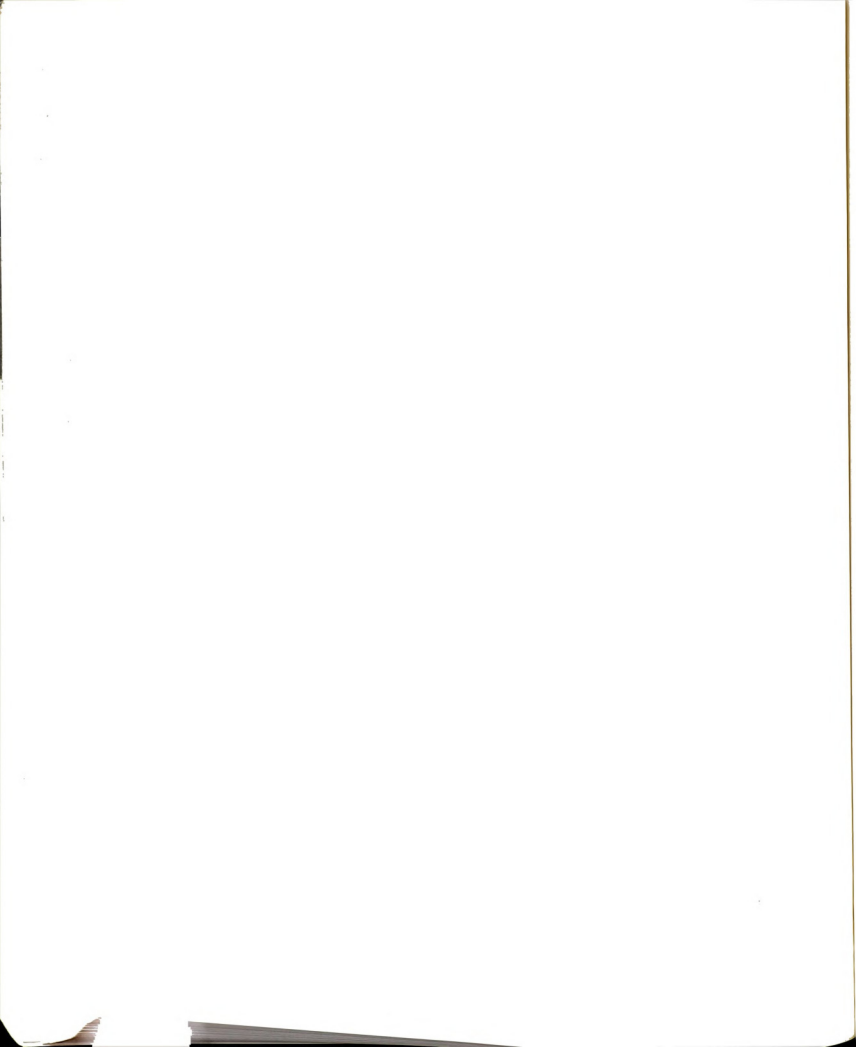
For the SPSF research, this phase was accomplished using two types of review groups. The first group consisted of educators and consultants who have had experience using simulation models for distribution planning and operations. This group included O. K. Helferich,⁷ R. G. House,⁸ E. J. Marien,⁹ T. W. Speh,¹⁰ G. D. Wagenheim,¹¹ and D. C. Whybark,¹² and the SPSF Research Director, D. J. Bowersox. The procedure outlined above was repeated for these individuals who then provided their impressions. The second major review group consisted of actual decision makers who would be using the model from the two sponsor firms. This group consisted of eight individuals whose responsibilities ranged from

analyst to director. Such a group provides a broad scope of input in terms of capabilities, interests, and viewpoints. It is advisable to gain the input of as many people as possible since modeling definitely requires group interaction. A great deal of information was obtained from the industry review. Suggestions were made concerning certain event processes and report formats. After some discussion, many of the suggestions were included as revisions in the model.

Following this qualitative analysis of the model and its capabilities, credibility began to build. However, just as before, the differentiation between some model responses proved difficult to detect manually. The following question addresses this problem and suggests a methodology for solving it.

MODEL STABILITY

The third question concerning the methodology of establishing the model's operational validity addresses the problem of model stability. Although this analysis is commonly performed when utilizing simulation models in general, the literature review did not identify any situations where it had been done for distribution models. Two possible reasons exist for the failure to consider an analysis of stability. The computer expense is a primary reason since a stability analysis would generally require



significantly longer runs for the same parameter set. Another reason for the lack of consideration is the difficulty of establishing a response variable which adequately reflects model stability. The situation is particular difficult when using actual data as input, since the data are usually not stable. For one or both of these reasons, the analysis is not being performed and the result is that all differences in output are implicitly assigned to be the effects of experimental changes while, as Meier et al. point out, the effects of starting conditions and random fluctuations are unknown.¹³

Thus, two problems must be addressed when considering this question. The first concerns the model's initial starting conditions while the second considers the effect that random processes may have on model results.

When using an integrated distribution simulation model, one basic concern is where to initialize the status variables. As an example, when an actual distribution system is operating, most facilities have some inventory, in addition to replenishment orders in the pipeline. However, the modeled system does not automatically have the stock on-hand and in-transit unless it is set artificially. Therefore, when the model begins operating, it experiences some shock as the system attempts to adjust the inventory levels and fill up the pipelines. The shock is similar to,

but more serious than, the shock described by Forrester in his analysis of dramatic changes in the environment of distribution systems.¹⁴ Performance during the shock period does not reflect the experimental results, however, since the actual system does not have to endure that shock. Thus, a methodology is needed that either minimizes the shock or establishes when the shock's effects no longer exist. The shock's effect can be reduced by judiciously initializing facility and channel inventory before beginning the simulation. However, this method could backfire by initializing inventory too high, and eventually forcing the system to adjust from a shock anyway. Another problem is that judiciously selecting the correct initial inventory level is an art. An individual with a great deal of experience may be able to do so but, without experience, the selection would be difficult.

Even if the inventory level is initialized, it is difficult to know what effect the initialized level had on the model's performance. Therefore, whether or not one initializes the status variables, a methodology is needed to determine when the initial effects have passed.

A model's stochastic processes are provided by a series of uniformly distributed random variates. In particular, the SPSF model uses a standard FORTRAN random number generator (RANF). Since the effect of the model's stochastic

processes depends on the random number sequence used, the model can yield different results for different sets of random numbers even if the experimental conditions are identical. Ideally, the different random numbers should not cause the model to generate significantly different results; however, there may be a difference. Since each record of performance from the model is actually an estimate for the true system performance parameter, the purpose of this analysis is to establish the limits on the output variance. The real question is: How can one observe this variance and what can be done to evaluate its effects?

ANALYSIS METHODOLOGY

Now that the problem has been identified, a general methodology is proposed to address it. The methodology discussion remains general since, even within the limited constraints of physical distribution modeling, adaptations will have to be made. The discussion of the methodology as used for the SPSF research provides an insight into some of the specific problems.

The most difficult task within the process of establishing model stability is the definition of an appropriate response variable. The variable ought to reflect total model interaction in terms of both the status and flow variables. The variables that are often considered

for distribution modeling include demand, inventory, and sales. The demand measure does not meet this requirement since it does not consider the effect of inventory levels. Similarly, inventory alone is not a good measure of activity. The sales measure may be a good variable to test for stability if the demand levels and inventory policies are relatively stable. If the demand and inventory are not stable, however, the sales variable will not be stable, even though the model itself may be stable. In the process of establishing the operational validity of the SPSF Testing Environment, a number of variables and combinations were tested. In particular, the ratios of inventory to demand and inventory to sales were tested. Neither had the theoretically appealing properties. The researcher desired a variable which would theoretically stabilize under any demand and inventory condition. A variable that satisfied these criteria proved to be the regression coefficient for a simple regression that relates the percentage of demand first met (PDFM) to demand (D). Mathematically, the relationship is:

$$\text{PDFM} = a + b \times D$$

Where:

a = intercept;

b = slope;

PDFM and D are as defined above.

The hypothesis is that b should stabilize if, and only if, the model stabilizes. This relationship has the intuitively appealing property that, holding the inventory policy fixed, if D goes up, the PDFM should decrease; if D goes down, PDFM should increase. Utilizing the above measure, it is now possible to compare model performance across periods that have different demand levels. This measure is also consistent with the previous statement about using sales as the measure only when demand is relatively constant since the equation can be reduced to:

$$S = a + b \times D$$

Where:

S = sales;

a , b , and D are as above.

Not only does the suggested measure reflect the interactive effects of demand and inventory, the measure also reflects the performance of the integrated system. Only when the system is stable and performing consistently will b remain relatively stable.

Once the measurement variable is defined, ordinary Analysis of Variance (ANOVA) can be used to determine when the model has stabilized. The only two problems when using the ANOVA technique here are selecting appropriate modeling periods as observations and gathering enough observations for the analysis.

The first question concerns how many simulation days ought to be aggregated to form each individual observation. While one can obtain more observations by aggregating fewer days, the observations would have increased variance since it takes time for the system to respond to environmental changes due to the lead time components. On the other hand, an observation period that is too long will destroy the variance in addition to decreasing the number of observations that can be obtained from a single run. Existing simulation models do not provide insight into this problem. On the basis of this research, it was found that the number of simulation days per observation should be slightly larger than the average total system cycle time. The total system cycle time is defined as the elapsed time that it would take an item to pass through the distribution system from the manufacturer to the consumer. The use of such an extended time provides a more accurate measure of system performance since it should reflect the system response over different inventory positions. As an example, if a shorter time period were used, the measure may reflect a period of low inventory which may provide a lower measure of performance.

The second problem is obtaining enough observations with which to perform the ANOVA. For research use, it is sometimes possible to use multiple identical products which can then be used as independent observations. For actual

applications, since the products would probably have different performance characteristics, multiple runs must be made, with each one providing an observation for each product for each period. Keep in mind that the observation is used when creating the regression equation described earlier. The regression coefficient obtained from the observations can then be compared across periods or random number streams to determine when the model has reached stability. Other statistical or manual analysis may be appropriate when it is not reasonable to make the simulation runs necessary to generate the large number of observations. A sequential sampling approach may also be used when attempting to establish when the model has stabilized. To accomplish this, the analysis is performed repeatedly with a decreasing number of observations until the result changes. At the point where the results are significantly different, too few observations were included. However, the analysis with the next larger number of observations appeared to be acceptable, so the number of observations required could be decreased.

To determine the effects of the starting conditions, a parallel test with the data is performed. As a worst possible case, the starting conditions stipulate that there would be no initial inventory in-storage or in-transit. Using the regression coefficient, taken at different points

during the run, an ANOVA test is employed to isolate the length of time required for the response variable to stabilize. The treatment groups for the test are blocks of simulator time. Table 21 illustrates the basic ANOVA table. The ANOVA is performed repeatedly, progressively deleting the beginning report observations until the corresponding F-test is met satisfactorily. First, the initial report observation is deleted. If the remaining observations are significantly different, then the model is still not stable, so the next report observation is deleted. The process continues until the remaining observations demonstrate stability. The basic hypothesis is that, after an initial start-up time, the output from the individual report periods should be statistically identical when the demand input is stable. When the demand data are not stable, the test must be modified to reflect the degree of input instability. If the model does not demonstrate convergence, then one should conclude that the model does not compensate for poor initial starting conditions even after an extended running time. Such a possibility would decrease confidence in the simulation model.

The second question seeks to isolate the random fluctuations caused by random processes from those caused by experimental changes. The intent is to establish that, given stable yet stochastic input, the model produces stable

TABLE 21
WARM-UP ANOVA SAMPLE

Report Periods Runs	1	2	3	. . .	M
1					
2					
.					
N					

responses. Specifically, if different sequences of random numbers yield a significantly different response, the model response would have little credibility. As an example, suppose that under identical test conditions the use of one random number stream produced a performance measure of 100 percent service level while a different stream produced a 50 percent service level. Since the only variable between the tests is the random number stream, the performance measure difference must be due to that. Under the above conditions, the model would not be acceptable since one would not know whether significant differences were due to random number streams or experimental differences. The appropriate statistical procedure for this test is also an ANOVA with the treatment groups being the different random number streams. Table 22 illustrates the appropriate form.

Once the effects of the initial conditions and the random processes have been isolated, the decision maker can proceed to use the model to determine the effects of experimental changes. The remaining experimental runs may be evaluated on a more qualitative basis to determine whether model output corresponds with decision maker intuition.

In a generalized form, the above methodology is somewhat complex although it is much simpler in practice. The basic point of this discussion is that the problems with regard to model stability are significant, particularly when

TABLE 22

STABILITY ANOVA SAMPLE

<u>RUNS</u> Report Periods	Random Number Stream	1	2	3	. . .	N
1						
2						
. . . .						
M						

the medium is simulation. If one does not understand the effects of initialization and the random process, one can conclude nothing regarding the effects of changes in experimental conditions. Existing distribution models have not faced this question at all. The above procedure identifies a measurement variable which can be used for the analysis as well as the analysis required. In some cases, it may be difficult to obtain the observations necessary to perform the statistical analyses, but some consideration should be given to these factors.

SAMPLE ANALYSIS

The procedure is now illustrated by investigating the SPSF model stability. The system design used in stability validation consisted of the manufacturer, wholesaler, retailer distribution channel. For the analysis, five identical products were processed through the channel. The manufacturer was assumed to have infinite inventory. The wholesaler represented the only stocking location in the channel. At the outset of each simulation, the wholesaler had zero inventory and no open orders. Replenishment cycle time was specified as seven days on the average. Manufacturer-to-retailer inventory replenishment was on an EOQ-ROP policy. The ROP at the wholesaler was specified as eight days and the EOQ was specified as five days average

sales. Retailers were structured to process all customer orders to the wholesaler on a daily basis.

For validation, two extreme test conditions were established regarding three environmental variables. The control variables for each test condition were daily demand, transit time, and communication time. Under Test Condition I the variation around the mean was low for all variables (LLL), while it was high (HHH) in the second test condition. In the low variance situation, mean daily sales of fifty units with a standard deviation of fifteen were selected for demand. The remainder of the variables for Test Condition LLL are illustrated in Table 23.

For the high variance test condition, all of the variable means remained unchanged. However, the standard deviations for demand were increased to thirty units. Table 24 presents the distribution for communication and transit times under the HHH test conditions.

For each test condition, a set of simulation runs consisting of 200 days or twenty ten-day periods was completed. To judge stability, the output of the two-run sets was utilized to test two relationships.

1. That the model stabilizes after an identifiable time period and produces consistent relationships after than period. This characteristic is referred to as Initialization Stability.

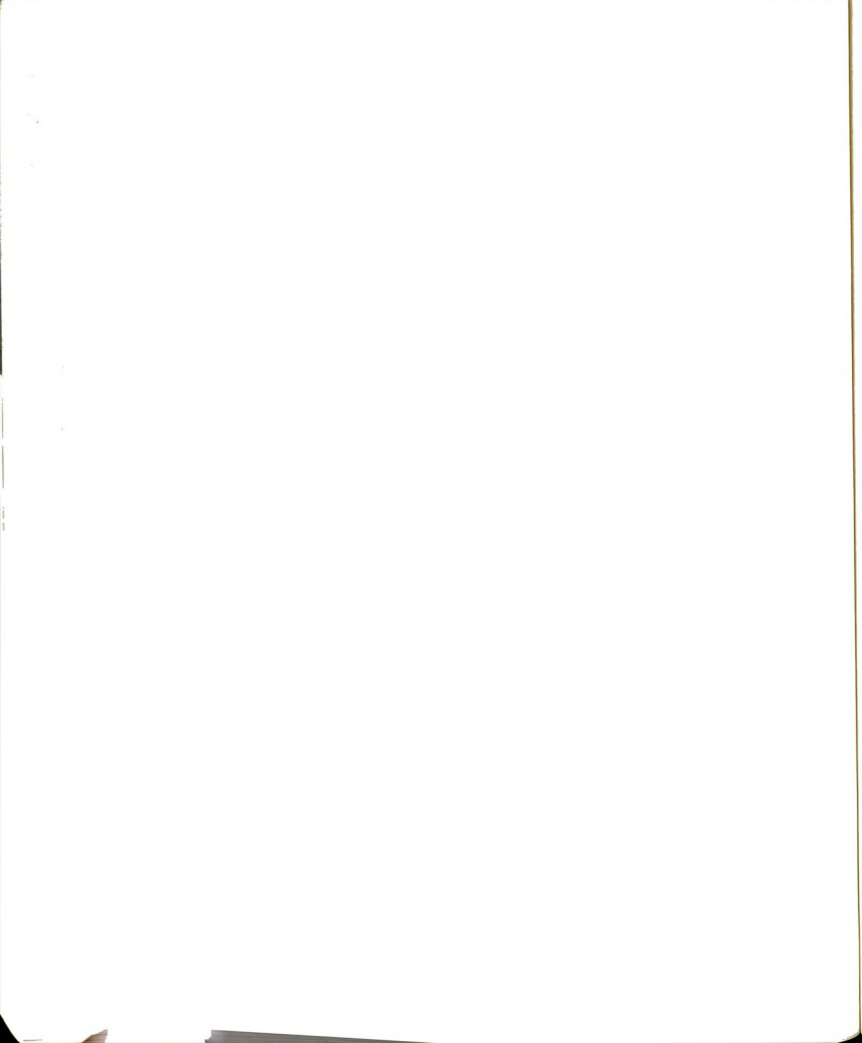


TABLE 23

STABILIZATION VALIDITY LOW VARIANCE TEST
CONDITIONS (LLL)

	Transit 0-5,000	Time 5,000- 15,000	Days Truck- load	Communi- cation Time Days	Proba- bility
	6	7	4	1	.407
	7	8	5	2	.292
	8	9	6	3	.248
	9	10	7	4	.053
Mean	7	8	5	2	
Standard Deviation	1	1	1	1	

TABLE 24

STABILIZATION VALIDITY HIGH VARIANCE TEST
CONDITIONS (HHH)

	Transit 0-5,000	Time 5,000- 15,000	Days Truck- load	Communi- cation Time Days	Proba- bility
	5	6	3	0	.190
	6	7	4	1	.217
	7	8	5	2	.217
	8	9	6	3	.181
	9	10	7	4	.129
	10	11	8	5	.066
	7	8	5	1	
	1.71	1.71	1.71	1.71	

2. That the model's output is not affected by the random number sets. This characteristic is referred to as Comparative Stability.

The procedure and results of evaluating each relationship are reported in the following three sections.

Initialization Stability

To validate Initialization Stability, the relationship between product demand for a period and the percentage of that demand met by available inventory when it first occurred (termed percentage first met) was examined. The relationship should vary over the initial period as the model stabilizes, but remain relatively constant once the model has stabilized. The demand and percentage first met for each of the five products were recorded. The five pairs of data points for each period were then utilized to generate a regression line for each report period. From each run, twenty such regressions were obtained.

In order to obtain enough data points for analysis of any given period, the data for that period over several runs were utilized. Each run yielded five data points for any given period. For example, Figure 20 illustrates the number of data points obtained if Period 4 was analyzed utilizing five runs. A total of twenty-five points was available for each of the 20 periods when five runs were examined.

Period Run	1	2	3	4	...	20
1				$n_{1,4}=5$		
2				$n_{2,4}=5$		
3				$n_{3,4}=5$		
4				$n_{4,4}=5$		
5				$n_{5,4}=5$		
Total				$n_4=25$		

Where: $n_{1,4}$ = number of data points in Run 1, Period 4.

Fig. 20. Stabilization Validity Data Matrix
for Warm-Up Time Stability

A sequential sampling methodology was used to determine the quantity of runs required to perform statistical analysis. The initial analysis in each run set was performed using five runs or 25 data points. Analysis was repeated with additional runs until the impact on the analysis results from adding runs and data points was negligible.

Run Set LLL

Table 25 presents the salient information on the regression lines determined for Run Set LLL with five runs. The regression line for each period is given as:

$$\text{PDFM} = a + b \times D$$

Where:

PDFM = percentage first met;

D = demand;

a = intercept;

b = slope.

The value of R^2 represents the percentage of the variation in Y that is explained by X. The higher the value of R^2 , the stronger the relationship between X and Y. The standard error (SE) represents a measure of the variation of the regression line. If the relationship between demand and percentage first met remains stable over time, the regression lines for various periods should group together. In fact, if control limits for an α of .05 (Control

TABLE 25
STABILIZATION VALIDITY REGRESSION VALUES FOR RUN
SET LLL WITH FIVE RUNS

Period	Equation	R ²	Standard Error (SE)
1	PDFM = 33.13 - .05D	.12	6.80
2	PDFM = 108.05 - .06D	.04	14.00
3	PDFM = 135.62 - .10D	.11	13.30
4	PDFM = 114.61 - .07D	.02	13.25
5	PDFM = 124.92 - .09D	.07	14.80
6	PDFM = 108.14 - .04D	.02	10.91
7	PDFM = 177.04 - .18D	.15	12.47
8	PDFM = 206.00 - .25D	.13	11.45
9	PDFM = 161.20 - .15D	.30	7.35
10	PDFM = 148.39 - .13D	.26	10.14
11	PDFM = 131.19 - .09D	.09	10.40
12	PDFM = 183.93 - .20D	.28	14.57
13	PDFM = 110.91 - .04D	.05	9.90
14	PDFM = 149.51 - .13D	.46	10.00
15	PDFM = 110.27 - .05D	.01	15.30
16	PDFM = 140.00 - .11D	.12	13.10
17	PDFM = 149.80 - .13D	.33	10.86
18	PDFM = 165.56 - .16D	.09	12.08
19	PDFM = 145.26 - .11D	.19	10.26
20	PDFM = 145.78 - .13D	.26	13.40

Limits = $\pm 1.96 \times \text{SE}$) are placed around the regression line for one period, all lines should fall within these limits when the model has stabilized. Control limits were placed around the period with the smallest standard error. This made the control limits as stringent as possible, yielding a conservative stability test.

Period 9 was chosen for Run Set LLL with five runs since it had the smallest standard error. Table 26 presents the calculation of the upper control limits (UCL) and lower control limits (LCL) for the relevant range. The relevant range for all analysis was defined as the most extreme values of demand contained in the range of data points over all 20 periods.

Figure 21 illustrates graphically the analysis of Run Set LLL with five runs. Period 1 is significantly different from Periods 2 through 20. However, Periods 2 through 20 all fall within the control limits. This tends to indicate that after Period 1 the model "warms up" and remains stable over time after that period. However, analysis of the regression results revealed a lack of significance of the R^2 values at the 5 percent confidence level for nine of the regression lines. This indicated these specific lines were not directly interpretable, casting some doubt on the stability of the model. For this reason, analysis was repeated with 10 runs.

TABLE 26
CONTROL LIMITS FOR RUN SET LLL WITH FIVE RUNS

Relevant Range: $420 \leq D \leq 550$

Run 9 selected as having smallest standard error.

$$@ D = 420 \quad \text{PDFM} = 98.2$$

$$\text{LCL} = \text{PDFM} - Z_{.05} (\text{SE})$$

$$= 98.2 - 1.96 (7.35)$$

$$= 83.79$$

$$\text{UCL} = \text{PDFM} + Z_{.05} (\text{SE})$$

$$= 98.2 + 1.96 (7.35)$$

$$= 112.61$$

$$@ D = 550 \quad \text{PDFM} = 78.7$$

$$\text{LCL} = \text{PDFM} - Z_{.05} (\text{SE})$$

$$= 78.7 - 1.96 (7.35)$$

$$= 64.29$$

$$\text{UCL} = \text{PDFM} + Z_{.05} (\text{SE})$$

$$= 78.7 + 1.96 (7.35)$$

$$= 93.11$$

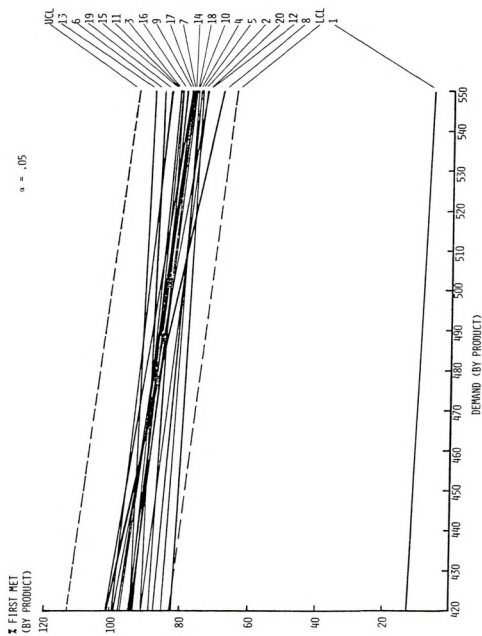


Fig. 21. Plot of Demand Versus Service Regressions
(5 Runs--Low Variance)

The resulting regression lines illustrated in Figure 22 once again indicated stability for Periods 2 through 20. However, despite the increased number of runs, five regression lines still were not significant at a 5 percent confidence level. A sample of 15 runs was tested next.

For 15 runs under Run Set LLL, Figure 23 indicates continued stability for Periods 2 through 20. At the 15-run level, only one period failed to demonstrate a significant R^2 value at the 5 percent confidence level. Although one non-significant period out of 20 is not an unacceptable level, another analysis with 22 runs was conducted to determine whether an increase in sample size of almost 50 percent over 15 runs would have an appreciable effect.

Figure 24 indicates continued stability with 22 runs. All lines had a significant R^2 value at the 5 percent confidence level. Thus, an increase in runs from 15 to 22 produced only marginal improvement with respect to the overall confidence of Initialization Stability. For Run Set LLL, the use of 15 runs provided adequate data to conclude that the model warmed up after one ten-day period and was judged valid with respect to time stability from that period on. To a significant degree, the fast warm-up resulted from a short inventory replenishment cycle (7 days) and the related EOQ-ROP parameters.

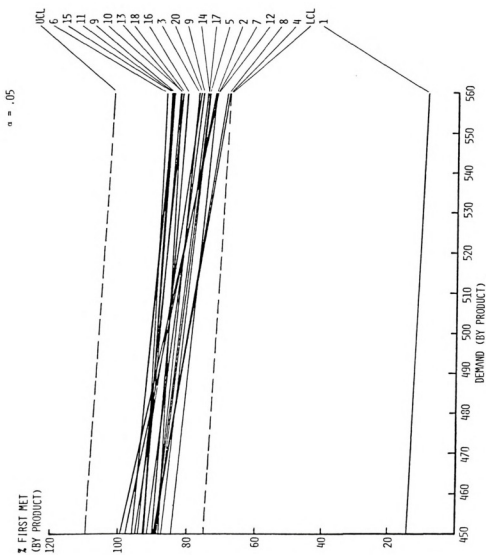


Fig. 22. Plot of Demand Versus Service Regressions
(10 Runs--Low Variance)

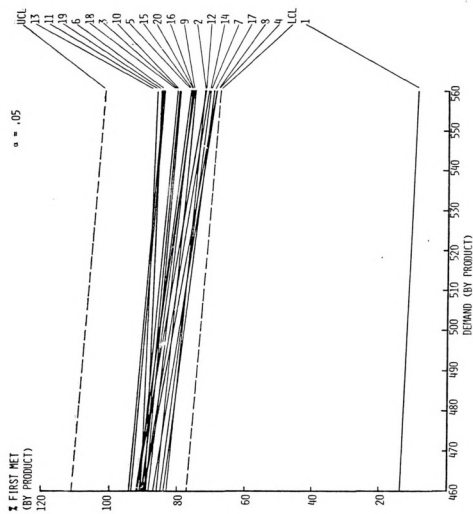


Fig. 23. Plot of Demand Versus Service Regressions
(15 Runs--Low Variance)

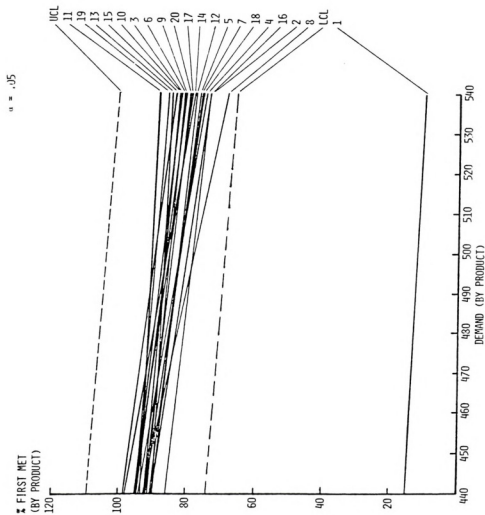


Fig. 24. Plot of Demand Versus Service Regressions
(22 Runs--Low Variance)

Run Set HHH

Analysis of Run Set HHH was initiated with five runs. In this analysis, a departure was made from the previous procedure of selecting the period with the lowest standard error. Since this period, Period 10, was relatively high compared to other lines, its selection could potentially introduce bias into the analysis.

As an alternative, an average regression line was calculated with Period 1 deleted. The standard error of Period 10 was still utilized to establish the control limits, however. Figure 25 indicates that for a 5 percent and a 1 percent level of confidence--even using the average regression line--several lines fall outside the control limits. This result was expected due to the high variance of the HHH set in comparison to the LLL Run Set.

The next step was to increase the analysis to include ten runs. The procedure adopted for Run Set LLL of selecting the period which had the lowest standard error was resumed based upon the data obtained. As Figure 26 indicates, the regression lines for Periods 2 through 20 fell within control limits. This result indicated that the varied characteristics of the five-period analysis were a function of insufficient sample size rather than inadequate warmup time. The R^2 factor for eight of the ten regression lines was significant at a 5 percent confidence level.

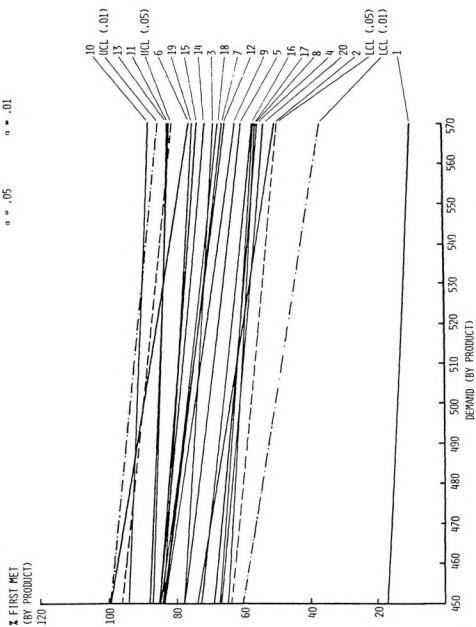


Fig. 25. Plot of Demand Versus Service Regressions
(5 Runs--High Variance)

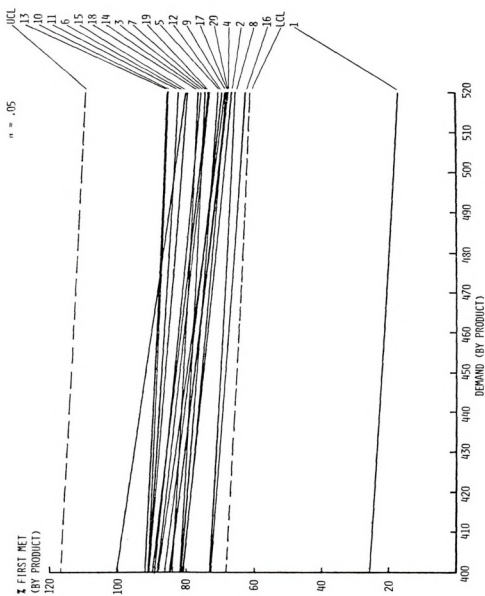
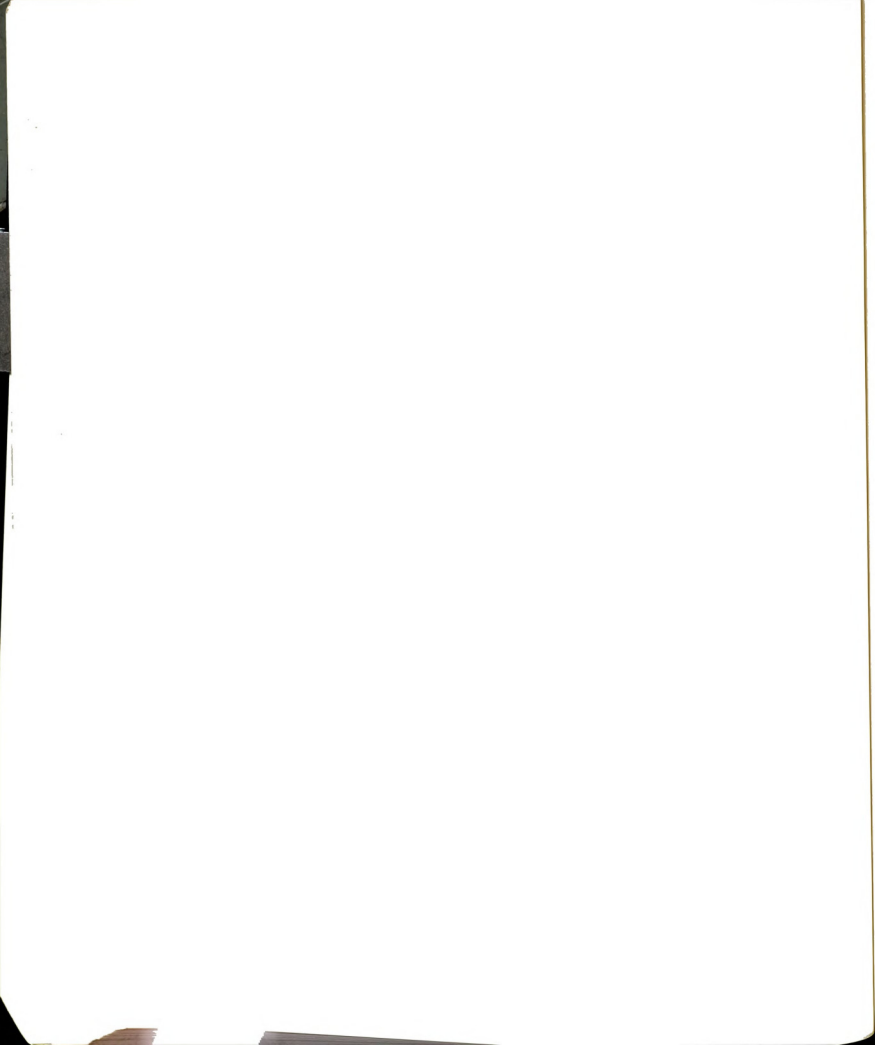


Fig. 26. Plot of Demand Versus Service Regressions
(10 Runs--High Variance)



Analysis of fifteen and twenty-three runs was conducted to test the added significance gained by increasing the sample size of runs. Figure 27 presents the results for fifteen runs and Figure 28 for twenty-three runs. Both runs substantiated the stability conclusions of the ten-run set. Analysis of fifteen runs resulted in only one period being non-significant at a 5 percent confidence level and, for twenty-three runs, all R^2 were significant.

Once again, similar to the LLL test analysis, elimination of the last non-significant period required more than a fifty percent increase in runs from fifteen to twenty-three. Since one non-significant period in twenty was deemed acceptable for Run Set LLL, the rule is continued here. Therefore, with a sample of fifteen runs, it was determined that the model did become stable even under high variance conditions.

Comparative Stability

The second test for operational validation was to determine that output is not affected by the particular random number stream used. To accomplish this, comparisons were made between runs within each of the two test run sets. Analysis of variance of percentage first met was utilized to test the relationship that no difference in the patterns of percentage first met existed between runs within a run set.

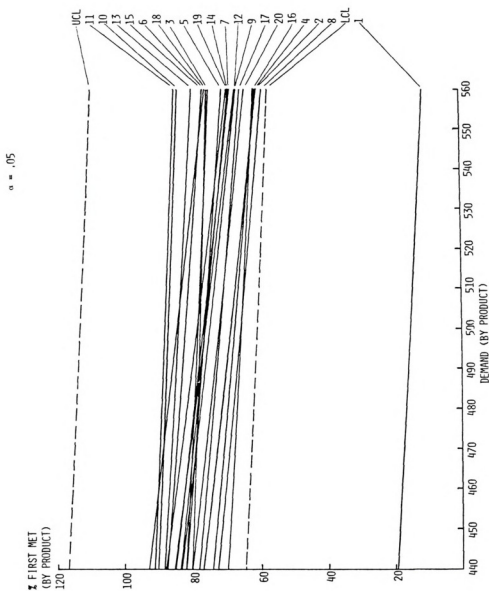


Fig. 27. Plot of Demand Versus Service Regressions
(15 Runs--High Variance)

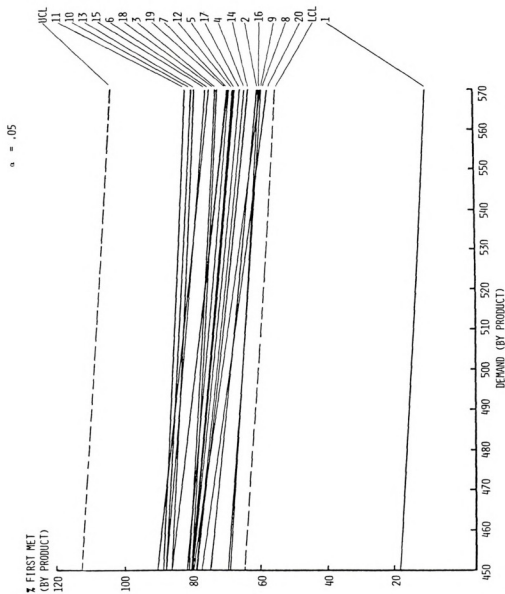


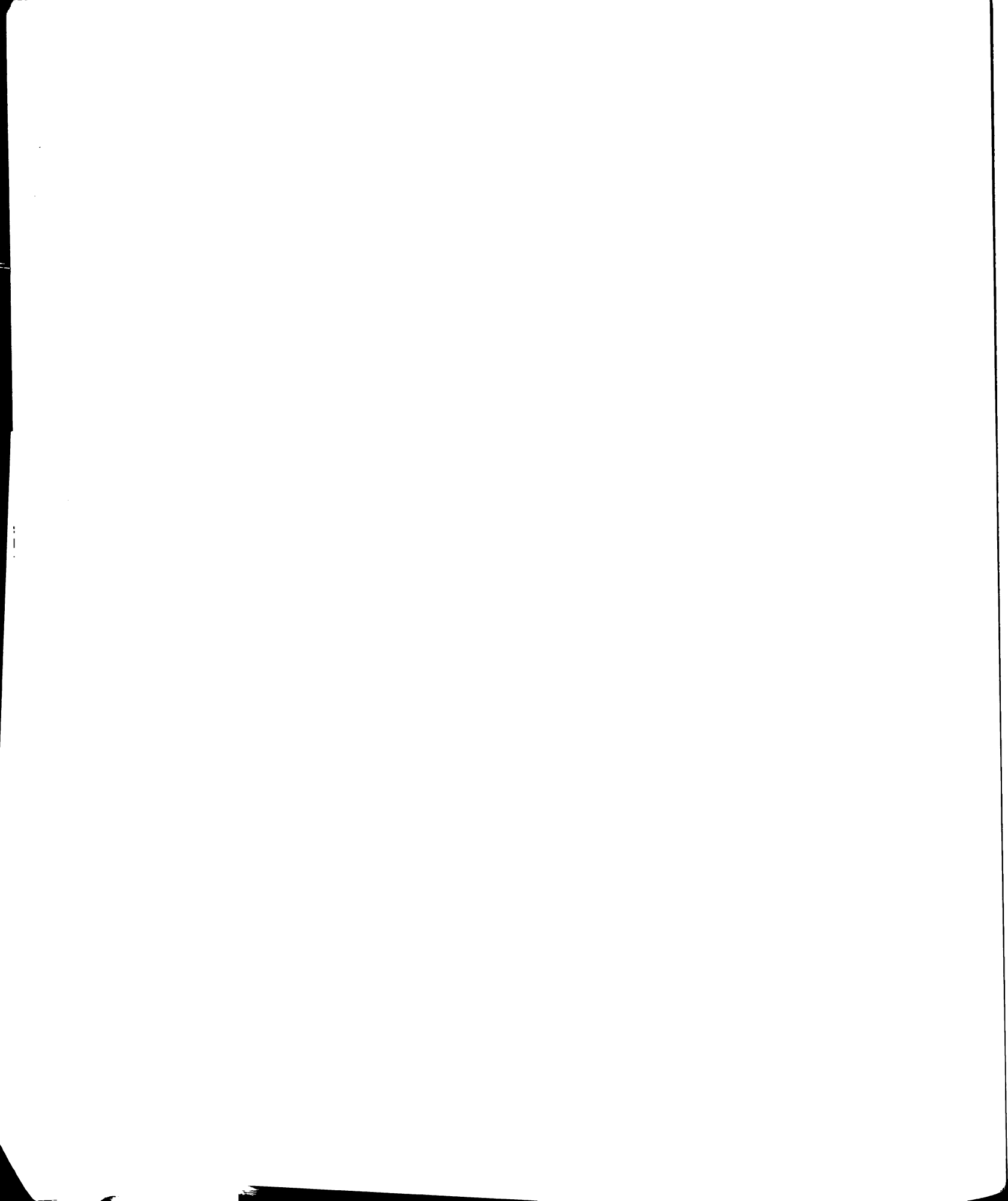
Fig. 28. Plot of Demand Versus Service Regressions
(23 Runs--High Variance)

Table 27 illustrates the results of this analysis for Run Set LLL. The value of the F statistic to test that no difference exists between runs as given on the line labeled "RUNS" is considerably below that required for a 5 percent confidence level. In terms of a significance range, an F of 0.0 to 1.57 indicates no significant difference at the 5 percent confidence level. Since F equals .528, the test indicated that no significant differences existed between the runs in Run Set LLL using randomly selected starting points.

TABLE 27
RUN SET LLL COMPARATIVE STABILITY

Source of Variation	Squares	DF	Square	F	Signif. of F
Main effects	2133.632	21	101.602	.528	.960
Runs	2133.632	21	101.602	.528	.960
Explained	2133.632	21	101.602	.528	.960
Residual	398230.680	2068	192.568		
Total	400364.311	2089	191.654		

The analysis for Run Set HHH is presented in Table 28. The level of the F statistic was again below the 5 percent confidence requirement, with the significance range of F between 0.0 and 1.55. Since F equals 1.401, this again



indicates that no significant differences existed between the runs in Run Set HHH using randomly selected starting points.

TABLE 28
RUN SET HHH COMPARATIVE STABILITY

Source of Variation	Squares	DF	Square	F	Signif. of F
Main effects	15315.910	22	696.178	1.401	.103
Runs	15315.910	22	696.178	1.401	.103
Explained	15315.910	22	696.178	1.401	.103
Residual	1074242.729	2162	496.875		
Total	1089558.639	2184	498.882		

MODEL SENSITIVITY

The final question that must be addressed when attempting to establish the initial validity concerns the model's ability to differentiate between experimental conditions. If the model does not generate significantly different results when expected, either the model is not sensitive to parametric changes or the intuition of the analysts and decision makers is wrong. If the model is not sensitive enough to accurately reflect the results of the changes, then it cannot be used for experimentation.

The ultimate test for investigating the model's responsiveness would call for a large number of different

runs reflecting different experimental changes. For each run, a number of actual simulations must be made to establish the estimate and variance for the response variable. Prior to the actual runs, however, the decision makers should use their insight to estimate the ranking of the response variables by experimental condition. A statistical analysis of the model results using tests of means and variances should then be used to determine the model's priority ranking. Any discrepancies ought to be resolved either through explanation or through model modification so that agreement is reached between the predictions of model and of the users.

As an example of the analysis, consider the relationship between inventory level and customer service. Theoretically, as the average inventory level increases, customer service ought to increase at a decreasing rate. Suppose the model was used to generate the expected customer service level and variance for inventory levels of 10, 15, 20, and 25 days of sales, respectively. Intuitively, one would expect that the customer service should increase as inventory increases from 10 to 25 days of sales. Using the Z-test on the model results, the relationship should be confirmed. A similar analysis using the F statistic can be used to determine whether different levels of variance for the environmental variables produces different levels of

variance in model results. Again, if this were not true, one should probably question the sensitivity of the model.

The model results from the HHH and LLL run sets presented earlier are compared to illustrate the procedure. Using percentage demand first met as the response variable, the theory would say that the percentage ought to be lower for the high variance situation, since demand is lost rather than back-ordered.

First, the variance of percentage first met for the two test run sets was compared. The following F statistic was utilized:

$$F_{\text{CALC}} = \frac{\sigma_{\text{HHH}}^2}{\sigma_{\text{LLL}}^2} = \frac{498.882}{191.654} = 2.60$$

Where:

F_{CALC} = the calculated F statistic;

σ_{HHH}^2 = the variance of percentage first met for Run Set HHH;

σ_{LLL}^2 = the variance of percentage first met for Run Set LLL.

Since there are about 2150 degrees of freedom for both the numerator and the denominator (5 products x 19 acceptable report observations x 22 runs), the significant F statistic range is from 0.0 to 1.0 for a 5 percent confidence level. The value of F_{CALC} is outside this range. Therefore, the test indicated that a significant difference

did exist in the performance of the system under different variance conditions.

To further test the desired relationship that different variance produces different output, the means of Run Set LLL and Run Set HHH were compared. The Z-test was utilized to test the relationship that the mean of percent first met for Run Set LLL equaled the mean of Run Set HHH, or:

$$M_{LLL} - M_{HHH} = 0$$

Where:

M_{LLL} = population mean of Run Set LLL;

M_{HHH} = population mean of Run Set HHH.

If the model was valid with respect to Run Set Sensitivity, it should be found that M_{LLL} did not equal M_{HHH} . The mean of Run Set LLL was 84.9 and the mean of Run Set HHH was 75.9, leading to the statistic:

$$\bar{X}_{LLL} - \bar{X}_{HHH} = 9$$

Where:

$\bar{X}_{LLL}$ = mean of percentage first met for the runs of Run Set LLL;

$\bar{X}_{HHH}$ = mean of percentage first met for the runs of Run Set HHH.

Since the previous test found the variance to be unequal, the formula for the pooled standard error of the statistic, $\hat{\sigma}_{\bar{X}_{LLL} - \bar{X}_{HHH}}$, was required.

$$\hat{\sigma}_{\bar{X}_{LLL} - \bar{X}_{HHH}} = \sqrt{\frac{\hat{\sigma}_{LLL}^2}{n_{LLL}} + \frac{\hat{\sigma}_{HHH}^2}{n_{HHH}}}$$

Where:

$\hat{\sigma}_{\bar{X}_{LLL} - \bar{X}_{HHH}}$ = the pooled standard error;

$\hat{\sigma}_{LLL}^2$ = the variance of percentage first met for Run Set LLL;

n_{LLL} = the sample size for Run Set LLL;

$\hat{\sigma}_{HHH}^2$ = the variance of percentage first met for Run Set HHH;

n_{HHH} = the sample size for Run Set HHH.

Figure 29 illustrates the test with $M_{LLL} - M_{HHH} = 0$ at the center of a normal distribution of the possible values of $\bar{X}_{LLL} - \bar{X}_{HHH}$. The critical values for a 5 percent confidence level are:

$$CV_1 = (M_{LLL} - M_{HHH}) - z_{.05}(\hat{\sigma}_{\bar{X}_{LLL} - \bar{X}_{HHH}})$$

$$= 0 - 1.96(.57)$$

$$= -1.12$$

$$CV_2 = (M_{LLL} - M_{HHH}) + z_{.05}(\hat{\sigma}_{\bar{X}_{LLL} - \bar{X}_{HHH}})$$

$$= 0 + 1.96(.57)$$

$$= +1.12$$

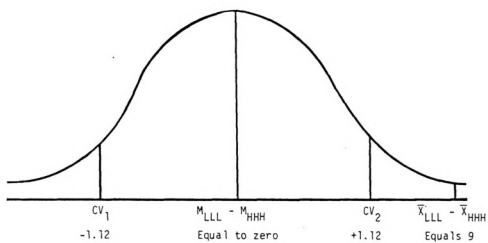


Fig. 29. Differences of Means for Run Set LLL and HHH

Since $\bar{X}_{LLL} - \bar{X}_{HHH}$ is outside of these values, the statement that $M_{LLL} - M_{HHH} = 0$, or that the means of the run sets are equal, is rejected. Therefore, the test indicated that different conditions of variation produced different means. Considering the results of the test of variance and means, the tests indicated that different conditions of variation produce different output.

CONCLUSION--METHODOLOGY

Chapter V has presented a discussion of four basic questions that should be considered when establishing the operational validity of a distribution simulation model. Most of the questions have been completely overlooked in existing physical distribution models due to economic and conceptual problems. Although little can be done about the economic considerations until less expensive simulations are developed, this chapter has addressed some of the conceptual problems with a methodology and an illustration. It is hoped that some insight has been provided concerning the problems and their effects.

The illustrations in the chapter have served to demonstrate the methodology. It is not to be inferred, however, that once the prescribed tests have been completed the model is automatically and unquestionably valid for all situations. A distribution model which is valid for all

situations is impossible to attain; it could only be reached through testing all situations, which is neither practical nor possible.

The above rigorous analysis ought to be performed on a model at least once to establish credibility. Particular attention should be paid to the variables that will form the basis for decisions made with the model. If the specific problem concerns inventory and service, then the analysis should focus on those variables.

The procedure discussed here considers the problems that have always been inherent in simulation but have never been considered in physical distribution models. It is by no means perfect, but the methodology does provide a practical means of determining the limitations of the model. As alternatives, we could suggest a complete analysis of these large-scale models. Such an analysis would be both costly and endless. The other alternative would recommend that we continue to ignore the problem. Thus, the most practical approach, from a research and decision-making point of view, is to compromise as suggested here until both technology and experience increase.

CHAPTER V--FOOTNOTES

¹J. R. Emshoff and R. L. Sisson, Design and Use of Computer Simulation Models (New York: Macmillan Publishing Co., Inc., 1970), p. 206.

²D. J. Bowersox, D. J. Closs, J. T. Mentzer, Jr., and J. R. Sims, Simulated Product Sales Forecasting (East Lansing, Mich.: Bureau of Business Research, Michigan State University, forthcoming 1978), Chapter 8.

³R. E. Shannon, Systems Simulation: The Art and Science (Englewood Cliffs, N.J.: Prentice-Hall, Inc., 1975), pp. 217-28.

⁴Ibid., pp. 76-8.

⁵Bowersox et al., Simulated Product Sales Forecasting, Chapter 7.

⁶Discussions with D. Clay Whybark concerning the validation procedure in East Lansing, Michigan, June 1977.

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¹⁰Assistant Professor of Marketing, Miami University, Oxford, Ohio.

¹¹Assistant Professor of Marketing, Michigan State University, East Lansing, Michigan.

¹²Professor of Management, Indiana University, Bloomington, Indiana.

¹³R. C. Meier, W. T. Newell, and H. L. Pazer, Simulation in Business and Economics (Englewood Cliffs, N.J.: Prentice-Hall, Inc., 1969), pp. 307.

CHAPTER VI

MANAGERIAL UTILIZATION

The final research question considers the problems faced by decision makers as they attempt to use the model for applications research. Although the primary motive in model development is to aid in decision making, either in a prescriptive or descriptive manner, there is little discussion concerning the model utilization procedure, particularly when concerning the validation phase. Existing literature presents the capabilities of distribution modeling¹ or a list of common concerns.² Such approaches may be appropriate when introducing modeling, its capabilities, and its processes to physical distribution managers. However, when simulation technology is applied to problems in distribution, its limitations ought to be considered as well. In the past, again probably for both economic and practical reasons, the output of physical distribution simulation models has not been adequately analyzed. Within the distribution field, model stability and the experimental runs are not adequately investigated. Model logs are not maintained to provide a performance record. With these deficiencies in mind, the research question addressed by Chapter VI is:

What should the procedure be for analyzing of model applications and for judging model performance?

Each time any model, particularly a simulation model, is used, the analysis must be done to determine the conditions under which the model reflects reality. The broad managerial question can be decomposed logically into four specific sub-questions that outline an analysis procedure. Conceptually, the procedure is based on the last part of the utilization methodology described by Emshoff and Sisson. The four basic questions that must be addressed as part of the managerial utilization procedure are:

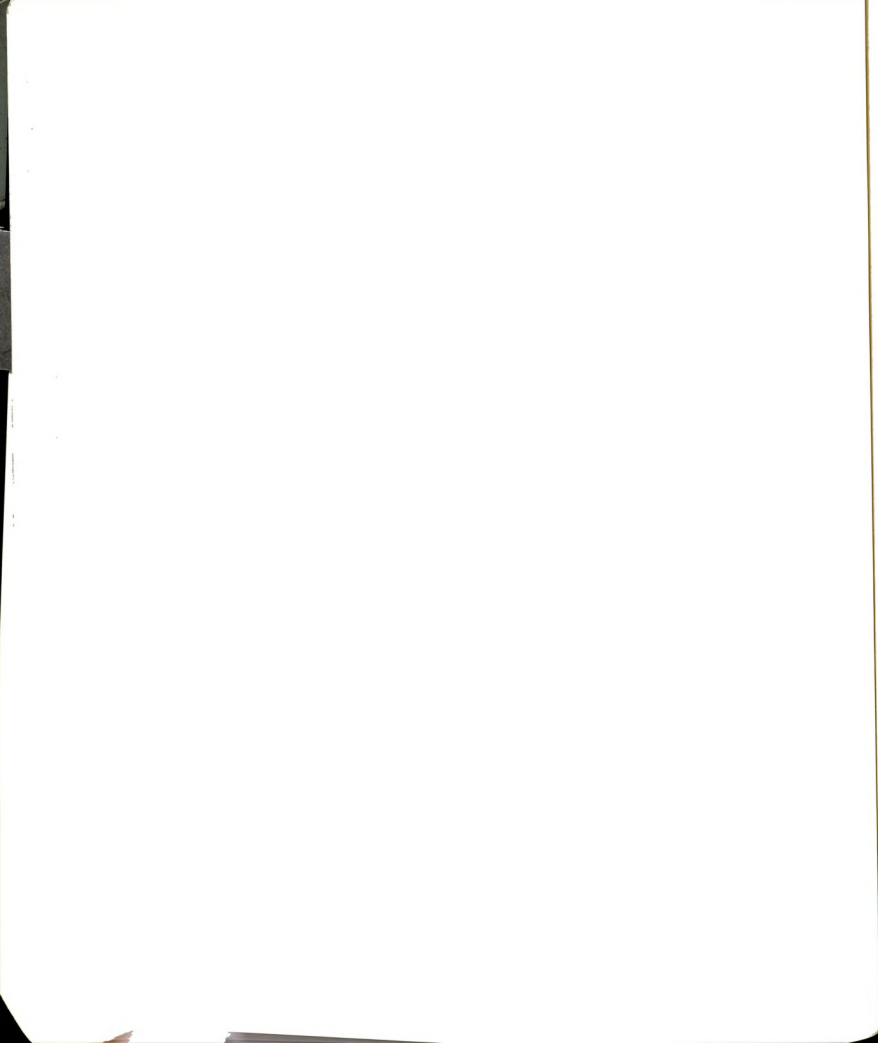
1. Do the aggregate and detailed outputs of the model match with the historical data that is available for the situation?
2. What are the effects of the initial startup conditions and the alternate random number streams and what is the impact on model utilization strategy?
3. Does the model output for experimental runs correspond with the intuition and knowledge of the analysts and decision makers?
4. What procedure is appropriate for the development and maintenance of documentation of model implementation, flexibility, and performance?

Each question is addressed in the following sections of the chapter with the discussion centering on the problem, a methodology for solving it, and the results of the related SPSF research.

HISTORICAL FIT

The first question concerns the model's ability to create output which matches with the historical data available for the application. Existing model applications place all of their validation effort on this one test since it is the most obvious to management. If a manager cannot see a facsimile of his firm in the model output, he will have very little trust in the model results. This researcher's experience has been that any difference at all must be studied and explained to decision makers even though it is impossible for the model to duplicate exactly the performance of the real system. One reason that managers and researchers have concentrated on historical fit validity may be that fit was the only type they thought was necessary. The problems of stability and response sensitivity are much more subtle, particularly when the researchers are application rather than model oriented. Nevertheless, the historical fit problem cannot be overlooked since managers still give the fit measure a great deal of weight when assessing credibility.

Ideally, the evaluation of fit should attempt to compare model output with historical fact for as many variables as possible. The variables may include sales, service, inventory, and cost for individual products and facilities. When a significant difference exists between actual and



observed, the problem should be isolated and explained to extend model credibility.

The methodology for such an historical fit analysis depends on the scope of the research as well as the availability and accuracy of existing data. A statistical analysis may be appropriate with large amounts of accurate data; however, this is generally not the case. Distribution accounting is generally quite poor. An appropriate analysis, whether automated or not, would compute the percentage of error for either a sample of items or for each depending on the size of the problem. The percentage of error can be calculated using the following formula:

$$PE = \frac{O - H}{H} \times 100$$

Where:

PE = percentage of error;

O = modeled value of the variable;

H = historical value of the variable.

The percentages should then be evaluated either manually or statistically to determine which are outside a predetermined limit. An acceptable limit might be a 5 or 10 percent error depending on the reliability of the historical data. Bowersox et al. suggest a series of ten quantitative techniques for use in evaluating the match between observed and historical variables.³ Some of these

methods include: (1) graphic analysis, (2) analysis of variance, (3) multiple comparison, (4) the Chi-square test, (5) Theil's Inequality Coefficient, and (6) spectral analysis. Whatever the method of analysis, the results ought to be reviewed by both the decision makers and the researchers to isolate and explain any unacceptable level of error.

For the two user applications of the SPSF research, a manual analysis was performed to evaluate the fit between the model and historical variables. The subject variables included sales, percentage first met, inventory levels, and distribution costs by facility and warehouse. System A consisted of a multi-echelon structure that modeled the flow of ten aggregate consumer durables. Figure 30 presents a graphic illustration of the system. In comparison, application System B was a multi-echelon structure that treated four aggregate consumables. Figure 31 illustrates its configuration.

The acceptable error level for both models was set at 5 percent, which is relatively strict. However, the applications did have a very good data base with which to validate. The manual analysis pointed out some specific problems in the inventory-service tradeoff for both applications. In particular, the inventory levels were correct but the service level was different from expected. However, to effect a change in service, the inventory levels would have

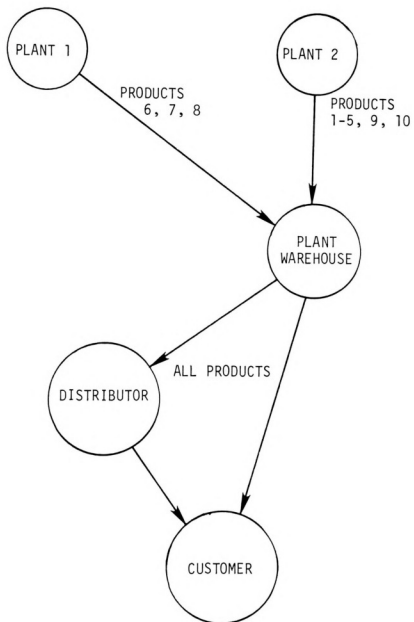


Fig. 30. Application System "A" Structure

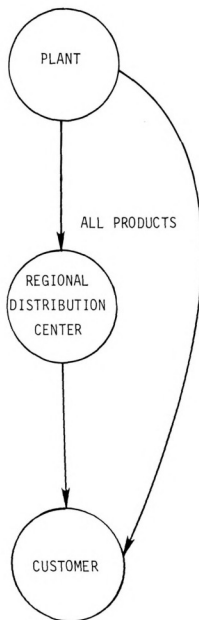


Fig. 31. Application System "B" Structure

had to be changed. A more detailed analysis of the discrepancy led, in one case, to a reassignment of some orders, and in the other case to an adjustment of the service level measurement. In both situations, the analysts and decision makers concluded, after minor adjustments, that the model output fit the historical data within acceptable limits.

The historical fit test is viewed as the primary test of validity by decision makers. Once this test is met, the model application is judged valid and suitable for testing alternatives. However, researchers must consider the importance of other factors that affect model validity and reliability. The factors should be investigated in a procedure which is practical and simple enough for managers while providing insight into the problem. The remaining three questions provide an outline for that procedure.

MODEL STABILITY

The second question that ought to be considered when applying the model concerns simulator stability across starting conditions and random number streams. Chapter V discussed the same question from the point of view of the initial model validation. However, since the problems of initial starting conditions and stability across random number streams are situation dependent, a similar process

must be repeated every time the model is used for a new situation.

As a review, the initial starting condition problem refers to the effect that artificial initialization conditions have on model response. For example, how long must the model run before the effect of zero pipeline inventory is negligible? The second problem deals with the effect of different random number sets on model response. Ideally, all number sets should produce a response variable that is equal to the true population parameter. On a practical basis, this will not happen. However, it is necessary to know the degree of the error to evaluate the model predictions adequately.

Even though either of these may be a serious problem, existing distribution simulation models do not consider either factor. Problems of measurement, lack of modeling knowledge, and resource limitations would appear to be the primary reasons. The major problem of stability assessment can be overcome only by addressing the measurement and knowledge problems while remaining within the resource limitations. The following procedure attempts to maintain this fine balance of criteria. The procedure ought to provide some insight into the problem while remaining practical for use by decision makers.

Just as in the prior analysis, the first step here requires the selection of an appropriate measurement variable and observation length. The selection of a measurement variable is made somewhat more difficult since the input (i.e., demand stimulus) is not necessarily stable. In fact, the demand stream probably reflects a certain amount of trend and seasonality which would definitely affect the stability of the response variable whether it be sales or percentage first met as before. Even if there are trend and seasonality components within the historical data, it is possible to remove these elements from the data. The trend component can be removed through the technique of first differences, which uses the differences between two subsequent observations as the data points rather than the actual elements themselves. Thus, if the difference remains relatively constant, then the actual observations exhibit stability even though they are increasing. Similarly, it is possible to factor out the seasonality effects from a data stream when they are known a priori. One need simply divide the sales level by the percentage of demand that is normally experienced for that period. Once the two adjustments are made to the stimulus, the response variable should demonstrate stability across time and across random number streams.

Although sales, on either a product or aggregate level, is the most likely subject for this analysis, other variables which should logically demonstrate stability can also be tested. Such variables that ought to remain relatively stable include cost elements, service levels, inventory levels, and cycle times.

The second issue that must be addressed in this analysis concerns the definition of an observation. As before, each simulation day could reflect an observation or a sequence of days could be aggregated to provide an observation. The rule offered here is, as in Chapter V, that one should aggregate a series of simulation days at least as long as the total system cycle time. One logical grouping might be a month since businesses generally maintain records over that period.

Once the measurement variable and the observation period have been selected, the next task is actually running the simulation and assembling the data. A series of runs should be made with the only difference being the random number set. Each run should be long enough to allow the model to display stability. SPSF experience has demonstrated that ten operating periods provide enough data for the analysis.

When the data has been gathered and adjusted, model stability can be tested using the ANOVA procedure discussed

earlier. Using the observation periods as treatment groups, the test can successively eliminate the initial observations until there is no significant difference between observation periods. When the observations are found to be statistically equal, the model has reached stability. The test results provide insight into the length of time that it takes the model to stabilize from the starting conditions, whatever they may be. Such knowledge is critical in establishing model run strategy since a long period of instability implies that initial response measures are questionable. Only when the model has stabilized can the response measures be counted as meaningful. For an unstable model, either the runs must be long or further analysis is required to decrease the length of the stabilization period required.

The second stability measure can be obtained by using the random number sets as the treatment groups in another ANOVA procedure. The appropriate hypothesis is that no significant difference exists between runs utilizing different random number sets. This analysis provides insight into the degree of response variance. If the response variable displays a large degree of variance, a larger number of random variable sets will be required to accept the hypothesis. Correspondingly, if a large number of sets is needed to verify the hypothesis, a large number of sets is

also needed to provide an accurate estimate for the true response parameter. In terms of model run strategy, a high level of response variable variance implies that either a large number of replications is needed for each experimental condition or the implementation of a variance reduction technique is required to reduce the variance level.

An example of the procedure outlined above can be described using the initial model applications. For both applications, aggregate sales at the distribution center were used as the response variable, with the observations being selected as an aggregate of 20 simulation days. Each simulation was run for ten observations, or a total of 200 days. For each application, ten different random number sets were modeled. Table 29 illustrates a sample worksheet for the analysis of the applications. Although there was no trend apparent in either application, the seasonality component did have to be removed prior to analysis. In both cases, the analysis found that the variance across random number sets was very low so an accurate estimate for a true parameter could be gained with less than five runs. In terms of the warm-up aspects of stability, the results from the two applications were significantly different, even though initial inventory levels were set to zero for both cases. Application A did not appear stable until after

three observation periods or 60 simulation days had passed. On the other hand, Application B demonstrated stability throughout the simulation. The probable source of the difference was the complexity of the alternate systems and the different inventory policies.

The impact that either of these two factors may have on run strategy is unknown. In general, however, as can be seen from the above applications, the impact may be significant. Thus, analysis of the stability characteristics of each application is an important step in selecting the appropriate run strategy.

EXPERIMENTAL RUNS

Once the historical validity and the stability of an application have been established, the analysis can proceed with the experimental runs. However, acceptable answers to the previous two questions discussed in this chapter do not imply that the model is perfectly valid. The prior answers only lend more credibility to the model and provide insight into its utilization strategy. The next phase in the model validation and utilization process designs and analyzes the experimental runs. The experimental design is influenced by the research objectives as well as the historical fit and stability characteristics of the application. If the inventory-service relationship is under investigation, a series of simulations may be used to

determine the relationship. Whatever the experiment, the model results ought to be analyzed by both analysts and decision makers to determine whether or not the response variables conform with their intuition. If there is no match, model credibility is questioned while a correspondence builds model credibility.

A four-step procedure is appropriate to provide the analysis of the experimental runs. Step one calls for specification of the runs to address the research problem. An appropriate design might include alternative inventory levels or channel designs. The run strategy ought to depend on the application characteristics identified in the earlier questions. The specifications for the individual simulations should include the parameter settings for each run. The intuition and insight of the analysts and decision makers are combined in step two to provide predictions of what the model response ought to be. The forecasts of model response ought to be as detailed as possible to facilitate comparisons. Step three addresses the task of actually making the simulations and estimating the true model response parameters. Step four contains the actual "analysis and action" phase where the model results are compared against predicted results. Any serious discrepancy should initiate explanatory or corrective action depending on the source of the problem. If the problem lies in the model rather than the predictive

ability of the individuals, appropriate modifications should be made and steps two through four ought to be repeated again. The four-step procedure provides a systematic means of integrating managerial experience with model results to aid in establishing model validity.

The two applications initially implemented on the SPSF Testing Environment were subjected to the above procedure. In addition, another contrived data set--The Demonstration Run Set--was tested in a series of experimental runs. For each application, the run design specified a series of ten runs which tested a number of distribution configurations and policies. A prediction of run results was made by the analysts and decision makers involved. Upon comparing the run results with the predictions, there were no serious discrepancies between the predicted and observed results. Since the results of the experimental runs for the specific applications are proprietary, a series of fourteen demonstration runs were performed to illustrate model application validity. Figure 4 illustrates the basic configuration of the system used. The basic questions investigated concerned alternate channel design, split product sourcing, flexible product sourcing, and the effects of lead time uncertainty at various points in the channel. The detailed results of the analysis are discussed in the SPSF research monograph.⁴ The results of this series of demonstration runs also corresponded with expectations.

RECORD MAINTENANCE

The procedures presented previously in this chapter can serve only to build model credibility, not to guarantee it. It is only through repetitive model use in different situations that the probability of valid results approaches one. In the past, although distribution models have been applied or used in many situations, no consistent record of performance has been maintained. It appears that each analysis is done independently with no ongoing integration to assist in either theory building or future model applications. As Emshoff and Sisson point out, it is only by continually demonstrating cases of model validity that ultimate model validity can be established. The basic problem is to develop a means and motivation for maintaining records of model application. The mechanism for maintenance of this information is not simple since the range of applications and objectives can differ widely. Service may be a significant variable for one application while costs may be significant for another. Even the channel structure and policies may differ to such a degree that results for one application have little implication for alternative applications. The second, and probably more serious, drawback to record maintenance is a lack of motivation. With the always present time constraints, researchers do not wish to use their limited resources to fill out a complex form

which records model performance. In addition, proprietary data may be involved, thus limiting ability as well as motivation.

The basic problem in testing ultimate model validity is that of record-keeping. Only when the records are maintained over time for comparison to actual results can actual model performance be evaluated. As the final phase in the managerial utilization procedure, this dissertation suggests a means and a framework for developing the record base. The means consists of a log book which contains run reports for each model application. A record of the results observed when an alternative is actually implemented is also included. The inclusion of implementation records would undoubtedly be somewhat limited due to the proprietary nature of the information, however. The framework consists of a three-part form which solicits qualitative responses about the research, particularly model utilization.

The first entry addresses the general scope of the research and considers such questions as model use objectives, channel configuration and parameters, results of validation for historical fit and stability, special problems faced, and special model techniques tried. Appendix B illustrates the general applications log sheet. There would be only one general log sheet per application.

A second entry, illustrated in Appendix C, is used to record the particulars of a specific run. The items included are a brief description of the experimental conditions, technical model performance data such as run time or cost, and a brief discussion of run results. The run report is only completed for different experimental conditions, not for runs with different random number sets. In particular, the run report ought to reflect the aggregate results obtained from as many different random number sets as are necessary to determine an accurate and true response parameter.

The final research entry in the log would be a brief synopsis of the model results. Rather than try to restrict the discussion to a specific format, a free-form paper seems most appropriate here. This segment could take the form of an article or working paper. As with any research article, the discussion ought to cover the objective, results, implications, and potential for future research.

The existence of the above framework provides a means for recording model performance although there is still little motivation. The only real motivation that can be offered is the resultant existence of a data base providing information for easier model use. The same data base also increases model credibility for all future projects.

CONCLUSION

Chapter VI has presented and illustrated a four-phase procedure for model utilization for actual management decision problems. In the past, the only phase that has received any attention has been the question of historical fit. Although such a test of model credibility is important, the utilization procedure ought to address other problems that are characteristic of simulation problems. In particular, the last three questions addressed in this chapter have major implications for building model credibility. Although the problems have been discussed in general simulation texts, distribution models have chosen to ignore them. On the other hand, this procedure must be practical enough for implementation on large-scale simulation models while remaining within economic constraints. Decision makers must also be convinced that it is to their benefit to perform the procedure. Without proper justification and a practical procedure, the problems in managerial utilization will continue to be ignored.

CHAPTER VI--FOOTNOTES

¹A. M. Geoffrion, "A Guide to Computer-Assisted Methods for Distribution System Planning," Sloan Management Review (Winter 1975):17-42.

²O. K. Helferich and R. W. Kallock, "A Way to Achieve Effective Distribution Planning," Handling and Shipping (September 1976):58-60.

³D. J. Bowersox et al., Dynamic Simulation of Physical Distribution Systems (East Lansing, Mich.: Bureau of Business Research, Michigan State University, 1972), pp. 182-5.

⁴D. J. Bowersox, D. J. Closs, J. T. Mentzer, Jr., and J. R. Sims, Simulated Product Sales Forecasting (East Lansing, Mich.: Bureau of Business Research, Michigan State University, 1978), Chapter 8.

CHAPTER VII

SUMMARY AND CONCLUSIONS

Chapter VII summarizes the research and presents the major conclusions. The first section contains a brief summary of the research purpose and design. The next section reviews the research questions and findings, and subsequent sections discuss the research contributions, amplifications of the model and procedure, and implications for business executives and academicians. The chapter closes with suggestions for future research.

SUMMARY OF RESEARCH PURPOSE AND DESIGN

The research purpose has been threefold. The first phase addressed the specification and implementation of an integrated distribution planning model. A search of the appropriate literature in physical distribution and modeling provided a base for decisions concerning model processes and the means of modeling them.

Phase two addressed the problems of operationally validating the model to provide the foundation for establishing model credibility. The validation procedures for existing distribution models as well as simulations in general

were reviewed. A procedure to test the model's initial validity both quantitatively and qualitatively was then proposed and illustrated.

Phase three addressed the managerial problems of establishing model validity for an individual application and providing a long-run record of model performance. The literature review included a discussion of validation procedures for distribution models. This research provides the details for a normative procedure that addresses the questions of establishing application validity for management. The data base used for validation of the research concept and procedure included both contrived data for operational validation and actual data from two firms for validation of the utilization procedure.

REVIEW OF RESEARCH QUESTIONS AND FINDINGS

This section reviews the research findings with respect to the major research questions identified in Chapter I.

What functions are necessary for modeling an integrated physical distribution system and what process is appropriate for implementing the model?

This question addressed the design and implementation of the model. The question was divided into four sub-questions which were treated in Chapter IV. The first question identified the method of analysis to be used when

specifying a model. The method found to be appropriate was a functional approach which treated the system as managers and academicians were accustomed to viewing it.

Question two concerned the appropriate model characteristics for developing an integrated distribution planning model. The research concluded that such a model ought to be a dynamic simulation which utilized a discrete time advance mechanism, stochastic environmental components, and detailed record maintenance. Consistent with the functional approach identified in the first question, the research also concluded that the model itself ought to be implemented with an event orientation.

The third question addressed the actual implementation process in terms of the techniques and language used. To facilitate use and modifications, the research concluded that an efficient yet flexible parameter structure ought to be used to provide model dynamics. Linked list structures and maintenance routines were found to satisfy these requirements. This question also addressed the language and computer resources to be used. To promote additional research at other locations and by more individuals, it was concluded that generally available computer resources ought to be used along with a language that was as universal as possible. The FORTRAN-based GASP IV simulation language met these requirements. In addition, the basic structure of the

language was well known to the researcher and could be modified easily to incorporate the linked list structures.

Question four concerned the functions required for analysis of an integrated physical distribution system. On the basis of the framework developed in Chapter II, the research identified twelve events necessary for modeling the system. Table 5 summarized these functions.

What methodology is required for building the validity of the integrated distribution model?

Research question two addressed the task of building model validity. With an analysis of four sub-questions, a methodology was defined and illustrated for establishing initial model credibility.

The first question treated the process of testing the implemented model in terms of programming procedure and basic transformations. Manual observation tested model logic while statistical analysis tested the basic stochastic transformations.

Question two concerned the pragmatic tests imposed by managers and decision makers. The measures here included detailed reviews of the modeled physical distribution processes by experienced analysts and decision makers.

The third question addressed the task of determining model stability over time and across runs. The research identified two problem areas, characteristic of all

simulations, which have been inadequately treated in distribution modeling. A statistical procedure for testing model stability and determining its impact was suggested and illustrated.

The fourth question concerned the test of model results under different environmental conditions. The last test of operational model validity posited that, to be valid, the model ought to demonstrate significantly different responses when significantly different parameters or environmental conditions are utilized. A test procedure was described and illustrated.

Once the procedure developed in response to research question two was completed, initial model validity was established. The procedure ensured that no basic conceptual problems existed in the model and that a response variable was well behaved under sample operating conditions.

What should the procedure be for analyzing model applications and judging model performance?

The methodology and results found in research question two do not provide a validity test for all applications. Such a complex and costly methodology is beyond the scope and resources of most model applications. Nevertheless, the problems of validation still exist and ought to be considered. Research question three addressed this problem and proposed a utilization procedure to test model validity. The analysis was again segmented into four sub-questions.

The first question concerned the model's ability to match the historical data available for the application. The importance of this test and the tests that can be used for establishing fit were discussed. The test results for applications using the SPSF Testing Environment were provided as examples.

Question two considered the sources and the impact of model instability. Initial start-up conditions and alternate random number sets were of particular interest. The literature review revealed that these problems had not been addressed in distribution models even though these sources of model instability may have significant implications for model run strategies. Two actual applications of the SPSF Testing Environment were used to illustrate the procedure for analyzing impact in specific situations.

The third question concerned the correspondence of model predictions with the intuition of managers and decision makers. The research found that such a matching was a very important part of establishing model credibility. A review and analysis process was proposed and illustrated.

The final question within the managerial utilization phase considered maintenance of historical data regarding model performance. A performance record provides a basis for matching predictions with reality and aids future model applications. A format was suggested for maintenance of performance information.

RESEARCH CONTRIBUTIONS

The major research contributions are:

1. Simulated Product Sales Forecasting Testing

Environment. Existing distribution modeling literature was reviewed and used as a guideline for the development of a simulation model that considers all aspects of physical distribution. The model integrates the firm's demand environment, its procedure to predict that demand environment, and its operations to meet the predictions. Since the model considers each aspect with a range of alternative operating procedures, it provides a unique testing environment for the study of physical distribution operations and planning. The model offers the capability to isolate sources of error in the system and then provides an environment for evaluation of potential solutions. Other applications include customer service tradeoff analysis and channel cost-revenue analysis. The ability to modify and control environmental conditions provides the opportunity to perform contingency analysis. The model concept and implementation is validated through a procedure using both contrived and actual applications.

2. Development and specification of a procedure for designing a distribution operations and planning model.

The review includes a discussion of the questions that must be addressed and the alternatives that are available. The procedure includes steps for both model design and computer implementation.

3. Analysis of model validation problems and a methodology for addressing these problems. Past distribution modeling processes have overlooked the problems of model validation. This research has discussed some of the potential problems deriving from that oversight. A procedure is suggested that provides an initial foundation for model credibility while remaining within the realm of practicality. The procedure is suggested for use when a distribution model is initially developed or when major modifications are completed.

4. A procedure for use in establishing model credibility and performance characteristics for each application. The methodology proposed in the third contribution is not appropriate for each model application. Nevertheless, since validity tests are dependent on the data, some type of analysis is necessary to establish application validity. The research concludes that the important criteria when validating an application are historical fit, stability, and intuitive matching. The importance of each is stressed and a procedure is outlined for evaluating the model's ability to meet the criteria.

AMPLIFICATIONS OF THE MODEL

Although no major problems were encountered when applying the model to either contrived or actual data, both situations required a detailed data base for at least a limited geographic area. The data, which must describe both the physical distribution environment and operations, required considerable effort to assemble and convert to a form acceptable for the model. This process was greatly facilitated by the data bases of the firms that applied the model. The data requirements for model utilization, particularly in contingency situations, may make the model impractical for some users.

A related issue is a thorough understanding of both the performance of the model and the actual system. Although the model will always produce results, interpretation of those results requires extensive analysis and insight on the part of analysts and decision makers. The research sponsors' level of sophistication enabled them to use model results effectively. Others, less experienced in model interpretation, may become too involved in details to appreciate the model's true impact. Model development is an art, and model utilization and interpretation requires an equally high level of sophistication.

The model, although a generalized tool for analysis of an integrated physical distribution system, does not

include capabilities to treat special situations such as "push" distribution systems, consolidated shipping, or derived demand. Application of the model in such situations would require a modification of the process in modeling the distribution activity. Although the model is designed with enough flexibility to facilitate such an adjustment, implementation of the generalized process would be difficult.

The model is designed to perform very detailed analysis for limited channel operations within the firm. Although the limited analysis simplifies the data gathering process, it also requires extrapolation of the conclusions to the entire system. There is little experience to guide this extrapolation procedure. Future research will have to provide further insight into this question.

The firm's manufacturing environment is not treated in detail by the model. Raw material acquisition, raw material inventory control, and production transformations are generally unique to the firm and could probably be modeled with a specific application much more effectively than with a generalized procedure. However, such amplifications could be integrated into the model to provide a tool for analysis of the total logistical coordination process.¹ Although the model data base could support such an integration, the interface of the purchasing, production, and physical distribution functions is beyond the scope of this research.

The tests of model validity describe a process which begins to establish credibility in both the model itself and individual applications. However, the only way that the model can actually be proved valid, regardless of the results of the manual and statistical analyses suggested here, is through experience. The basic question remains: Does the real world behave in the way that the model predicted it would? Only time will provide a definitive answer.

IMPLICATIONS

The research holds many implications for both business executives and academicians. The review revealed that past modelers have failed to consider all aspects of distribution systems. Although the omission was deliberate in many cases, a more significant problem in previous distribution research is the failure to consider model validity.

Existing research has placed a heavy emphasis on the firm's performance of relatively few distribution functions. Current analysis methods and models have not investigated interactive effects. For example, the firm's total channel design or inventory policy is often studied but the interaction of the multiple functions involved in the distribution process is not. As a result, little is known about the various tradeoffs that may occur in terms of either improved performance or lower cost. Application of an integrated

methodology should lead to a more thorough understanding of system performance and a more rational allocation of effort and resources.

The validation and utilization methodologies proposed for existing distribution systems have been inadequate. The models have not been subjected to sufficient testing to ensure that their performance is both realistic and statistically appropriate. Although a model is only an aid in analyzing the system under investigation, it inherently incorporates many assumptions and subjective judgments. Because of the secondary emphasis placed on the model itself, its structure and performance are not always investigated adequately. A probable reason for this deficiency is the lack of knowledge on the part of distribution model users. Beyond the question of historical fit, simulations require additional analysis to gain insight into the model's stability and past performance characteristics. These issues have been overlooked in the past, not only in model development but also in model application. Such incomplete analyses may lead to significant errors in model interpretation, thereby promoting the incorrect alternative and decreasing future model credibility.

SUGGESTIONS FOR FUTURE RESEARCH

This research demonstrates a substantially different approach than that offered by previous distribution models.

The analysis looks at the interactive effects of the various functions of distribution operations rather than the overall effects of a relatively few functions. In addition, a detailed procedure is outlined for utilization of this and other simulation models when investigating the performance of distribution systems. The tool and the procedure for analysis are now available. The following paragraphs address the possible directions of future research in the area of distribution system analysis.

1. The model may be used as a classroom aid to demonstrate the concept of tradeoff between various distribution functions. Students could also gain experience in the research design, execution, and analysis of a distribution research project.
2. As discussed previously, any discrepancy between the actual and potential level of sales in a single period may be the result of either an inaccurate forecast or the inability of the physical distribution system to support demand levels. The SPSF Testing Environment provides the capability to analyze the relative and absolute impact of such discrepancies. Each type of error results from a distinct type of uncertainty. Forecast discrepancy results from uncertainty about the level of future demand.

Operating discrepancy results from uncertainty in the performance of the distribution operating system. On an experimental basis, each form of discrepancy can be identified and measured to formulate improved forecast procedures and operating policies.

3. Using the SPSF Testing Environment, the relationship between the levels of customer service, system sales, and total operating cost can be simulated. In addition, the impact of selected policy changes on system performance can be evaluated. For example, changes in transportation costs, inventory costs, and corresponding service levels resulting from a decrease in order cycle times can be quantified. Likewise, the response of service and cost to changes in base and/or safety inventories can be analyzed.

4. An additional area for potential research is comparative evaluation of alternative channel designs. The structure of existing distribution systems has evolved in response to changing conditions. The evolution has been painful economically because of the inability to create complex system designs in anticipation of such changes. The SPSF Testing Environment provides the means through which the firm can reduce the extent of uncertainty accompanying any planned change in system design. For example,

the actual performance of the firm's channel system over a period of time can be compared to the simulated performance of what would have been achieved using an alternate or modified structure. The modifications could be in the form of either structure or operating policies. For example, the system concentration of inventories might be systematically simulated and analyzed from one echelon to another to determine the structure offering the highest degree of efficiency. On a system basis, repeated simulation can be employed to investigate the relative cost-benefit of push versus pull distribution systems. Once a valid replication of an actual operation is achieved, the testing environment offers a way to evaluate modified distribution structures and/or policies.

5. A final broad area of potential research is contingency planning and evaluation. The response of an operating system to environmental changes and acts of nature can be simulated under specific experimental situations. For example, the performance of the distribution system under varying degrees of recession or economic boom can be analyzed in conjunction with the demand module. Another form of contingency planning could evaluate the impact of

supply restrictions on inventory availability and services using the operations module. Similarly, the impact and potential of a given restructure to perform "reverse distribution" can be determined. The above examples are only a selected few from among the wide variety of contingency planning situations that can be evaluated using the SPSF Testing Environment.

CHAPTER VII--FOOTNOTES

¹Donald J. Bowersox, Logistical Management, 2nd ed.,
(New York: Macmillan Publishing Co., Inc., 1978),
pp. 15-17.





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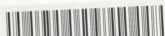
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APPENDICES

APPENDIX A

MODEL BIBLIOGRAPHY

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MODEL BIBLIOGRAPHY

Appendix A discusses each model identified through the literature review in detail. The analysis provides a broad description of model objectives and capabilities. In particular, the environmental, controllable, and target variables are identified. The model characteristics, as defined in Chapter II, are described. The model logic in terms of force variables and results is then outlined. Finally, the model review identifies the application areas for which the model is appropriate.

BALLOU

Ballou, R. H. "Dynamic Warehouse Location Analysis."
Journal of Marketing Research (August 1968): 271-76.

The dynamic programming model developed by Ballou presents a methodology for solving the long-range location problem. The solution method is a two-step process which utilizes any available location simulation to evaluate data representative of successive time periods. The results of the discrete time period simulation are then viewed on an overall basis to determine the optimal location strategy over time. The logistical network and costs that can be considered in this model depend on the particular location simulator selected. The variables used in the locational phase also depend on the particular location model. The Ballou model does not provide a specific static simulator, but one application proposes the use of a static location model similar to that proposed by Mossman and Morton¹ for each year in the planning period.

Most characteristics of the Ballou model depend on the specific static simulator used in conjunction with dynamic programming. The particular model may

be either general or specific with regard to its capability to handle different types of distribution systems. The question of deterministic or probabilistic also depends on the model used in the first phase, although most locational models are deterministic.

The second phase, dynamic programming, performs a deterministic analysis. In terms of long-range planning, the model provides a means for dynamic analysis since it allows the results of past years to influence location selection in future years. However, the preliminary model itself is not dynamic. The model design allows for simulation of logistics structures over time. The model does not provide a structure that would allow analysis of typical distribution events. The dynamics of the model are implemented within a discrete time frame where the period of simulation is one year. The model determines the best set of locations over the entire planning horizon. Although the locations may change from year to year, the model considers the costs incurred by facility re-location. However, the problem cannot be resolved simply by moving each year to that year's

maximum profit location because of the costs incurred with each move. Through dynamic programming, the locations chosen in a particular year are evaluated to determine when a move is advantageous and, if it is, which location should be moved. Beginning with any particular warehouse location, a path is developed which ideally traces the lowest cost system of locations for the entire planning period.

More recently, Wesolowsky and Truscott² have addressed the dynamics involved in the multiperiod locational problem. Specifically, an integer programming approach is contrasted with a dynamic programming approach for different types of problems.

BALLOU

Ballou, R. H. "Time Delay Effects in Computerized Physical Distribution Systems." International Journal of Physical Distribution, Vol. 6, No. 4 (1976):183-211.

The second model described by Ballou is primarily an inventory testing mechanism for systems that incur various types of stochastic delays. The model is applied on a regional basis for orders experienced at a single facility although each customer order may contain multiple products. Environmentally, the model considers customer demand as well as various cycle time components. Ballou has treated two types of time delays, specifically perception delays and operation delays. Perception delays are caused by the failure to instantaneously communicate changes in inventory position due to sales or replenishment. Operation delays are the normal order cycle time components such as communication and transit times. The minimum and maximum inventory levels and replenishment policies constitute the controllable variables. The service level provides the target variable for analysis.

The model events occur on a dynamic basis, thus

treating the effects of inventory feedback on a day-to-day basis. Each of the time components are treated stochastically to model the desired degree of uncertainty in the environment.

Inventory and replenishment parameters must be specified for each product prior to the simulation. During the simulation, the customer orders are placed against the inventory on hand as determined by the parameters specified. Analysis of inventory management policies provides the primary application for this model.

BENDER

Bender, P. S. Principles of Physical Distribution Systems Configuration Design. Washington, D.C.: Marketing Publications, Inc., 1971.

The analytical model introduced by Bender incorporates the model elements essential for distribution system analysis into a standard linear programming package (MPS) offered by International Business Machines. Data preparation and reporting modules are included with the model. The system was developed and is offered by Drake Sheahan/Stewart Dougall Inc. (DS/SD). The model provides the capability to analyze relatively large logistical systems which may include vendors, manufacturing facilities, warehouses, and customers. Up to 99 commodities may be considered in the analysis. The model allows consideration of most operational costs, including freight, handling, fixed, and limited analysis of the inventory component. In addition, non-linear cost functions can be approximated using piecewise linear equations. The environmental variables used in the model include customer demand which is input to the model exogenously, and cost functions which are generally based on facility

throughput. The model parameters, which may be controlled by the user, include existing and potential facility locations and inventory stocking policies. The target variables include the optimum set of location assignments for least cost operation of the distribution system, and the sensitivity of optimum cost to changes in system configuration.

The Bender model appears to provide adequate flexibility to analyze most alternative system configurations. Writeups on the model indicate the capability to treat up to 1,000 nodes, which may be distributed as desired into supply, plant, warehouse, and demand nodes. In addition, up to 4,000 network connections or links may be defined, including any origin-destination combination for a commodity. Use of the piecewise linear cost functions increases flexibility. The DS/SD Generalized Distribution Model provides an analytical technique to describe and test a relatively complex distribution system without requiring simplifying assumptions.

The uncertainty inherent in the operation of distribution systems is not considered by the model;

therefore, the DS/SD model is deterministic. Any analysis of the effects of uncertainty must be done either outside the model or through the use of multiple runs. The information feedback characteristics of the model were designed to be static. The developers felt that the sensitivity of distribution systems to change in the basic parameters of the system did not justify the complexity of dynamic modeling. Application of the model is limited to analysis of structures, particularly the number of plants and/or warehouses. The structural model also provides a method for selecting the best assignment for customer-commodity demand.

Execution of the model involves three phases. The first phase consists of input validation and matrix generation steps. The demand, supply, cost, and capacity functions are checked for consistency and are assembled into a format compatible with MPS 360, the IBM mathematical programming package. The second phase is the optimization phase which uses the capabilities of MPS 360. The final phase uses the output of the optimizing phase to produce reports. These reports include an inbound/outbound

report for each location, a cost summary, and a ranging report. The ranging report provides sensitivity analysis for each of the variables in the final solution.

Since Bender's model is structurally oriented, its primary application is in the area of facility location planning. This model does offer two elements which are unique among the analytical models reviewed. It has the ability to test alternative plant locations in combination with alternate warehouse locations. And the model's capability to perform sensitivity analysis within a single run offers potential savings in alternative analysis. The structural analysis of DS/SD is supplemented by other modules which are incorporated into the model to perform inventory analysis and further sensitivity range.

BUFFA

Buffa, Frank R. "A Model for Allocating Limited Resources When Making Safety Stock Decisions." Decision Sciences (April 1977): 415-26.

Buffa proposes an optimization model for establishing safety stocks in a fixed-interval, variable order quantity inventory system. The constraints placed upon the system include limited storage space and capital. The modeling technique used is a subset of linear programming known as goal programming. The model optimally determines levels of safety stocks within a single location structure in a multiproduct firm. The model operates dynamically over a multiple month operating cycle. A forecasting model must be utilized to generate the demand to drive the model. The target variable for the goal programming model is the minimum cost allocation method within the constraints of the system. The alternative to which this is compared is an allocation method which does not optimally satisfy the constraints. The costs considered by the model include holding costs, stockout costs, and the costs of exceeding available resources in order to maintain the safety stocks.

The goal programming model is a special case of linear optimization designed to accommodate more than one objective or goal into the model solution. In particular, the model attempts to minimize the necessary deviations from a desired level of safety stock while considering the constraints. Different priorities or costs may also be placed on the deviations. Similar to other linear programming models, goal programming provides an optimum allocation within the deterministic environment of the system. However, the model is flexible because it can be adjusted for changes in goals, priorities, ranks within priorities, and environmental constraints. The primary feature of this model is its demonstration that significant reductions in cost can be obtained by using a goal programming model to set safety stock levels in a multiproduct firm.

CAMP

Camp, R. C. "The Effect of Variable Lead Times on Logistics Systems." Ph.D. dissertation, Pennsylvania State University, 1973.

In his doctoral dissertation, Camp introduced a heuristic model to test the effects of variable lead times on a logistics system. Some of the features included for customer assignment are a localized search to determine the source with the lowest transportation cost, the use of the total distribution cost criterion, and sequential testing of potential cost reductions within desired tolerances. The distribution network used by Camp permits a single product within a one-echelon warehouse structure. The effects of alternative modes of transportation and shipment sizes can be studied.

The Camp model allows the researcher to observe the cost and service characteristics of alternative warehouse configurations. The model's flexibility allows public and private warehouses to be introduced in various combinations. While the single echelon structure limits applicability, the different transit modes available add to the model's generality.

The model contains both deterministic and probabilistic components. The lead time from plant to warehouse -- which is composed of transit time, placement time, and processing time elements -- is determined by means of continuous probability functions whose parameters are defined by the user. The safety stock, cycle stock, and in-transit inventories are deterministic and based on type of warehouse, demand, and lead time. The level of safety stock is quantified using essentially a deterministic relationship.

The Camp model is static. There are no information feedback loops which would allow past results to be used as inputs to later operations.

The model's primary functions include the capability to evaluate location and structure problems, with some consideration given to the effect of variable lead times on inventory levels. However, according to the author, "This research quantified the level of safety stock on what is essentially a deterministic basis. The research results should, however, be extended to include a stochastic inventory simulation." (p. 126)

Aggregate yearly customer demand is traced through the model with assignments made on the basis of costs. The replenishment system is operated under conditions of variability in order lead time and demand distributions. The resulting effect on total system cost and safety stock level is compared as alternative numbers and locations of warehouses are evaluated in the system design.

DISTRIBUTION PLANNING MODEL (DPM)

Helferich, O. K., and Closs, D. J. "Computer-Assisted Logistics Planning for the Firm." Proceedings: 10th Annual International Logistics Symposium. Society of Logistics Engineers, 1975:25-31.

Helferich, O. K. Distribution System Design Techniques. East Lansing, Mich.: By Cleveland Consulting Associates, 1976.

DPM was developed to provide an efficient means for testing alternative distribution configurations. The model has the capability to simulate multiple echelons, multiple facilities, and multiple product systems within program-established limits. The model evaluates total distribution costs for each configuration tested. Cost elements include inbound and outbound freight, warehousing, and inventory. The simulated or actual demand, the driving force of the model, is the only environmental variable. Controllable variables include cost functions as well as facility locations and stocking points. The target variables for analysis include total cost and a spatial measurement of the service characteristics of the system.

DPM provides a structure to facilitate simulation of most distribution systems without program

modification. The model is deterministic in that the program does not use probability functions to affect the flow of the model. This characteristic implies that the model is totally predictable and replicable. DPM is also static in that only one period is simulated at a time and there is no information flow between periods. The basic objective of the model is to model distribution networks or structures. Each alternative structure is tested to observe its cost and service performance relative to other structures.

Customer demand, which may be broken down into products, transportation modes, and transportation weight breaks, provides the input for DPM. Each segment of demand is assigned to a distribution source based on one of the selection algorithms. The quantities are traced back through the distribution system until a production point is encountered. Since the model has no temporal dimension, all activities are assumed to occur in a single time period. DPM can also delete locations based on a lowest marginal cost concept. This capability allows the analyst to give the model a list of locations from which it can systematically reject the most inefficient ones. For

each configuration of locations, the model output consists of the cost and service characteristics of the system. Applications of DPM include facility location and configuration design.

DSS

International Business Machines Corporation. Distribution System Simulator (DSS). For System 360/370, Program Number: 5798-ATY, 1973.

Connors, M. M.; Coray, C.; Cuccaro, C. J.; Green, W. K.; Low, D. W.; and Markowitz, H. M. "The Distribution System Simulator." Management Science (April 1972): 425-53.

The Distribution System Simulator (DSS) was developed and marketed by IBM. The model considers the major factors involved in the operation of a distribution system such as the characteristics of customer's demand for products, buying patterns of customers, order filling policies, replenishment policies, transportation, distribution channels, factory locations, and production capabilities. DSS directly treats most of the individual cost components inherent in a distribution system. The categories of costs available in DSS include:

- (1) inventory holding, (2) in-transit, (3) order filling, (4) lost sale, (5) back-order, and
- (6) transportation.

The types of variables included are uncontrollable, controllable, and environmental. The uncontrollable variables, the inputs that cannot be affected by the firm, include demand characteristics

and cost functions. The controllable variables are those which can be manipulated by the firm and include distribution system structure and order processing policies. Target variables are primarily measurements of system cost and customer service.

The DSS model provides a capability for testing many types of distribution systems. The particular relationships among the components of the system are left entirely to the discretion of the user. The generality of the model is further enhanced by the availability of different modules for use in processing orders. Another characteristic of DSS that allows it to be applicable to most distribution system configurations is its capability to structure multiple-echelon, multiple-facility, and multiple-product distribution systems.

DSS allows the various model components to operate in either a deterministic or probabilistic mode. The modules that are stochastic, which include lead times, production quantities, and order quantities, allow the use of either a constant function or one of several probability functions.

The DSS model is dynamic. The operation of each period influences the model performance in all

succeeding periods. For example, the order lead time assigned to a replenishment shipment will directly affect inventory availability for the following periods.

The DSS model has the ability to model both the distribution system structure and the events that comprise distribution operations. This characteristic allows the model to be used for testing alternative configurations as well as for testing policy alternatives throughout the system. With its capabilities as both a structure and an event model, DSS offers a wide range of potential applications related to distribution system design and operational planning.

Another major characteristic of the model is its timing mechanism. Although it is technically discrete, the fact that it uses small time increments (minutes) permits the methodology to be considered continuous for all practical purposes.

The DSS model is a unique approach to modeling in that the user creates the program by answering a series of questionnaires. The complete questionnaires are input to an editor program which generates a simulation model appropriate for a particular

application. The data required for the simulation are also specified by the model generation package.

The driving force of the DSS model is demand, which may be either actual or simulated orders. Other operating functions, such as inventory management, order shipment and arrival, and forecast review, are scheduled as necessary. In addition, it is possible to incorporate other algorithms such as vehicle scheduling, forecasting techniques, production schedules, and pricing and costing techniques. These algorithms can increase flexibility in the DSS model. A record is made of each event as it occurs so that reports can be generated when necessary. The potential applications for DSS include both structural and operational questions.

FORRESTER

Forrester, J. W. Industrial Dynamics. Cambridge, Mass.: The MIT Press, 1961.

Forrester developed a model of a production-distribution system which allows for isolation and observation of the dynamics inherent in the system performance. According to Forrester, the process of matching flow rates of production with consumer sales is a recurring problem in most industrial companies. The network used by Forrester includes a multiple-facility, multiple-echelon system. However, the model uses only a single product and a single distribution channel. Since the model is designed to study repercussions from disturbances occurring primarily at the retail level, no costs are used in the system. These last mentioned items provide the three basic variables of the Industrial Dynamics model. Organizational form includes the facilities and echelons at which inventory exists, such as manufacturing plants, distributors, and retailers. Delays in the flow of information and of goods are used to introduce dynamics into the model. Management policies provide

parameters that govern the purchase and inventory activities.

The Industrial Dynamics model provides a tool for analyzing the interactions of a specific structure. This model could not be used to study most distribution systems because of the single channel constraint. The level of demand is deterministic, while the production level responds to this demand as it is filtered through probabilistic lead times. The interaction between these two levels when the system equilibrium is disturbed is the source of the dynamics. Due to limitations on the network, the model is of relatively little use when testing actual structural problems. However, the detail in which the time relationships can be defined in the model allows it to be used to observe dynamic interaction among events. The types of events appropriate for analysis include order processing, order picking, and order shipping. The Industrial Dynamics model approximates continuous time periods for scheduling events and reporting results.

The force variable is the demand level which is directed at the retail level. Inventory is maintained at each level in the system and reorders

are made to the next level in the channel when necessary. Small disturbances can be made in the demand and the effects of this impact observed as the system adjusts to an equilibrium state.

Applications of the Industrial Dynamics model are limited by its restricted size. However, the concepts proposed by Forrester have provided the basis for many dynamic models.

GEOFFRION AND GRAVES

Geoffrion, A. M. and Graves, G. W. "Multicommodity Distribution System Design by Bender's Decomposition." Management Science (January 1974): 822-44.

The model developed by Geoffrion and Graves is not a simulation technique. The method uses integer programming in combination with Bender's Decomposition to provide an analytical technique with provisions for enough detail to allow a realistic research device. This technique provides a method for analytically modeling a relatively complex distribution system which can include multiple facilities, multiple echelons, and multiple products. The model can include most of the cost elements inherent in distribution through its transportation, fixed, and variable components. In addition to the basic cost functions, the model allows consideration of the economies of scale characteristic of distribution operations. The controllable variables used in the model primarily include warehouse configuration. The uncontrollable variables are provided by the demand which is generated or developed externally. The target variables are the cost characteristics of the system and the best source of supply for customers.

This mixed integer programming model provides one of the few analytical methods general enough to be used realistically to solve distribution structure problems. The detail available with respect to cost functions and system structure size permits successful analysis of many problems which were formerly unsolvable with analytical means. As with most analytical models, the Geoffrion and Graves model approaches analysis within a static and deterministic framework. Because of these constraints, problem solutions are the optimum at a point in time with no regard for the impact of uncertainty over time.

As noted earlier, this solution technique integrates integer programming with Bender's Decomposition. This approach provides the optimizing capabilities of linear programming models along with enough capacity to allow for realistic modeling. This technique, combined with that used by Bender, differs from simulation techniques in that it can optimize the configuration of locations without the use of deletion or branch and bound techniques. Thus, all locations are considered equally when determining the optimal configuration.

The problem is decomposed into separate commodity problems which are solved independently using a mixed integer programming technique. The individual commodity solutions are then combined and evaluated in the master program to obtain a compatible solution for all commodities. If the model determines that further refinements are possible, more iterations can be made through the commodity/master program steps until the model finds that it has reached an optimum structure. The decision-making power of the model is restricted to problems involving the number and/or location of warehouses and the source of supply for customer-commodity groups.

GPFS

Gross, D., and Ray, J. "A General Purpose Forecast Simulator." Management Science (April 1965): 119-35.

The General Purpose Forecast Simulator (GPFS) was presented by Gross and Ray. This model provides a structure for testing forecast procedures against various demand patterns. The structure provided by the model is enough to replicate the interface between the customer demand point and a stocking point. Since distribution cost elements are not directly relevant in forecasting, the model does not include cost components. The controllable variable is the forecast technique used in a test. The model includes nine techniques, including alternative types of moving average and exponential smoothing. The uncontrollable variable is the demand function which can be input externally or generated internally via a pseudo-random number generator. The target variable is the forecast error that results from the use of a particular forecast technique with the demand pattern.

The model allows the user to analyze the outcome of the forecasting event when a particular forecast

technique is used in conjunction with either a probabilistically generated demand function or an externally input demand pattern. The GPSF has six phases:

Phase 1: Read in or generate time series under study to represent demand

Phase 2: Make the forecast

Phase 3: Calculate forecast errors

Phase 4: Print out error results

Phase 5: Make a forecast projection

Phase 6: Plot the results

The results of each simulation illustrate the accuracy with which a particular demand pattern can be predicted using one of the forecast techniques. This information can then be used to select an appropriate forecast method given the characteristics of the demand at a location over time.

KUEHN AND HAMBURGER

Kuehn, A. A., and Hamburger, M. J. "A Heuristic Program for Locating Warehouses." Management Science (July 1963):643-666.

The Kuehn and Hamburger model provides a tool to aid in selection of an optimum distribution center network given a demand situation. The model allows for flexibility in system design since it is capable of treating multiple facilities, multiple echelons, and multiple products. The model considers the flow related costs of the distribution function, including the transportation, throughput, and fixed components. With the exception of time dependent costs such as inventory and storage, the Kuehn and Hamburger model provides a total cost method of evaluating distribution systems. The input variables used include primarily those controllable by the firm, except for customer demand. The target variables are the optimum warehouse configuration and cost characteristics of that configuration.

The flexibility of the model allows it to be used to study the characteristics of different configurations involving various distribution systems. The flexibility is enhanced further by the possible combinations of

plants-warehouses-customers-products that may be included in the structure. Since the model was introduced as a method to evaluate distribution structures or networks rather than distribution operations or events, the temporal elements of the model are static rather than dynamic. A feedback mechanism is implemented through the bump and shift routine which attempts to improve the configuration being tested by dropping or shifting warehouses. However, this does not add to the model's dynamics. The results generated are entirely deterministic, which is consistent with other locational simulators.

During each iteration the customer-product demand is assigned to the lowest cost warehouse for a source. This decision is directed on the basis of total variable and transportation costs. When the flow of goods has been traced through the distribution system, the cost characteristic of that configuration is obtained. The model iterates through different combinations of locations to "determine the geographical pattern of warehouse locations which will be the most profitable to the company by equating the marginal cost of warehouse operations with the

transportation cost savings and incremental profits
resulting from more rapid delivery" (p. 643).

LOCATE

House, R. G. LOCATE: A Distribution Center Location Model. Columbus, Ohio: College of Administrative Science, The Ohio State University, 1977.

LOCATE is an interactive computer program which acts as a tool for managers who are attempting to analyze multiple facility distribution systems. The model allows for a two-echelon structure with a maximum of forty facilities and ten products. However, the designer has noted that the flexibility of the model allows for changes to be made in either the size or the processes used in the model. The model evaluates the cost and service implications for any system desired. Cost elements include inbound freight, outbound freight, and warehousing. Demand is the only environmental variable considered by the model. Aggregate yearly demand provides the force variable for the model. Controllable variables include the facility locations and stocking points. For ease in creating and manipulating the data base, LOCATE uses three-digit ZIP codes as locations for both customers and distribution facilities. The target variables for analysis include total cost and spatial measurement of the system service characteristics.

LOCATE provides a real-time model and structure to facilitate analysis of distribution systems. The model is both deterministic and static in that it treats the system over an aggregate time period with no allowance for uncertainty.

Customer demand, which may be segmented into products, transportation modes, and transportation weight breaks, provides the input for LOCATE. Each segment of demand is assigned to a distribution source either on the basis of least cost or externally by the analyst. The demand quantities are traced back through the distribution system until a production point is encountered. The model incorporates no temporal dimension so all activities are assumed to occur in a single time period. For each configuration of locations, model output consists of the cost and service characteristics of the system. The model's interactive feature allows another configuration to be entered and tested immediately. Facility location offers the primary application of the LOCATE model.

LREPS

Bowersox, D. J. Logistical Management. 2nd ed.
New York: Macmillan Publishing Company, Inc.,
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Operations with Dynamic Simulation." Journal
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Gilmour, P.; Lawrence, M. L.; Morgan, F. W.;
Rogers, R. T. Dynamic Simulation of Physical
Distribution Systems. East Lansing, Mich.:
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East Lansing, Mich.: By Cleveland Consulting
Associates, 1976.

The Long Range Environmental Planning Simulator
(LREPS) provides a model which may be used for full
distribution system planning. The model was developed
at Michigan State University under a grant from the
Johnson & Johnson Domestic Operating Company.

The environmental variables can be grouped into
categories of demographic, technological, and acts of
nature. These variables constitute the factors
affecting the firm that cannot be controlled by
management. The controllable variables are the

factors that can be managerially controlled, such as system design, mode usage, and inventory policy. The target variables represent the output of the model and include customer service and total cost related to a particular system design and set of operating policies.

The LREPS model is designed to simulate the operations of the entire physical distribution system and it is therefore capable of modeling most individual system components. The model is composed of customer geographic demand points, manufacturing and distribution warehouse locations, and communication and transportation linkages. These entities can be molded into many different combinations, making the network capable of representing various distribution configurations. This attribute renders the model general since it can simulate different types of systems without modification.

The LREPS model is both deterministic and probabilistic. Generally, all events which occur at the nodes are deterministic while those that occur on the links are probabilistic. For example, whether or not an order can be filled at a storage point is

determined by the inventory level, while the actual order processing or transit time experienced for a particular order is based on a probability distribution.

The model can be used to simulate both structures and events. LREPS is capable of simulating both strategic design and tactical planning. Within a given configuration, the model can be used to test such operational policies as inventory safety stock levels and small shipment consolidation.

Another characteristic of the LREPS model, and one that is tied directly to its capability to simulate events, is that it is dynamic. This attribute is most apparent in the model's feedback capabilities in such areas as order cycle time and inventory policy components.

The LREPS model operates in both a continuous and discrete time spectrum. The flow measurements are taken at discrete time points and are then averaged over each time interval to obtain what approximates a continuous function.

The LREPS model is driven by customer orders which may be internally simulated or obtained from sales history. The simulated orders are placed against

a warehouse where the inventory is checked and the order is shipped if possible. If sufficient stock is not available, one of the model's stockout policies may be invoked to either create a back order or measure a stockout. As the orders are shipped, it is possible to model the shipment consolidation process. When necessary, a replenishment order is made to the appropriate source. The functions for the order processing and shipment activities for reorders are similar to those of the activities for customer orders. This demand buildup process flows back to the manufacturing facility where the production process is simulated. Concurrent with the operation of the model, the measurement subsystem measures status and flow variables and computes the relevant target variables. The simulator can be run for as many operating periods as necessary with the dynamic feedback element always existing between periods.

MARKLAND

Markland, R. E. "Analyzing Geographically Discrete Warehousing Networks by Computer Simulation." Decision Sciences (April 1973):216-36.

Markland, R. E. "Analyzing Multicommodity Distribution Networks Having Milling-in-Transit Features." Management Science (August 1975):1405-16.

Markland, R. E., and Newett, R. J. "Production-Distribution Planning in a Large Scale Commodity Processing Network." Decision Sciences (October 1976):579-94.

The simulation model developed by Markland provides the necessary elements for modeling the entire distribution system, with particular emphasis on the facility location and product allocation components. The network used by the model is composed of the production, distribution, and wholesale sectors. Within these three echelon limitations, the model can be applied to any multi-source, multi-destination, and multi-product distribution system. The Markland model provides a total cost distribution system simulator. The cost categories maintained by the model include fixed, warehousing, transportation, and penalty. These elemental costs are assessed against the flow of products through each of the nodes. The variables

can be divided into levels, flows, and delays. This detail allows cost elements to be computed directly rather than through transformations. Facility locations and capacity limitations provide the primary controllable variables for the model. The uncontrollable variables include demand and penalty costs for stockout situations. The target variable, which is total system cost, provides the measure of effectiveness for alternative distribution configurations.

The Markland model provides a method for analyzing many types of distribution systems. The multiple-echelon, multiple-facility, multiple-product structure allows the same technique to be applied to a wide number of situations. The model is deterministic in all of its components. This characteristic is consistent with most other models whose primary purpose is to determine the number, size, and location of warehouses. Although the Markland model has dynamic characteristics, its primary emphasis and capability is in structural situations. If the original form of the model is not modified, very little analysis can be performed for distribution events. However, the model's structure does provide a base for adding more detailed event

processing. The model operation in the application is discrete with a one-month operating period.

The force variable for the Markland model is customer or retail demand. Demand is impacted against product inventory at the wholesale level during each operating period. The action taken at the wholesale level may include shipping the order, searching for another location to fill the order, or back order. The search algorithm is performed on the basis of least distance. The inventory management function is performed during each period to schedule re-supply. The flow through each node and over each link is measured so that the effectiveness of the system can be measured via the cost components.

The model's applications include location and allocation problems. The unique feature of this model is its capability to search for an alternative source for shipments during stockout situations. Thus, a dynamic solution is applied to the dynamic problem of allocation.

Recent literature has reported that the Markland model has been extended, particularly with respect to consideration of the milling-in-transit privileges often found in agribusiness.

PACKER

Packer, A. H. "Simulation and Adaptive Forecasting as Applied to Inventory Control." Operations Research (July - August 1967):660-79.

The simulation model developed by A. H. Packer provides a tool for testing and evaluation of parameters for inventory control and forecasting rules. Since the emphasis of the model is primarily on the inventory component, the structure has been restricted to a single location and single echelon. Packer's model evaluates the inventory question from the perspective of two types. The first type is the overhead inventory used in support of the manufacturing plant which generally has deterministic demands, while the second is composed of asset inventories used as a component in production which generally has probabilistic demand patterns. Since only the inventory component of the system is under analysis, the cost functions used in the model are those that affect the decision concerning inventory level. These functions include the carrying cost of inventory and the fixed cost of ordering.

The variables used in the model are controllable, uncontrollable, and effectiveness. Packer's approach

to the problem suggests that the effectiveness variable is a function of the controllable and uncontrollable variables. The four uncontrollable parameters of the inventory system are: (1) demand, (2) the cost to procure an item, (3) the cost of carrying inventory, and (4) the cost of being out of stock. The three controllable variables are the decisions routinely made in any inventory system: (1) when to order, (2) how much to order, and (3) the review period. The effectiveness, which can be measured using the total cost of the system, is the result of the relationship between the input variables.

The Packer model provides a tool for analysis of inventory policies and parameters for most systems. However, the single location limits its use in systems where locational interdependence is a factor. The absence of randomness in the model provides for deterministic results in the effectiveness measure. Even though Packer states that the model uses a static decision process, this model does incorporate dynamics via feedback control loops. Because of the model's inability to perform any type of structural or network analysis, it must be classified as strictly an event simulator.

In particular, the three events simulated in the Packer model are order processing, inventory management, and forecasting. From the information available, it could not be determined whether the computer model developed by Packer was continuous or discrete.

The force function of the Packer model is the stochastic demand pattern. Selected methods presented by R. G. Brown are used as the forecasting base. Forecasts are used to establish inventory parameters for order point and order quantities. The impact of the demand patterns against the existing inventory is measured as the service effectiveness characteristic of the system.

The primary application of the Packer model is to test and establish the optimal order point and order quantity given a particular set of uncontrollable variables. Further sensitivity analysis can be performed to ascertain the effect of variations in the uncontrollable variables on the effectiveness of the system. The model also permits sensitivity analysis to be performed on the exponential smoothing α factor.

SHYCON AND MAFFEI

Shycon, H. N., and Maffei, R. B. "Simulation: Tool for Better Distribution." Harvard Business Review (November - December 1960):65-75.

One of the first simulation models proposed for studying physical distribution systems was the Shycon and Maffei model presented in 1960. The configurations capable of being simulated include multiple-echelon, multiple-facility, and multiple-product systems. The model provides a total cost approach to analysis of distribution systems. The factors included are the transportation, fixed, and variable costs. The elements are further divided into accounting costs such as rent, taxes, storage, and handling. The controllable elements include the configuration. The target variables include the configuration of the distribution system, the system cost, and the source of supply for each of the customers.

This model was the first developed with the capability to treat many of the economies peculiar to distribution systems. In addition to treating many configurations of plants, warehouses, and customers, the model incorporates economies of scale

and capacity limitations on the locations. Customers also have the option of using multiple channels, depending on product and mode, for example. The Shycon-Maffei model is capable of analyzing only distribution structures rather than operations. As a result of this concentration, no probabilistic or dynamic elements are inherent in the system. The simulations are run at a point in time using the aggregate demand for a single period, whose costs are found in a deterministic manner.

The force variable of the model is customer demand. The volume is measured and costed as its flow is simulated through the configuration. A separate routine can be used to adjust variable costs to reflect the economies of scale available at that throughput level. Additional iterations can be made through the demand to determine any changes in the configuration resulting from the adjusted costs. The primary applications of this model include location and source of supply questions, particularly where a large amount of detailed data is available and necessary for an accurate solution.

WHAMOL

Whirlpool Corporation. WHAMOL -- Whirlpool Corporation
Heuristic-Analytical Model of Logistics. Benton Harbor,
Mich.: Whirlpool Corporation.

WHAMOL provides a tool for analyzing the total distribution operations of a consumer durable manufacturer. The model network allows for simulation of a multiple-echelon, multiple-location, and multiple-product distribution system. The model provides a total cost approach for analyzing distribution operations. Cost components included in the analysis are transportation, handling, inventory, and storage. The environmental variables of the model include demand and, to some extent, costs. Controllable variables include system configuration and inventory parameters. The target variables for the system are the cost and service characteristics obtained from the simulation run of a specific distribution configuration.

Although the model was developed with the distribution organization of a specific corporation in mind, its implementation does allow options in attempting anything from a relatively small simulation to one with almost unlimited capacity. This generality

allows the model to be readily applied to different situations. Since WHAMOL is primarily structural in concept in that it attempts to assign customers to the best warehouse, it does not provide stochastic relationships. Delay times and inventory availability are completely deterministic. Since the model does not provide feedback information for future decisions, particularly with respect to lead times and inventory availability, WHAMOL is considered a static simulator.

The model's operation follows four basic steps. The first step is the data input function. Data are composed of both fixed and variable components, which include all costs, locations, and policies within the restrictions of the model. The second step, generating customer orders, is performed with a statistical factoring procedure. The third step is to determine the optimum channel for distribution to each customer. The two elements considered in this decision are the order cycle time and the total distribution costs for each channel. The final step is report generation through which the service and cost characteristics of the system are accumulated and printed.

The detail designed into the WHAMOL model allows it to be used to study many distribution options. Some of the general applications include mode utilization, local delivery modes, in-transit capabilities, long-range sales volume, and channel selections.

WHYBARK

Whybark, D. C. "A Comparison of Adaptive Forecasting Techniques." The Logistics and Transportation Review (July 1973):13-26.

The Whybark simulation model was developed to test various adaptive forecasting techniques. The simulated inventory system, characterized by instantaneous replenishment, a fixed ordering cost, and an inventory carrying cost assessed against average inventory levels, provides the driving mechanism to test four forms of adaptive forecasting.

The model is general in that it could be used to test other forecast techniques. But since it uses only a single stock point system, the complexity of the network to be tested is restricted. This simulation model contains primarily probabilistic components, including the time period and level of the demand quantities which are selected from normal distributions. The dynamic properties of the simulator are provided through the effect of inventory levels on the replenishment process. Whenever inventory is reduced to zero, an order equal to the amount of the economic order quantity is initiated. The costs associated with replenishment are calculated,

but the effects of stockouts are not analyzed since cycle time is zero. The model is event oriented. The event processes it simulates include forecasting, customer order processing, and replenishment.

The Whybark model uses four measures of performance to evaluate the forecast techniques. The first measure is the inventory cost based on the average daily inventory. Measures of forecast error are used as the second basis for evaluation. Qualitative analysis provides the third measure, which is primarily accomplished through plotting the actual demand points against the forecasted demand points. The fourth measure of performance is computational time required for the forecast event. This element is important since the purpose of the model is to evaluate forecast techniques which may be used with a large data base.

APPENDIX A--FOOTNOTES

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G. D. Wesolowsky and W. G. Truscott, "The Multi-period Location--Allocation Problem with Relocation of Facilities," Management Science (September 1975):57-65.

APPENDIX B
APPLICATION LOG SHEET

APPENDIX B
APPLICATION LOG SHEET

1. Research Scope (problem definition, constraints).

2. Model Use Objectives (What are the research questions?).

3. Illustrate the basic channel configuration using network symbols.

4. For each type of facility and link in the modeled system, list the relevant policies and parameters as requested on the following pages. (See Tables 10 through 16 for examples.)

FACILITY POLICIES AND PARAMETERS

Forecasting Methodology:

Inventory and
Stocking Policies:

Order Processing Time:

Review Period:

Demand Bleed-Off
Functions:

Source of Supply:

Costs:

Fixed

Handling

Storage

Inventory

Order Processing

LINK POLICIES AND PARAMETERS

Source: _____

Destination: _____

Communication Times: Average _____

 Variation _____

Transit Characteristics:

<u>Mode</u>	<u>Weight Break</u>	<u>Average Time</u>	<u>Variance Time</u>
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PHYSICAL PRODUCT CHARACTERISTICS

ProductPriceCostWeightCube

5. Historical Fit Validation (variables used, degree of fit, special problems). _____

6. Stability

6.a. Start-Up Stability (What variables were used? What were the initial conditions used? How fast did the model stabilize?). _____

6.b. Random Number Set Stability (What variables were used? How stable were simulation results from different random number sets?). _____

7. Special problems faced during model validation and utilization. _____

8. Special techniques used for model application. _____

APPENDIX C
RUN LOG SHEET

APPENDIX C

RUN LOG SHEET

1. Run description and definition of experimental conditions.

2. Simulator performance (What was run time or cost?).

3. General model results (What were the overall run results and what do they imply? Were they expected or unexpected, and why?).

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