This is to certify that the

thesis entitled

SIMULATED PRODUCT SALES FORECASTING:
ANALYSIS OF MARKET AREA DEMAND
SIMULATION ALTERNATIVES

presented by

John Thomas Mentzer, Jr.

has been accepted towards fulfillment
of the requirements for

DOCTOR OF PHILOSOPHY degree in Department of Marketing and Transportation Administration

Donald J. Bowersox
Major professor

Date July 12, 1978

O-7639

SIMULATED PRODUCT SALES FORECASTING: ANALYSIS OF MARKET AREA DEMAND SIMULATION ALTERNATIVES

By

John Thomas Mentzer, Jr.

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 Administration

1978

G113490

ABSTRACT

SIMULATED PRODUCT SALES FORECASTING:
ANALYSIS OF MARKET AREA DEMAND
SIMULATION ALTERNATIVES

By

John Thomas Mentzer, Jr.

To develop a computer simulation model of the operations system of a firm, it is necessary to accurately replicate demand. Without this accurate representation of demand, the validity of any conclusions drawn from the simulation model are suspect. Therefore, the objective of this research was to measure the accuracy of various demand generation (replication) methods under different environmental conditions.

Three methods of demand generation were identified as applicable to operations system computer simulation models. The stochastic method randomly generates demand from standard probability distributions. The firm demand method generates demand for the firm through use of regression analysis. The industry demand method generates demand for the industry and firm market share through use of regression analysis.

The stochastic method and three different levels of correlation in the regression analysis of both the firm demand and industry demand methods were utilized to develop

seven approaches to demand generation. These seven demand approaches were tested for accuracy under ten environmental conditions. The environmental conditions were determined by various changes in the trend, seasonality, and variation of the demand patterns that were to be replicated by the demand approaches. The SPSF Testing Environment was used to conduct the research. Seventy experimental simulation runs were conducted for a test period of two hundred days each.

The major conclusions of the research are:

1. The comparison for accuracy of each demand generation approach to the demand pattern to be replicated for each environmental condition revealed that the simplest method of demand generation, the stochastic method, was by far the most accurate under any environmental condition where seasonality did not exist.

2. As seasonality was introduced, the stochastic method lost accuracy but was still superior to the firm demand and industry demand methods. However, at high levels of seasonality the stochastic method was less accurate than either the firm demand or industry demand methods.

3. Comparison of the accuracy of the demand approaches developed from the firm demand and industry demand methods revealed the level of correlation in the regression analysis has a negligible effect on the accuracy of demand generation.

4. In the environmental conditions where the firm demand or industry demand methods were more accurate than the stochastic method, the added accuracy outweighed the extra cost of data gathering for the regression analysis required in the firm demand and industry demand methods.

5. A number of implications for the use of demand generation in simulation research follow from the results of this research. Previous simulation research has mostly utilized the stochastic method. However, this research suggests that the stochastic method would be preferred only for simulations in which seasonality is either non-existent or at a low level. If large seasonal fluctuations exist, which represents a large percentage of actual business situations, either the firm demand or the industry demand methods should be utilized. This indicates that previous simulation models have utilized a less accurate method under conditions of high seasonality. Finally, the stochastic method is of no use in the analysis of factors which affect demand. Therefore, in any situation where the demand generation method will also be utilized for demand factor analysis, the stochastic method should not be utilized.

To:

Brenda,

Minnie and Tom

ACKNOWLEDGMENTS

This dissertation was completed with the support and assistance of many individuals. Their contributions are sincerely appreciated and must be recognized.

The dissertation committee deserves more recognition than can possibly be expressed in these few lines. The committee consisted of Dr. Donald J. Bowersox and Dr. Donald A. Taylor, Professors of Marketing and Transportation, and Dr. M. Bixby Cooper, Assistant Professor of Marketing and Transportation, at Michigan State University.

Dr. Bowersox, as committee chairman, provided a sense of purpose and direction to the entire research project. His knowledge and perception in the areas of marketing and distribution had a significant impact on the structure and relevancy of the completed research. His moral and inspirational support throughout the research were greatly appreciated.

Dr. Taylor's assistance helped to solve many problems which arose throughout the research. His even and logical approach always proved most beneficial and was extremely valuable in the original conceptualization of the dissertation.

Dr. Cooper helped to put the research in perspective and guide it in the proper direction. His efforts in the initial structuring of the dissertation and his continued enthusiasm and assistance were most appreciated.

Particular appreciation is expressed to fellow members of the SPSF Basic Research Team. Dave Closs and Jeff Sims were both instrumental in the development of the SPSF Testing Environment upon which the research was conducted. Special appreciation goes to Jeff Sims for his continued willingness to offer his insights and moral support in the implementation of the research.

The Johnson and Johnson Domestic Operating Company and Whirlpool Corporation are gratefully acknowledged for their continued support of the SPSF Basic Research. The National Council of Physical Distribution Management deserves special appreciation for awarding a special grant of the A. T. Kearney Research Grant based on the research proposal of this dissertation. Without their assistance the financial burdens of this research would have been considerable.

The typing and clerical efforts put forth for this dissertation were outstanding. Pam Cook's work on the first draft was exceptional. Her patience and cooperation were very much appreciated. Grace Rutherford typed the final draft, and her ability to simultaneously type, edit, and organize was magnificent. Mrs. Rutherford is a professional in the highest sense of the word.

To my wife, Brenda, and my parents, Tom and Minnie, belong a very special appreciation. Their continued patience, understanding, encouragement and love throughout the research and my entire doctoral program gave me the necessary inspiration to complete the task.

TABLE OF CONTENTS

LIST OF TABLES

Table Page

LIST OF FIGURES

Figure		Page

CHAPTER I

INTRODUCTION

The creation of a model of market area demand can be for either of two purposes: (1) forecasting and/or (2) demand generation. The first represents the development of a model of demand for the purposes of analysis of the factors which affect demand for certain goods in a market area and/or forecasting of future demand levels.

For example, such a model could be utilized to forecast demand for dishwashers. Regression analysis could be utilized with such factors as housing starts, apartment starts, and disposable income to forecast dishwasher demand in a particular market area. This model could serve not only to forecast dishwasher demand, but the factors mentioned above could be analyzed over time to determine what effect each has upon the demand. These can be termed forecasting models.

Thus, the development of such a model can represent an attempt to forecast future demand and/or test various hypotheses pertaining to what factors affect demand. Numerous examples of such demand modeling attempts have been reported.[1]

The second purpose for the development of a model of demand for a market area is the use of such a model as the force variable for a simulation model. These can be termed demand generation models. The demand generation model creates a stream of demand for a market area and impacts upon the simulation model attempting to replicate the operations of a firm in the market area.

For example, a simulation model of the physical distribution system of a particular firm may be developed. Included in this model would be the locations at which inventory is stocked, the communication and transportation links between the locations, sourcing policies, and the products to be simulated. However, the system will not function unless there exists some driving force, termed the force variable, to pull the products through the physical distribution system. This force variable is the demand for the simulated products. The demand is created by some demand generation model. Numerous applications of such demand generation models have been reported.[2]

The development of any model of market area demand can have as its objective either or both of the above purposes. The fact that the major impetus for the development of a demand model is the creation of a force variable for another simulation model does not preclude its use for the furtherance of understanding of the factors that affect demand or for actual forecasting itself. The reverse is also true. However, unless specifically designed to serve both purposes, there is no a priori reason to believe that a given model will perform both. For example, a model designed for creation of a force variable for another simulation model will not necessarily also function as an accurate forecasting model. Its accuracy in forecasting must be tested before this generalization can be made.

The major thrust of this research was experimentation with demand generation models. Although some of the discussion and conclusions of this research applies also to forecasting models, the major criterion for inclusion of a particular model was usefulness in demand generation.

General Problem Statement

Management today is becoming increasingly difficult as systems developed to control the operations of a firm become more complex. This complexity derives from the increasing size and interrelations of business organizations and the physical systems with which they interact.

For example, at the turn of the century the inventory transfer function of logistics for most manufacturing firms merely entailed the movement and storage of work-in-process inventory within the confines of one building. This small scale activity required little coordination and could be understood and controlled merely by observing the inventory flow. However, many present day firms have a multitude of in-process facilities spread all over the United States and the rest of the world. General Motors Corporation has over 100 such facilities in the United States alone. Work-in-process inventory now travels not only across the plant, but across the city and even across the continent to numerous stocking and processing plants.

Such large, complex systems are difficult to visually conceptualize, much less understand. Not only are the system components more geographically dispersed, but more components, interrelationships, and products are involved. Control of these systems demands some method of analysis for assisting the manager to understand and analyze this myriad of interrelationships. The science of systems analysis has evolved to assist managers in the analysis, understanding, and control of these complex systems.[3]

Systems analysis derives its foundation from the systems concept which posits the following principles; "(1) It is the performance of the total system that is singularly of importance. . . . (2) Components need not have optimum design on an individual basis because emphasis is based upon their integrated relationship in the system. . . . (3) There exists between components a functional relationship, which may stimulate or hinder combined performance. . . . (4) It is explicit that components linked together as a system can, on a combined basis, produce an end result greater than that possible by individual performance."[4]

The application of the systems concept and systems analysis to business applications often entails the development of models of corporate systems. A model can be defined as "a representation of an object, system, or idea in some form other than that of the entity itself."[5] Models can be categorized as physical, analog, or mathematical. An example of a physical model is a representation of a DNA molecule. Constructed of plastic on a scale thousands of times greater than reality, this model does not represent a functioning system, merely a physical replication of the molecule for demonstration purposes.

An analog model is intended as a representation of a specific phenomenon and serves no other purpose. For instance, a thermometer is an analog model of temperature. It is considered analog because it serves no other purpose but to measure temperature.

The third is a mathematical model which utilizes mathematical relationships to replicate real world systems.

Computer simulations are examples of such mathematical models.

Computer simulation is particularly applicable to business situations. Such simulation models attempt to replicate the performance of a firm or some segment of the firm. The usefulness of such simulation is the ability of the manager to observe the performance of the firm under controlled conditions. Through controlled experimentation with the simulation model it is possible to further understanding of the factors affecting operations. Contingency analysis can also be performed to analyze the effects of operations decisions on the simulation model before implementing them on the actual corporate system.

Many modeling attempts in marketing deal with simulation of the logistical components of facility location, transportation, inventory, and material movement.[6] Others address themselves to the sales forcasting aspect of communications,[7] while still others replicate the effects of various marketing strategies on the target market.[8] Such models of complex systems can further understanding and augment analysis of the systems.

However, the validity of any such simulation model of a corporate operations system is highly dependent upon the accuracy of the demand given the model. Demand for such an operational model must be of a short range nature--

defined as a stream of daily demand--to fit the planning horizon of the model. Therefore, of major importance to the functioning of the model is the accurate replication of short range demand. Just as customer demand generally provides the force variable for a firm's operations, the demand generation model provides the force variable for a model of a firm. In an experimental model designed as a test environment, the applicability and validity of the results are greatly dependent upon the method of demand generation. For example, once a physical distribution system is defined such that the parameters and operating policies of each node replicate a firm's operating procedures, the analysis of potential system efficiency rests on the capability of the system to distribute inventory to satisfy some form of demand. Regardless of the validity of the operational system, if the representation of demand is unrealistic or provides an inadequate approximation of the actual demand situation confronted by the firm, the modeling results will have little, if any, operational validity. The applicability of the results for purposes of decision guidance is directly proportional to the degree to which the experimental demand can model actual short range market situations. Thus, knowledge of the relative accuracy of various methods of short range demand generation for the purposes of creating the force variable for simulation models of business operations is extremely useful.

Numerous studies have been conducted to test the relative accuracy of forecasting models under different environmental conditions. Among others, Whybark[9] and Gross and Ray[10] tested various time series forecasting models and Rao[11] and Bass[12] tested different regression and econometric models. However, efforts to test the relative accuracy of short range demand generation methods under various environmental conditions has not been presented in the literature. This lack of literature dealing with comparative studies of short range demand generation methods provided the initial impetus for this research. Therefore, it was this type of comparative study with which this research was concerned. For the sake of brevity, short range demand generation methods will henceforth be referred to as demand generation methods.

Detailed Problem Statement

To initiate this comparative study of demand generation methods, it was necessary to identify the methods available and select those applicable to market area demand generation. Five methods of demand generation are reported in the literature. The first and most common method is the use of actual historical orders as the demand input. This method affords the advantage of extreme simplicity. The past demand history is the only data required. However, the fact that historical orders are to be utilized limits the method to only simulation of demand situations that have previously occurred. This excludes the method from simulation of many of the environmental extremes that may be necessary for reliable planning.

The second method utilizes consumer panel data to develop probabilistic models of brand switching. This method is termed micro-demand simulation or "buyer behavior models." Historical data from consumer panels is used to develop probability distributions for purchasing a given brand in a particular situation. This method probabilistically simulates individual buyer behavior patterns. The method lends itself well to the investigation of the effect of various marketing factors upon individual buyer behavior and has been utilized to generate market area demand.[13] However, this research took a more macro orientation in that demand was broken down from macro levels rather than built up from individual demand. Therefore, the micro-demand method was not utilized.

The third method of demand generation utilizes standard statistical functions such as normal, log normal, erlang, and poisson to generate demand. This can be termed the stochastic method. The data requirements for this method are quite simple, but no factors which may affect demand are included. Therefore, the method could prove to be unrealistic and inaccurate.

The fourth method of demand generation uses correlation analysis to obtain some measure of individual firm demand. This is accomplished by obtaining historical data on certain factors which correlate well with firm demand and regressing them against historical records of firm demand. For example, if it is felt that firm demand in a particular market area correlates well with income and birth rate, historical monthly data on these two variables can be regressed against historical monthly demand to determine an equation for firm demand. Thereafter, for any particular period under generation, the respective estimates of income and birth rate can be input to the regression equation to generate an estimate of firm demand.

Correlation analysis can be utilized with any number of independent variables, those factors affecting firm demand, and can be used for either linear or logarithmic relationships. Thus, considerable latitude exists in the types of situations which can be analyzed. Not only does the method offer the potential for an effective means of demand generation, but several statistical techniques also can be applied to the results to test the validity and accuracy of the model. The major drawback to the firm demand method lies in the potential difficulty of obtaining the historical data necessary to develop valid regression equations.

The fifth method is actually composed of two sub-methods. The first sub-method is similar to the firm demand method except that industry demand, rather than firm demand, is estimated. Therefore, the independent variables utilized are those that correlate with industry demand. Previous statements regarding accuracy, validity, and flexibility of firm demand generation can be applied to industry demand generation.

The second sub-method attempts to measure the firm's effectiveness in various marketing factors affecting demand in contrast to the effectiveness of the industry as a whole in these same factors. If the former is placed in the numerator and the latter in the denominator, the resulting fraction is a measure of market share for the firm in question. This formula can be subjected to a logarithmic form of regression analysis to generate firm market share. This determination of market share is theoretically accurate. In reality, however, the accuracy of this determination depends directly upon the ability to obtain measures of competitive firms' efforts in the relevant factors (for instance, price, advertising, and product quality) and to measure accurately the effectiveness of these efforts.

The two sub-methods can be combined by multiplying the market share fraction by the value of industry demand for a period. This combination provides firm demand for the period. This method can be termed the industry demand method.

The actual historical demand, micro-simulation, stochastic, firm demand, and industry demand methods of demand generation were all found in the literature and considered for this research. However, the first method is not actually demand generation, but merely a repetition of history. Therefore, it was not included as one of the demand generation methods to be tested in this research.

The second method represents demand generation on an individual rather than a market area basis. It would not prove impossible to sufficiently aggregate the individual buying patterns inherent in this method to obtain a measure of market area demand. However, this method does not offer the macro approach desired for this research. Therefore, it also was not included as one of the demand generation methods to be tested in this research.

This left three methods of demand generation to be tested. Different values of the coefficient of determination (R^2) were utilized to develop three different demand approaches for the firm demand method and three for the industry demand method. The stochastic method in its entirety represented a seventh demand approach.

Thus, seven different demand approaches were tested under different environmental conditions. These environmental conditions were delimited by the patterns of demand the various demand generation approaches attempted to replicate. Different combinations of level, trend, seasonality, and variation were utilized to develop ten different demand patterns or environmental conditions for testing the accuracy of the seven demand approaches. These environmental conditions were termed demand test conditions.

Given these demand approaches and the ten demand test conditions, the detailed problem statement of this research was to test the relative accuracy of demand approaches representing the stochastic, firm demand, and industry demand methods of demand generation under various environmental conditions.

Researchable Questions

Based on the detailed problem statement, the following researchable questions were developed:

1. Which of the demand generation methods most accurately replicates the actual demand patterns in each demand test condition?
2. Is the performance of the firm demand and industry demand methods with respect to the stochastic method affected by the value of R^2 used in the regression formulation?
3. If the firm demand and/or industry demand method performs more accurately than the

stochastic method, is this superior accuracy worth the cost of the added complexity of the firm and industry demand methods?

4. Does the performance of each method change under the different demand test conditions?

From these researchable questions the research hypotheses were developed. These hypotheses will be discussed at length in Chapter V.

Thesis Outline

This dissertation consists of seven chapters. After the introductory chapter, Chapter II provides a review of the literature relevant to this research. The actual historical demand and micro-simulation methods are briefly described and the rationale for their elimination from this research are given. The remainder of the chapter is devoted to the discussion of the stochastic, firm demand, and industry demand methods of demand generation and a review of the literature pertaining to these methods.

Chapter III describes the logical progression from the stochastic, firm demand, and industry demand methods of demand generation to the demand alternatives available in the simulation model utilized. The development of the seven demand generation approaches utilized in this research from these methods and alternatives is also discussed.

Chapter IV details the ten environmental conditions, or demand test conditions, under which this research was conducted. Included is a discussion of the environmental factors considered important to demand generation research.

Chapter V details the research hypotheses to be tested. Additionally, the research methodology and the measures of system output are presented.

Chapter VI details the findings of the experimental runs.

Chapter VII summarizes the findings and suggests conclusions to be drawn from the research. Areas of further research and the limitations of the present research are also outlined.

The Appendix details selected statistical concepts that were utilized but not described in depth in the body of this dissertation.

CHAPTER I--FOOTNOTES

[1]Among others: Michael R. Lavington, "A Practical Microsimulation Model for Consumer Marketing," Operational Research Quarterly 21 (No. 1; March, 1970): 25-45; and Frank M. Bass and Leonard J. Parsons, "Simultaneous--Equation Regression Analysis of Sales and Advertising," Applied Economics 1 (March 1969): 103-124.

[2]Among others: Donald Gross and Jack L. Ray, "A General Purpose Forecast Simulator," Management Science 11 (No. 6; April, 1965): 119-135; and D. Clay Whybark, Testing An Adaptive Inventory Control Model, Herman C. Krannert Graduate School of Industrial Administration Paper, No. 289 (Lafayette, Ind.: Purdue University, October 1970), p. 7.

[3]Robert E. Shannon, Systems Simulation--The Art and Science (New York: Prentice Hall, Inc., 1975), p. 1.

[4]Donald J. Bowersox, Logistical Management (New York: Macmillan Publishing Co., Inc., 1974), p. 18.

[5]Shannon, p. 4.

[6]Models include those reported in Donald J. Bowersox et al., Dynamic Simulation of Physical Distribution Systems (East Lansing, Mich.: Bureau of Business Research, Michigan State University, 1973); Distribution System Simulator (DSS), Program Number 3798-ATY, International Business Machines Corporation, 1973; J. W. Forrester, Industrial Dynamics (Cambridge, Mass.: The MIT Press, 1961); and Omar Keith Helferich and David J. Closs, "Computer-Assisted Logistics Planning for the Firm," in Proceedings of the 10th International Logistics Symposium, Society of Logistics Engineers, 1975.

[7]Models include those reported in Donald Gross and Jack Ray, "A General Purpose Forecast Simulator," Management Science, April 1965, pp. 119-135; and D. Clay Whybark, "A Comparison of Adaptive Forecasting Techniques," The Logistics and Transportation Review 8 (No. 3; July 1973): 13-26.

[8]Models include those reported in John D. D. Little, BRANDAID II, Sloan School of Management Working Paper (Cambridge, Mass.: MIT, 1973), 687-73; Melvin Shakun, "A Dynamic Model for Competitive Marketing in Coupled

Markets," Management Science 12 (No. 12; August 1966): 525-30; and Glen L. Urban, "A Mathematical Modeling Approach to Product Line Decisions," Journal of Marketing Research 6 (No. 1; February 1969): 40-47.

[9] D. Clay Whybark, "A Comparison of Adaptive Forecasting Techniques," The Logistics and Transportation Review 8 (No. 3; July 1973): 13-26.

[10] Donald Gross and Jack Ray, "A General Purpose Forecast Simulator," Management Science 9 (N9. 8; April 1965): 119-35.

[11] Vithala R. Rao, "Alternative Econometric Models of Sales--Advertising Relationships," Journal of Marketing Research 9 (No. 2; May 1972): 171-81.

[12] Frank M. Bass, "A Simultaneous Equation Regression Study of Advertising and Sales of Cigarettes," Journal of Marketing Research 6 (No. 3; August 1969): 291-300.

[13] A. E. Amstutz, Computer Simulation of Competitive Market Response (Cambridge, Mass.: MIT Press, 1967).

CHAPTER II

LITERATURE REVIEW

The primary objective of this chapter is to give an overview of the literature that contributed to the design of this research and to review certain literature that was representative of the demand generation methods utilized. The literature considered most important is presented. The remainder of the sources are included in the Bibliography.

Methods of Demand Generation

In the review of relevant literature, five methods were investigated which use some form of actual data to develop a demand model. The first and most common method is to use actual historical orders as the demand input. This method affords the advantage of extreme simplicity. The past sales history is the only data required. However, the fact that historical orders are to be utilized limits the method to only simulation of demand situations that have previously occurred. This excludes the method from simulation of many of the environmental extremes that may be necessary for reliable planning. Due to its limited scope, the method was not utilized in this research.

Therefore, no further treatment shall be given to this method in the literature review.

The second method utilizes consumer panel data to develop probabilistic models of brand switching termed micro-demand simulation or "buyer behavior models." Historical data from consumer panels is used to develop probability distributions for purchasing a given brand in a particular situation.

In an article exemplary of this method, Lavington[1] presented a micro-simulation model which is applicable to certain types of markets for frequently purchased, consumer goods. The model incorporated consumer panel behavioral data and marketing factors that might affect demand.

A two-stage mathematical process was used. The first determined the consumer's prepurchase disposition to a particular brand based upon the firm's marketing strategies and the consumer's past usage of the brand. The marketing strategies consisted of distribution, price, promotional, and advertising policies.

The second stage converted the prepurchase disposition into an actual purchase. This was accomplished by computing the purchasing probabilities from the interaction of the prepurchase disposition and the retailer policies. The retailer policies consisted of offers-on-product packages, stocking position, and in-store displays.

The model was tested by comparing the purchasing record and the behavioral characteristics of the consumer panel with those simulated by the model. Although the author presented no actual results of this analysis, the statement was made that the "results were satisfactory."

This and other similar models utilize the method of probabilistically simulating individual buying behavior patterns. Although the method lends itself well to the investigation of the effect of various marketing factors upon individual buyer behavior, considerable aggregation from the individual consumer level would be necessary to obtain market area demand. The main thrust of this research was devoted to market area demand simulation from a more macro orientation. Therefore, the micro-simulation, or "buyer behavior model," method was not included in this research. Although many articles exemplary of the method are cited in the bibliography, no further treatment shall be given to the method in the literature review.

The third method of demand generation utilizes standard statistical functions such as normal, lognormal, erlang, and poisson to generate demand. This can be termed the stochastic method. The data requirements for this method are quite simple, but no factors which may affect demand are included. Therefore, the method could prove to be unrealistic and inaccurate. To test the relative accuracy of the method against methods that include factors which may affect demand, the method was included in this research. Therefore, a section of this chapter is devoted to a review of literature pertaining to the stochastic method.

The fourth method of demand generation uses correlation analysis to obtain some measure of individual firm demand. This is accomplished by obtaining historical data on certain factors which correlate well with firm demand and regressing them against historical records of firm demand. For example, if it is felt that firm demand in a particular market area correlates well with income and birth rate, historical monthly data on these two variables can be regressed against historical monthly demand to determine an equation for firm demand. Thereafter, for any particular period under generation, the respective estimates of income and birth rate can be input to the regression equation to generate an estimate of firm demand.

Correlation analysis can be utilized with any number of independent variables, those factors affecting firm demand, and can be used for either linear or logarithmic relationships. Thus, considerable latitude exists in the types of situations which can be analyzed. Not only does the method offer the potential for an effective means of demand generation, but several statistical techniques also can be applied to the results to test the validity and accuracy of the model. The major drawback to the firm demand method lies in the potential difficulty of obtaining the historical data necessary to develop valid regression equations.

The fifth method is actually composed of two sub-methods: (1) the industry demand sub-method and (2) the market share sub-method. The first sub-method is similar to the firm demand method except that industry demand, rather than firm demand, is estimated. Therefore, the independent variables utilized are those that correlate with industry demand. Previous statements regarding accuracy, validity, and flexibility of firm demand generation can be applied to industry demand generation.

The second sub-method attempts to measure the firm's effectiveness in various marketing factors affecting demand in contrast to the effectiveness of the industry as a whole in these same factors. If the former is placed in the numerator and the latter in the denominator, the resulting fraction is a measure of market share for the firm in question. This formula can be subjected to a logarithmic form of regression analysis to generate firm market share. This determination of market share is theoretically accurate. In reality, however, the accuracy of this determination depends directly upon the ability to obtain measures of competitive firms' efforts in the relevant factors (for instance, price, advertising, and product quality) and to measure accurately the effectiveness of these efforts.

The two sub-methods can be combined by multiplying the market share fraction by the value of industry demand for a period. This combination provides firm demand for the period. This method can be termed the industry demand method.

The stochastic method, firm demand method, and industry demand method were selected for analysis in this research. Literature reviews of these methods are presented in the next section.

Selected Demand Methods

Since the firm demand method and the industry demand method include factors which affect demand, both incorporate more relevant information and, therefore, offer the potential for greater relative accuracy than the stochastic method. For this reason all three methods are included in this research and in this literature review. The literature relevant to the stochastic method will be presented first, followed by the firm demand method and the industry demand method. A summary of the implications derived from this literature review will be presented last.

Stochastic Method

The development of a stochastic demand generation model has seldom been undertaken solely for that purpose. In every case encountered the model represented the force variable for some larger model. These larger models range from a model of market processes for marketing executive decision making to various forecast testing environments where the demand generated by the stochastic method represents the demand the various forecasting techniques attempt to predict.

In the market processes simulation model developed by Balderston and Hoggatt[2] three categories of participants were included in the market: manufacturers, wholesalers, and retailers. Demand for the model originated at the retailers. The stochastic method was employed to generate one independent demand curve for each retailer. Thus, the force variable of demand for the model was an independent stochastic process for each retailer.

For the purposes of demand generation in their General Purpose Forecasting Simulator (GPFS), Gross and Ray[3] utilized the stochastic method. The GPFS model was developed for the purpose of testing various time series forecasting techniques under prescribed situations. Demand, which functioned as the force variable for the model, was created by a pseudo-normal random number generator. The means and standard deviation of the normal distribution of demand remained constant over an entire simulation. Thus, the model presented the unrealistic assumption of static demand throughout the simulation.

In the construction of another model for testing time series forecasting techniques, Whybark[4] utilized a demand generator that randomly selected period demand. The mean of the demand was drawn from a uniform distribution. The length of time for which this mean remained stable was also drawn from a uniform distribution. After this time had elapsed, a new mean for demand was drawn.

The random fluctuations about the stable mean were composed of a normal distribution with the standard deviation specified by the user. This method of generation was utilized as the demand force variable for all experiments with the model. Therefore, the patterns of demand not only fluctuated around a mean, but that mean could randomly fluctuate at random intervals. The same approach to demand generation was also used by Whybark[5] in the development of a model for inventory control which was used in conjunction with an inventory management game.

In summary, the progression in complexity for models utilizing the stochastic method begins with simply supplying a probability distribution from which demand is randomly selected. By allowing the probability distribution to change over time, the static demand assumption is eliminated. This increases complexity and, hopefully, realism in the stochastic method.

Firm Demand Method

Unlike the stochastic method, the major application of the firm demand method has not been to demand generation. The majority of the literature pertaining to the firm demand method utilized it for forecasting demand. However, this literature is not at odds with the purposes of this research. If a model can effectively forecast demand, then the potential exists for demand generation or replication. In most of the articles reviewed, half of the historical data was utilized to develop the model which attempted to forecast the second half of the data. This, in effect, is replication or demand generation of the second half of the demand data.

It should be noted that the forecasts were for periods no shorter than one month. This is much too long for the purposes of generation of demand as a force variable. For this purpose the demand must be broken down into individual orders which sum to daily demand. Therefore, to use any of the literature reviewed in this section would require its combination with some method of breaking the monthly demand down into daily demand and individual orders.

Although the form of the models reviewed may vary considerably, their inclusion under the firm demand method is predicated solely on the fact that firm demand was determined through some form of regression analysis.

Bass and Parsons[6] developed a simultaneous equation regression model for forecasting demand, based on advertising expenditures. The analysis utilized sixteen years of bimonthly data from the A. C. Nielson Company to develop the model. The industry consisted of a few dominant firms producing a product that had reached "innovative maturity." Price competition was avoided and sales promotion and distribution were viewed as a given. Therefore, the industry emphasized considerable advertising expenditures.

Based on the industry description, a four equation model was built around the effects of advertising on demand, demand on advertising, and other brand advertising. The early data periods were used by the model to replicate the later periods. Although only graphical analysis of the accuracy was presented, the model appeared to closely replicate actual demand.

Bass and Parsons utilized the post-introductory stage of the industry to conduct their study. Parsons[7] repeated the study on the same industry for the earlier introductory stage. Utilizing this earlier stage, a two equation model was developed. The first measured the influence of current advertising and previous retail availability on current retail availability. The second measured the influence of advertising and retail availability on demand. As with the previous model the early data were used to forecast the later periods. Analysis of accuracy produced satisfactory results.

Rao[8] compared five models of demand utilizing 1945-1965 data from six major cigarette companies. These models were ordinary least squares regression, autoregressive ordinary least squares with serially dependent errors, a Koyck model of distributed lags[9] with serially independent errors, a Koyck model of distributed lags with serially dependent errors, and a simultaneous equation system using two stage least squares regression.

Fitting each of these models to the actual data resulted in the conclusion that no method fared better for all companies. The author further concluded that the simultaneous equation model did not excell over the others. Therefore, a researcher may be better off choosing among the single equation models. Utilizing mean absolute percent error (MAPE) to evaluate sensitivity, it was found that advertising-demand relationship was highly sensitive to whether demand was expressed in logarithmic form.

Rippe, Wilkinson, and Morrison[10] developed a model for forecasting demand in industrial markets based on anticipated future capital spending of the target markets. The authors first proposed a model which utilized an input-output type model of industry demand and determined market share by any of several techniques mentioned. One of these suggested techniques was regression analysis. Firm demand could be determined by multiplying industry demand by market share. Although this approach was mentioned, the authors selected a model that directly determined firm demand via the input-output type model. The model was applied to forecasting steel consumption for the 1970-1973 period.

The accuracy of the model was compared to two naive models via the measures of mean absolute percent error (MAPE) and root mean squared error. The authors' model was found to be the most accurate of the three.

Industry Demand Method

As with the firm demand method most of the literature on the industry demand method dealt with forecasting demand rather than generating demand. The comments pertaining to the use of the firm demand method for demand generation and the combination with some other method to obtain daily demand also apply to the industry demand method. The inclusion of the following literature under the industry demand method was predicated on the use of some form or regression analysis to determine industry demand and/or market share.

A model for estimating the demand for automobiles was developed by Dyckmon in 1965. Some of the variables reflect consumers' ability to buy, i.e., credit firms and consumer liquid asset holdings, which are regressed along with other factors such as the price index for cars, real disposable personal income, and present stock of autos.

Dyckmon, as mentioned by Hughes,[11] set up the multiple regression equation in logarithmic form, thus allowing one to obtain price elasticities as well as income elasticities directly from the computer results. The regressed coefficient of each independent variable can be interpreted as that factor's elasticity when the regression is done using common logarithms instead of the variables themselves.

Kitchener and Rowland[12] reported three market models of the razor blade market in the United Kingdom. The first two models assessed market share changes among two major brands. Although they are based primarily on advertising expenditures, they are reasonably accurate in predicting short-run changes in market share. The authors devised a third model to cover longer periods of time in which market share was limited by a company's production capacity. Company production capacity was, in turn, determined by the marketing impact of variables such as brand quality, price, company image, promotional activity, advertising, and distribution. While operationalizing the model, distribution and promotion were left out due to the lack of available data, but advertising was included both in terms of total expenditures and decay over time. The major attribute of such a model is that it can be set up to continually correct the division of market shares between brands as a result of the marketing impact of each of the above mentioned variables.

In the description of their Marketing Analysis Training Exercise (MATE) Kuehn and Weiss[13] developed an exponential regression model for the determination of firm demand. The first step in the model was the determination of industry demand through a multiplicative function of seasonality, growth, average industry price, total sales and promotional expenditures for the industry, and average per capita income. The exponent for each factor was treated as the elasticity of that factor to demand.

The second step was the determination of market share for a particular firm. This procedure was divided into two sub-steps. The first historically determined the percent of market share that was made up of habitual buyers of the firm's brand. The second sub-step determined the percent of market share that was new or switch-over buyers. This was accomplished through an exponential model that considered product characteristics, price, retail availability or distribution, and advertising. Again the exponents represented the elasticities of these factors to market share. Combination of these two sub-steps constituted market share. This figure multiplied by industry demand provided the simulated demand for the firm.

Lambin[14] began his article by describing the Dorfman-Steiner theorem in which industry sales are considered to be a function of price, advertising, and a product quality index. The author then extended this theorem to include competitive influences of each of these factors which gave an estimation of market share. This was followed by a formalization of the market share model and a description of the case used to verify the model empirically. The case involved deriving the elasticity factors for a consumer durable good sold in three European marketing areas. The data consisted of quarterly observations over an eight-year period from 1959 to 1966.

The remainder of the article was devoted to a discussion of the elasticities of price, advertising, distribution, and product quality for the three market areas. An appendix contained a mathematical derivation of a market share optimization rule based on the author's variation of the Dorfman-Steiner theorem.

In the development of his on-line computer model for marketing decision-making, Lambin[15] utilized a model of market share for a major oil company which considered the number of service stations, the number of other outlets, and total advertising expenditures. The model further considered the lagged sales effect of advertising and distribution. Since there was no price differential among the competing brands in the market studies, price was not considered.

The model was tested with corporate data in a linear and logarithmic form. Although the predictive accuracy of both was highly significant, the best fit was obtained with the linear form of the model.

Schultz's[16] model defined demand and market share response functions from empirical data on air passenger traffic in one two-city market. Demand was generated from regression of such variables as price, advertising, population, business income, discounts, seasonality, GNP, and personal income. Market share, on the other hand, was defined as a result of the regression of advertising share, population share, frequency share, demand, revenue, profits, measure of service, and equipment availability. The demand function was solved through simple regression, whereas the market share analysis was performed through a simultaneous equation regression model. The use of simultaneous equations was justified by the fact that the determinants of market share not only have an impact upon it, but also are influenced by its magnitude. The empirical test was done in lagged and non-lagged form. In the case of demand; price, personal income, and seasonality were the only variables found to be significant. Advertising, frequency, and population shares were found to be the significant variables when testing market share.

Sexton[17] initially discussed the inadequacies of previous market share models and progressed to a discussion of the author's two-model approach. Model I estimated a brand's share of total product sales as a function of distribution, advertising, and price. Model II estimated the product's share of sales of all competitive product classes based on the same variables. These models, combined with a time series model of total product class sales, provided an estimate of brand sales as a function of marketing policies. The models were further modified by a Koyck distributed lag function which attributed advertising effect to a partial sum of a geometric series over time. By taking the logarithms of the two models developed, linear multiple regression was applied to estimate the parameters contained within both models.

To verify the models empirically, 593 families of the Chicago Tribune consumer panel were questioned over a two-year span, aggregating 30,000 purchase records for three closely substitutable products. Model I was compared to three naive models, a linear model, a Cobb-Douglas function, and the Frank and Massey model, and outperformed all of them. Model II was compared to six alternative models with the same superior results.

Urban[18] began his article by describing the situation facing many firms in which several different products in the same product line are marketed. An example of such interrelated products is electric razors, safety razors, shaving cream, and after-shave lotion. In such a modeling situation, the author felt that the factors of behavioral and decision relevance were: (1) aggregate product class marketing mix effects, (2) product class interdependencies, and (3) intragroup relative competitive brand effects.

In keeping with this philosophy, a model was developed in which industry demand for a particular product was equal to a relative measure of the industry pricing, advertising, and distribution of the product multiplied by the aggregate effect of the industry pricing, advertising, and distribution of all complementary and competitive products in the product line. Further, the market share for any particular firm was equal to a relative measure of their pricing, advertising, and distribution divided by the total industry measure of pricing, advertising, and distribution. Not only does this appear to be an excellent means of calculating a firm's market share and sales volume, but if the formulation is written in logarithmic form and regressed with sufficient historical data, the elasticities of all the factors mentioned above can be effectively determined. An empirical verification using three product lines and 100 in-store audits produced what the author described as reasonable descriptive accuracy.

A regression analysis approach to determination of market share was utilized in a model developed by Weiss.[19] The author began by stating that the major manipulative factors affecting market share are price, advertising expenditures, retail availability, and physical product characteristics. However, price and advertising are the two primary influences on market share of competing consumer products.

A low cost consumer food item with high brand identification and three major competing firms was chosen for the analysis. Consumer panel data for the 1960-1963 period were obtained through the Chicago Tribune's Family Survey Bureau, The Harvard Business School, and the marketing policy group of one of the industry's principal firms.

Four linear regression models of market share were tested. The model, using a logarithmic transformation of price and advertising, proved to possess the most predictive accuracy. A fifth model was added which utilized dummy variables as proxies for product quality and distribution effectiveness. This model proved to be the most accurate of all five models.

Utilizing the same data base in a later article, Houston and Weiss[20] developed a model for forecasting competitive market share. The model incorporated the current effect of price and advertising expenditures on market share and the effect of lagged advertising. This last effect was incorporated as a constant exponential decay.

Two three-equation regression models were developed. One model was additive, the other was multiplicative. The results from both models were similar, but the multiplicative results were slightly better. In analysis of the multiplicative model it was found that for Brand 1 price, advertising, and cumulative advertising all affected market share. However, for Brand 2 cumulative advertising had no effect and for Brand 3 neither cumulative advertising nor present advertising affected market share. The authors felt these results were supported by the actual market conditions.

Wildt's[21] model incorporated econometric data with management decision variables to obtain an estimate of market share in a retail food industry dominated by three major brands. Market share was defined as a function of relative price, promotional expenditure, advertising expenditures and new variety activity.

The structural relationships were based upon nine endogenous variables (market share, advertising, and promotion for each of the three brands) and lagged exogenous variables (new variety activity, seasonal variables, and relative price). The logarithms of their values were used as the variables, with the corresponding coefficients having the properties of elasticities. The variables were combined in a multiple regression model and the coefficients estimated in a block recursive system using Aitken's generalized least squares method[22] and the Zellner-Aitken two-stage method with successive iteration.[23]

The model results illustrated the interactive effects of the competitive decision variables on market shares of each firm. The most significant determinants of market share were found to be the relative market position of the firm in the preceding period and the firm's relative price in the current period. The results also indicated the competitive influence of the varying advertising and promotional strategies used by each firm.

Summary

Five methods of demand generation were mentioned in this chapter. Three of these methods were considered germane to the generation of daily market area demand.

Review of the literature for these three methods produced some conclusions important to this research. First, it was found in many empirical tests that single equation regression models of demand performed as well, and often outperformed, simultaneous equation models.[24] Although it cannot be stated that this will always be the case, it is worth noting that in some situations the simpler, single equation model was better.

Second, a variety of measures were utilized for the comparison of the accuracy of different models. These measures often included the size of the coefficient of determination (R^2), the "reasonableness" of the results compared to actuality, graphic interpretations, and a variety of statistical measures. However, the statistical measure most often encountered was mean absolute percent error (MAPE).[25]

Third, the firm demand and industry demand methods in the literature were often found to be accurate methods of market area demand generation. However, this generation was on a monthly or longer time period basis. To utilize either of these methods for daily market area demand generation, another procedure must be added to break the monthly demand down into daily demand.

The next chapter will discuss the model which incorporates the stochastic, firm demand, and industry demand methods. The progression from these three methods to the specific demand approaches used in this research will also be discussed.

CHAPTER II--FOOTNOTES

[1]Michael R. Lavington, "A Practical Microsimulation Model for Consumer Marketing," Operational Research Quarterly 21 (No. 1; March 1970): 25-45.

[2]Frederick E. Balderston and Austin C. Hoggatt, Simulation of Market Processes (Berkeley, Cal.: Institute of Business and Economic Research, University of California, 1962), p. 4.

[3]Donald Gross and Jack L. Ray, "A General Purpose Forecast Simulator," Management Science 11 (No. 6; April 1965): 119-135.

[4]D. Clay Whybark, "A Comparison of Adaptive Forecasting Techniques," The Logistics and Transportation Review 8 (No. 3; July 1973): 13-26.

[5]D. Clay Whybark, Testing An Adaptive Inventory Control Model, Herman C. Krannert Graduate School of Industrial Administration Paper No. 289 (Lafayette, Ind.: Purdue University, October 1970), p. 7.

[6]Frank M. Bass and Leonard J. Parsons, "Simultaneous Equation Regression Analysis of Sales and Advertising," Applied Economics 1 (March 1969): 103-124.

[7]Leonard J. Parsons, "An Econometric Analysis of Advertising, Retail Availability, and Sales of a New Brand," Management Science 20 (No. 6; February 1974): 938-947.

Vithala R. Rao, "Alternative Econometric Models of Sales-Advertising Relationships," Journal of Marketing Research 9 (No. 2; May 1972): 177-181.

[9]J. M. Koyck, Distributed Lags and Investment Analysis (Amsterdam, North-Holland, 1954).

[10]Richard Rippe, Maurice Wilkinson, and Donald Morrison, "Industrial Market Forecasting with Anticipation Data," Management Science 22 (No. 6; February 1976): 639-651.

[11]George David Hughes, Demand Analysis for Marketing Decision (Homewood, Ill.: Richard D. Irwin, 1973).

[12] Alan Kitchener and David Rowland, "Models of a Consumer Product Market," Operations Research Quarterly 22 (No. 1; March 1971): 67-84.

[13] Alfred A. Kuehn and Doyle L. Weiss, "Marketing Analysis Training Exercise," Behavioral Science 10 (No. 1; January 1965): 51-67.

[14] Jean-Jacques Lambin, "Optimal Allocation of Competitive Marketing Efforts: An Empirical Study," Journal of Business 43 (October 1970): 468-484.

[15] Jean-Jacques Lambin, "A Computer On-Line Marketing Mix Model," Journal of Marketing Research 9 (No. 2; May 1972): 119-126.

[16] Randall L. Schultz, "Market Measurement and Planning with a Simultaneous Equation Model," Journal of Marketing Research 8 (No. 2; May 1971): 153-164.

[17] Donald E. Sexton, Jr., "Cluster Analytic Approach to Market Response Functions," Journal of Marketing Research 11 (No. 1; February 1974): 109-114.

[18] Glen L. Urban, "A Mathematical Modeling Approach to Product Line Decisions," Journal of Marketing Research 6 (No. 1; February 1969): 40-47.

[19] Doyle L. Weiss, "Determinants of Market Share," Journal of Marketing Research 5 (No. 3; August 1968): 290-295.

[20] Franklin S. Houston and Doyle L. Weiss, "An Analysis of Competitive Market Behavior," Journal of Marketing Research 11 (No. 2; May 1974): 151-155.

[21] Albert R. Wildt, "Multifirm Analysis of Competition Decision Variables," Journal of Marketing Research 11 (No. 1; February 1974): 50-62.

[22] Arnold Zellner, "An Efficient Method for Estimating Seemingly Unrelated Regression and Tests for Aggregation Bias," Journal of the American Statistical Association 57 (June 1962): 348-368.

[23] Ibid.

[24] Rao.

[25] Rao and Rippe, Wilkinson, and Morrison.

CHAPTER III

SPSF DEMAND MODULE--DEMAND APPROACHES

This research was concerned with testing the accuracy of different approaches to short range demand generation. Short range can be defined as the generation of a stream of daily demand. This is contrasted to such econometric approaches that generate demand for periods that are bimonthly or longer.

The short range approaches that were utilized in this research were developed from the stochastic, firm demand, and industry demand methods discussed in the previous chapter. The development of the approaches in this research from these three methods of demand generation is discussed at length in a later section of this chapter.

Before this task is undertaken, it is necessary to describe the environment under which these demand approaches were tested. The model utilized to create the environment for this research was the Simulated Product Sales Forecasting (SPSF) Testing Environment. Therefore, the next section of the chapter is devoted to a brief description of this model.

Although all four modules of the SPSF Testing Environment were functioning in this research, the Demand Module contained the demand approaches which this research sought to test. It is, therefore, of particular importance to this research. For this reason the second section of the chapter will present a more detailed description of the Demand Module.

The final section of the chapter will discuss the logical progression from the stochastic, firm demand, and industry demand methods of demand generation through the Demand Module to the demand generation approaches utilized in this research.

SPSF Testing Environment

To set the foundation for understanding the environment under which this research was conducted, it is necessary to briefly describe the simulation model which was utilized. The model was termed the SPSF Testing Environment. To properly understand this model, the SPSF concept and design are described.[1]

SPSF Concept

The SPSF concept is basic. To provide a test environment, the attributes of market area demand simulation, dynamic operational simulation, and statistical sales forecasting were combined into a single computer model.

The SPSF model is capable of rendering a sales forecast while simultaneously creating customer orders and replicating the physical distribution process of providing timely inventory to satisfy order requirements. Thus, through the combined efforts of two types of simulation and statistical forecasting, a time-sequenced record of events leading to forecasting deficiency is captured and documented. Such documentation provides the basis for postmortem evaluation of forecast error and formulates the basis for sensitivity analysis. Perhaps the most beneficial feature of the SPSF model is that it provides an environment for controlled experimentation.

Three assumptions are critical to a generated testing environment capable of controlled experimentation. First is the fundamental belief that if appropriate variables are identified and incorporated into forecasting, available statistical techniques can efficiently produce accurate demand estimates. Second is the assumption that operational performance can be captured for purposes of effectiveness analysis and the potential exists to quantify and incorporate such data as a forecast variable. The final assumption is that the results of experimentation from a testing environment can be accurately generalized to a broad range of markets without extensive duplicate analysis.

The next sub-section provides a review of the SPSF model design and introduces the four modules that formulate the testing environment.

SPSF Model Design

The SPSF Testing Environment contains the following four modules:

1. Demand Module;
2. Forecast Module;
3. Operations Module; and
4. Analysis Module.

Each module is briefly reviewed in terms of the overall SPSF Testing Environment. Figure 3-1 provides an overview of the SPSF Testing Environment General Design.

The Demand Module provides a methodology for creating potential demand. The purpose of this module is to produce synthetic orders from a specified geographical market area for which the Forecast Module is attempting to render a product demand forecast. Thus, the Demand Module is expected to quantify the pattern, level, and dispersion of product orders over the forecast period. The design approach of this module is of critical importance to the SPSF Testing Environment since it provides the primary data set for evaluation of forecast accuracy. In total, four alternative demand generating procedures are included in the Demand Module.

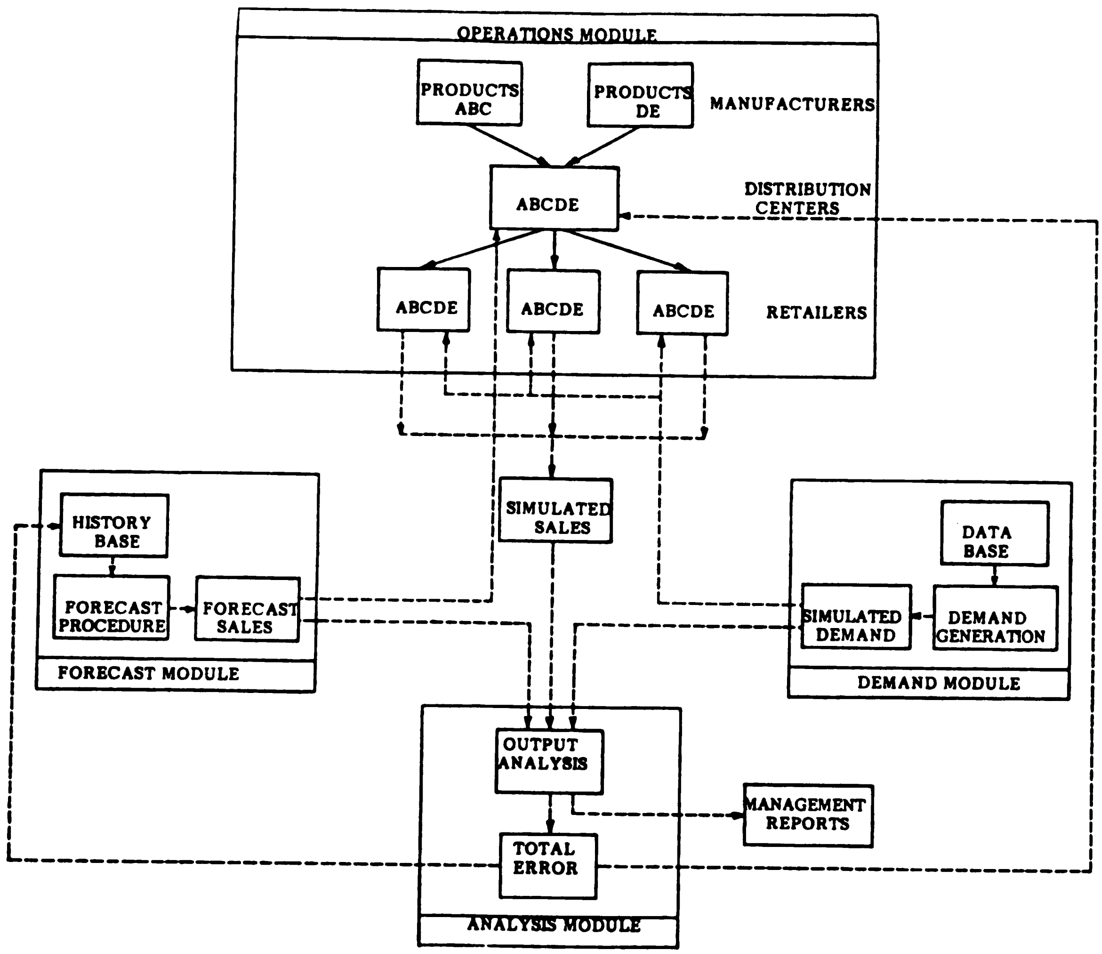

Figure 3-1. SPSF Testing Environment--General Design.

The Forecast Module provides software procedures for creating statistical forecasts. The purpose of this module in the SPSF Testing Environment is to produce forecasts of future product sales for purposes of establishing inventory levels for the Operations Module. Considerable difference exists between the degree of technical sophistication inherent in the forecasting techniques available for utilization in the Forecast Module. The SPSF Testing Environment provides an application of four short-range product forecasting procedures widely used in industry.[2]

The function of the Operations Module is to replicate the physical distribution system that supplies the test market. This module is capable of replicating inventory availability and movements based upon a variety of different replenishment policies. Utilizing input from both the Forecast and Demand Modules, the Operations Module traces the performance of the operating system across the forecast period. The Operations Module is designed on a stochastic basis and is capable of echeloned structure. To obtain maximum operational realism it functions on a dynamic basis wherein the state of the model at any given point in time is dependent upon the past performance and will to a significant degree formulate the operating basis for future periods. Dynamic simulation introduces the capability to replicate the time-dependent nature of operations in formulating the value of system state and flow variables. For example, the Operations Module adjusts inventory levels on a time dependent basis to replicate both receipts and shipments over time.

This time-dependent design feature permits the simulation of a specified physical distribution system's capability to satisfy sales requirements. Thus, the operational deficiency caused by uncertainty of demand or lead time as well as other disruptive factors may be measured for analysis purposes.

The Analysis Module is the fourth module of the overall testing environment. As the name suggests, the Analysis Module is primarily concerned with the diagnostic reporting of overall SPSF testing. The primary information flow for analysis is the time sequenced relationship between forecast sales, simulated demand, and simulated sales. Based on these linkages, this module provides management status, activity, and cost computation reports. To obtain the maximum measurement of SPSF activities, generalized cost equations are included in the Analysis Module to facilitate cost/revenue analysis. Finally, the Analysis Module quantifies the cause of forecast error, providing the opportunity to evaluate and modify future forecasts and/or operating policies.

As was stated previously, the Demand Module contained the demand generation approaches utilized in this research. For this reason the next section describes the design of the Demand Module in greater detail.

SPSF Demand Module

In the SPSF Testing Environment the applicability and validity of results are directly dependent upon the quality of demand generation. For example, once a physical distribution operating system is defined, the analysis of potential system efficiency rests on the capability to replicate or generate a specified demand pattern. If the representation of demand is unrealistic or provides an inadequate approximation of the actual demand, the modeling results will have limited, if any, operational validity. Similar relationships exist in all forms of simulation experimentation. In other words, the applicability of the experimental results are directly proportional to the validity of the demand replication.

The Demand Module of the SPSF Testing Environment provides four alternatives for daily demand generation. These alternatives reflect the actual historical orders, stochastic, firm demand, and industry demand methods discussed in Chapter II. The four alternatives are presented here, and sequentially numbered in the Demand Module, in order of complexity.

Actual Historical Orders

Alternative One of the SPSF Demand Module utilizes a historical stream of actual orders as demand and the force variable for the SPSF Testing Environment. Although the most realistic and simple alternative in the Demand Module, Alternative One can only replicate demand conditions that have occurred in the past. In fact, this alternative does not constitute demand generation, but merely a restaging of history.

Stochastic Demand

Alternative Two employs statistical distributions such as normal, log-normal, erlang, and poisson distributions to generate total daily demand. For each day of simulation the value of daily demand will be randomly selected from the specified statistical distribution. This is similar to the method used by Whybark[3] and Gross and Ray[4] in their simulation models.

Once the value of daily demand is identified, it is necessary to reduce daily demand into daily orders for use by the Operations Module of the SPSF Testing Environment. To accomplish this, random orders are selected from a predetermined order file until demand for that particular day is satisfied.

The statistical distribution for daily demand and the order file must both be specified for each period of time for which demand is to be generated. This specification by period allows for the incorporation into the demand pattern of periodic trend and seasonality. The flow of Alternative Two is shown in Figure 3-2.

Firm Demand

Alternative Three utilizes linear regression analysis to generate firm demand for each period, or:

$$FD = a + b_1 X_1 + b_2 X_2 + b_3 X_3 + b_4 X_4 + b_5 X_5$$

where:

FD = firm demand for the period in question;

a = the vertical axis intercept;

X_{1-n} = the independent variables that affect firm demand; and

b_{1-n} = coefficients of the independent variables.

The values for this equation are determined exogenous to the Demand Module through regression analysis. The values for a, X, and b are fed to the Demand Module for each period to generate period firm demand. Any trend to be in evidence in the demand pattern will be incorporated in the regression equation. However, seasonality must be input to the Demand Module to adjust the value of period demand generated from the regression equation.

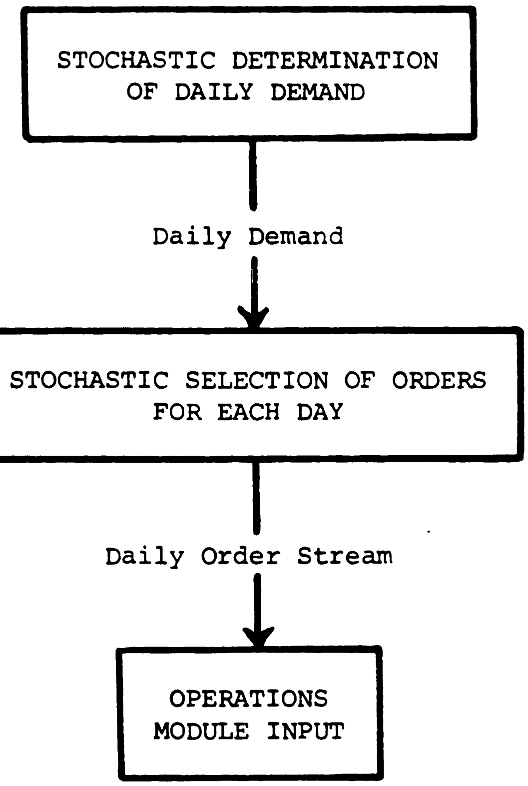

Figure 3-2. Demand Module Alternative Two.

Once period firm demand is determined, it is necessary to break it down into daily demand. For each day of the period a daily demand factor is randomly generated. The mean value of the daily demand factor is:

$$E\ (DDF) = \frac{1}{n}$$

where:

E (DDF) = mean value of daily demand factor; and

n = number of days in the period.

The generated value for the daily demand factor for each day is multiplied by period demand to obtain that value for daily demand. The individual orders that constitute the day's demand are selected via the same process used for order selection in Alternative Two. The flow of Alternative Three is illustrated in Figure 3-3.

Industry Demand

Alternative Four uses linear regression analysis to generate industry demand for each period, or:

$$ID = a + b_1 X_1 + b_2 X_2 + b_3 X_3 + b_4 X_4 + b_5 X_5$$

where:

ID = industry demand for the period in question;

a = the vertical axis intercept;

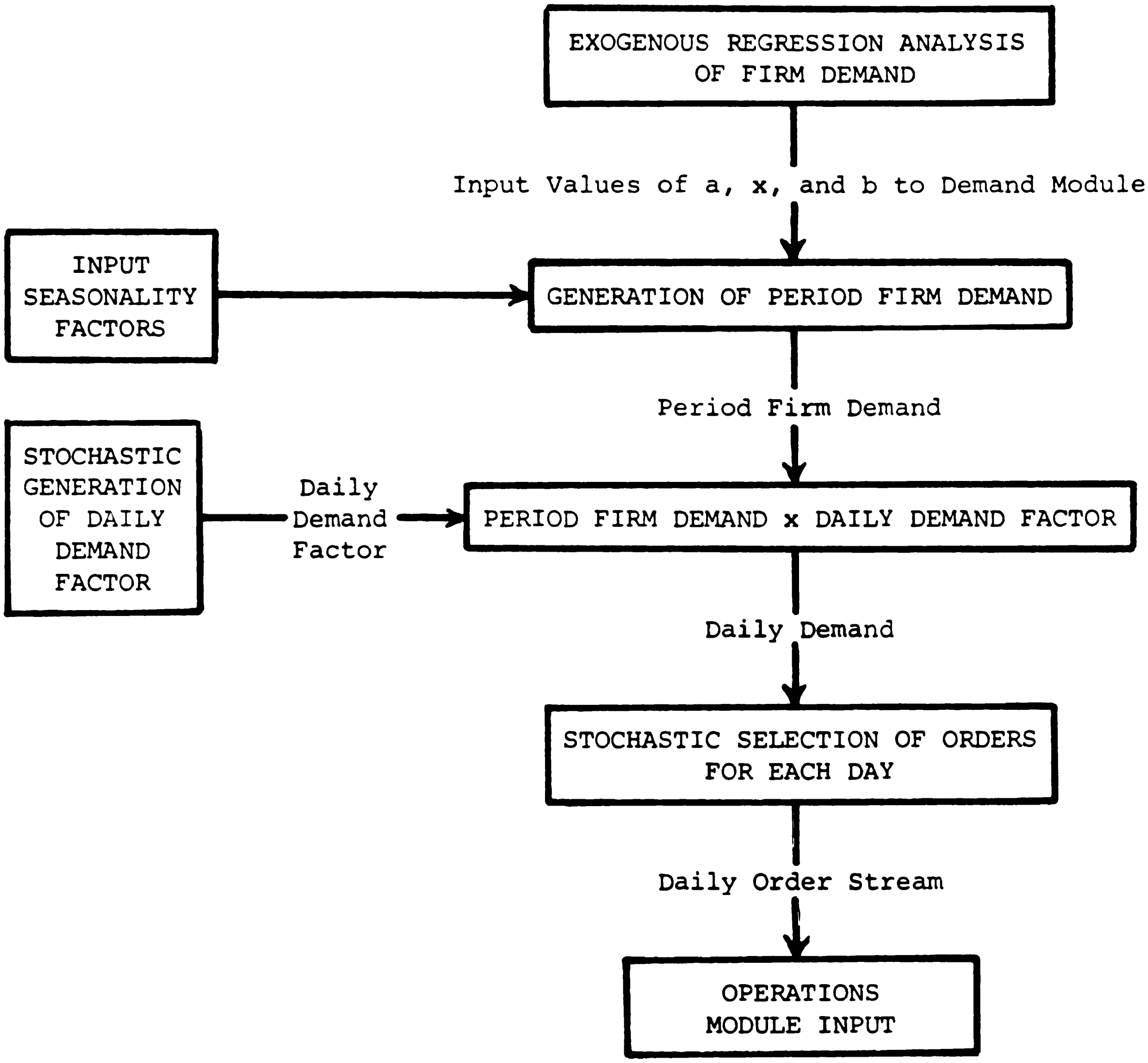

Figure 3-3. Demand Module Alternative Three.

X_{1-n} = the independent variables that affect firm demand; and

b_{1-n} = coefficients of the independent variables.

Similar to firm demand for Alternative Three, the equation is determined exogenous to the Demand Module through regression analysis and the values of a, X, and b are input for each period. Trend is incorporated in the equation, but seasonality must be input to the Demand Module.

To generate firm demand it is necessary to determine the fraction of industry demand that is firm demand. This fraction is termed market share and can be measured by the following equation.[5]

$$MS_1 = \frac{K_1 \ (F_{1,1})^{E_{1,1}} \ (F_{1,2})^{E_{1,2}} \ . \ . \ . \ (F_{1,5})^{E_{1,5}}}{\sum_{h=1}^{5} \left[K_h \ (F_{h,1})^{E_{h,1}} \ (F_{h,2})^{E_{h,2}} \ . \ . \ . \ (F_{h,5})^{E_{h,5}} \right]}$$

where:

MS_1 = market share for firm 1;

K_h = constant for firm h;

h = number of the firm;

$F_{h,1-5}$ = factors that affect market share for firm h; and

$E_{h,1-5}$ = elasticity of factors for firm h.

This equation can be converted to a logarithmic form of regression analysis to determine market share. This regression analysis is performed exogenous to the Demand Module and the value of market share for each period is input.

Firm demand is generated by multiplying industry demand for a particular period by market share for that period. Daily demand and the orders for each day are generated from period firm demand by the same procedure utilized in Alternative Three. The flow of Alternative Four is given in Figure 3-4.

Summary

The SPSF Testing Environment utilizes four of the five demand generation methods discussed in Chapter II to develop the four demand generation alternatives contained within the Demand Module. Figure 3-5 illustrates this development.

Specifically, the actual historical orders method constitutes Alternative One. The stochastic method constitutes Alternative Two. The firm demand method is combined with stochastic generation of a daily demand factor to produce Alternative Three. Similarly, the industry demand method is combined with stochastic generation of a daily demand factor to produce Alternative Four.

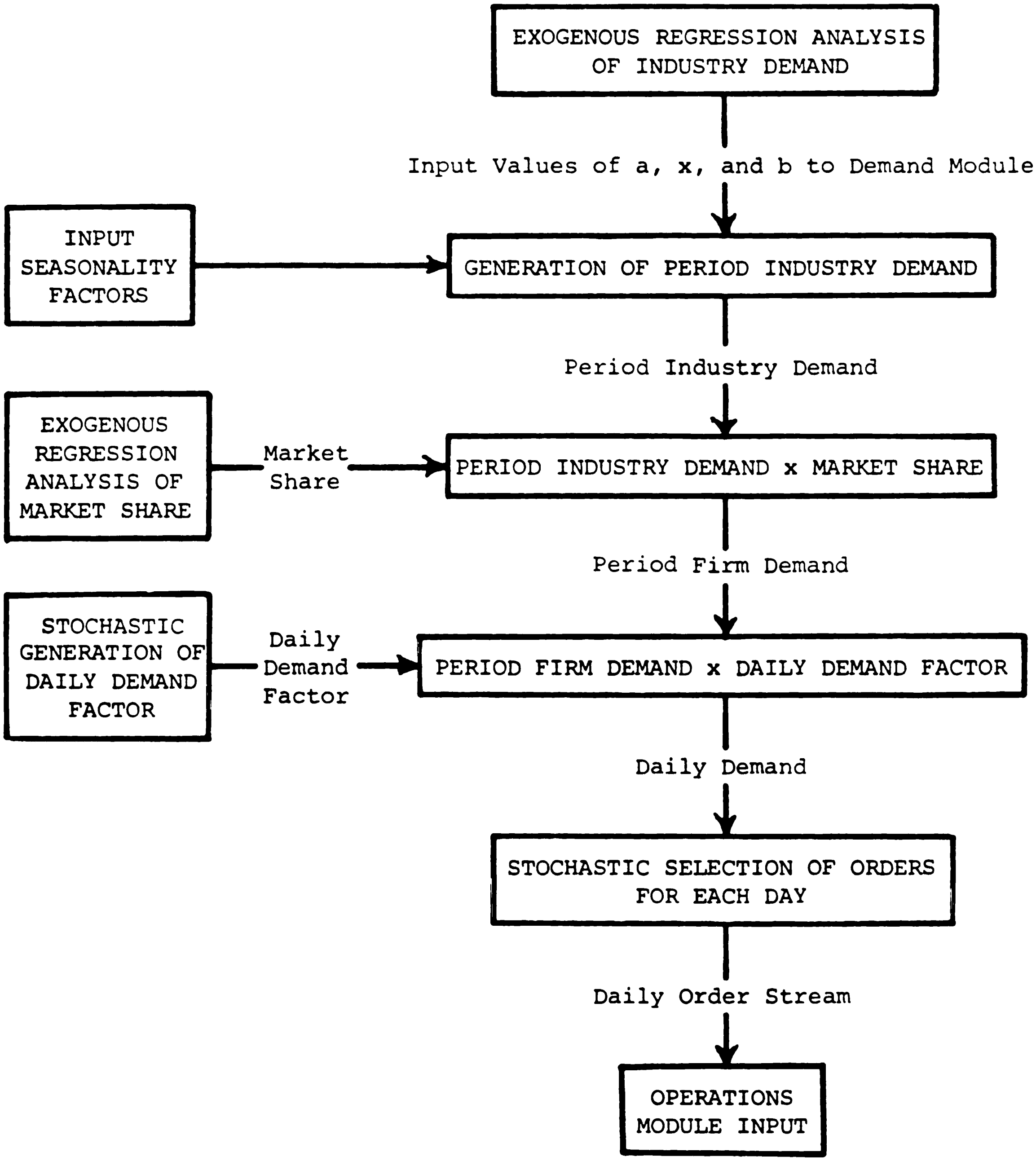

Figure 3-4. Demand Module Alternative Four.

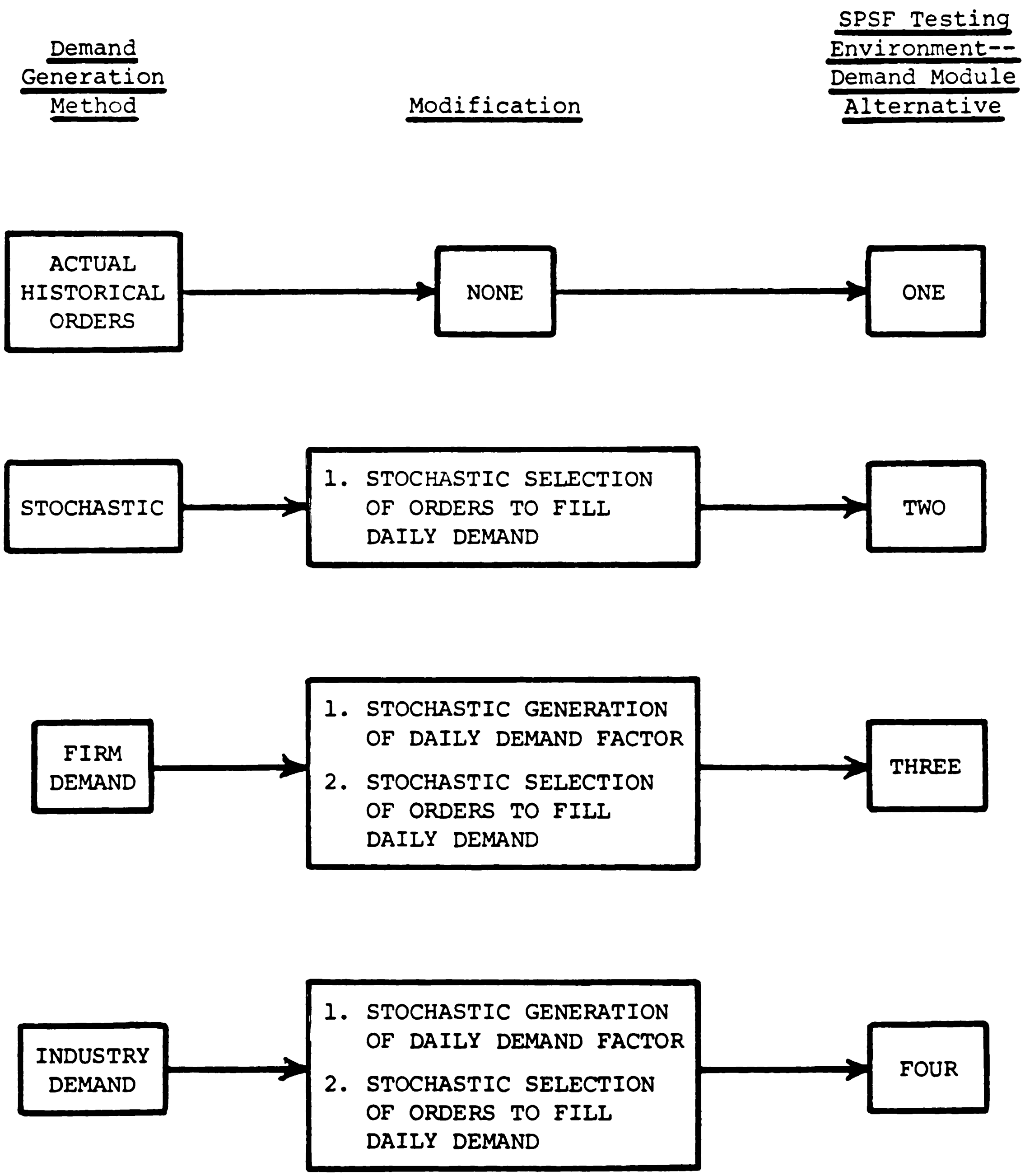

Figure 3-5. Demand Module Alternative Development.

The next section of this chapter will discuss the development of the demand generation approaches utilized in this research from the four demand generation alternatives in the Demand Module of the SPSF Testing Environment.

Demand Generation Approaches

The Demand Module alternatives were developed from four of the demand generation methods described in Chapter II. The demand generation approaches for this research were developed from the Demand Module alternatives in such a way as to reflect the range of sophistication available in the demand generation methods.

As was stated previously, Alternative One does not actually constitute demand generation, but rather a restaging of history. Since this alternative does not fall under the heading of demand generation, per se, it was not used to develop any of the demand approaches.

Alternative Two represents the stochastic method of demand generation. Therefore, it was used in its entirety to constitute the first demand approach for this research. This is labelled Demand Approach A and is presented in Figure 3-6.

The remaining demand approaches were developed from either Alternative Three, which constitutes the firm demand method, or Alternative Four, which constitutes the industry

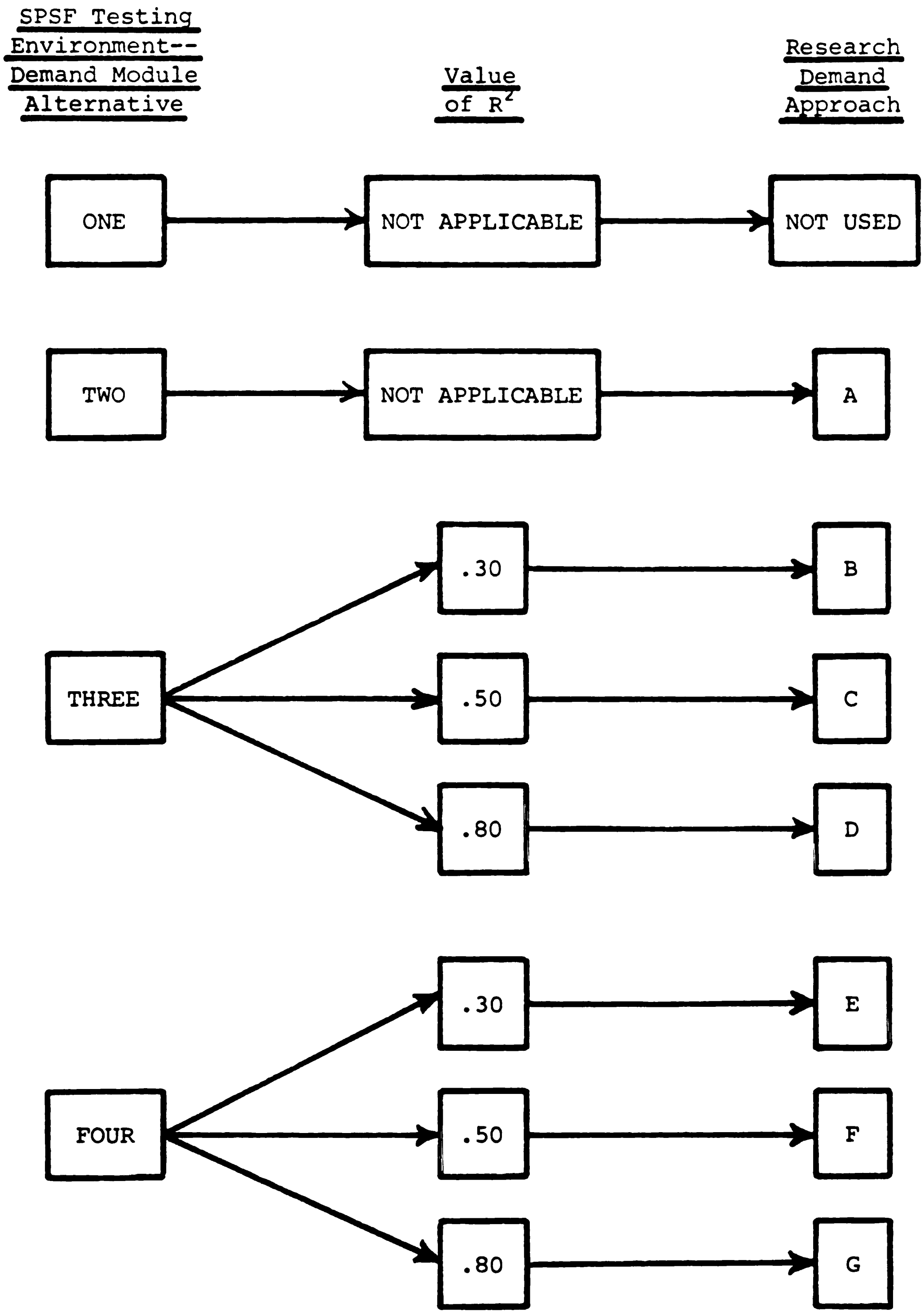

Figure 3-6. Demand Approach Development.

demand method. For each of these demand approaches the decision was not only which demand module alternative to use, but what level of correlation should be obtained in the regression analysis.

The coefficient of determination , or R^2 value, measures the degree to which the independent variables in the regression analysis predict the dependent variable (demand). Another way of stating this relationship is that the R^2 value measures the percent of variation in demand that is common to the independent variables used in the regression analysis. Therefore, the higher the value of R^2 the more accurate the regression analysis.

In this research the accuracy of the firm demand and industry demand methods could have been seriously affected by ignoring the value of R^2 obtained in the regression analysis. To measure the effect of the R^2 value on the accuracy of the results, a range of three R^2 values was selected for use with both Alternative Three and Alternative Four. Therefore, three of the demand approaches for this research were developed from Alternative Three and three were developed from Alternative Four. Each set of three represented different values of R^2 obtained in the regression analysis.

The values of .30, .50, and .80 were selected for R^2. These three values can be said to represent "low," "medium," and "high" R^2 values.[6] Figure 3-6 illustrates the combination of Demand Module Alternatives Three and Four with the different R^2 values to obtain the remaining six demand approaches.

Demand Approach B utilized Demand Module Alternative Three. In the regression analysis of firm demand, an independent variable with an R^2 value of .30 to firm demand was used. Similarly, Demand Module Alternative Three was used for Demand Approaches C and D. The independent variables in the regression analysis of firm demand had an R^2 value of .50 for Demand Approach C and .80 for Demand Approach D.

Demand Approach E utilized Demand Module Alternative Four. In the regression analysis for industry demand, an independent variable was found with an R^2 value of .30 to industry demand. Independent variables with an R^2 value of .30 for market share were also found for the market share regression analysis.

Demand Approach F utilized independent variables with an R^2 value of .50 to industry sales and market demand. Demand Approach G utilized independent variables with an R^2 value of .80 to industry demand and market share.

Therefore, seven demand approaches were utilized in this research. These demand approaches were developed from the alternatives available in the Demand Module of the SPSF Testing Environment. These alternatives were developed from four demand generation methods discussed in Chapter II. By combining Figures 3-5 and 3-6 the progression from the demand methods to the demand approaches can be illustrated. This combination is presented in Figure 3-7.

These seven demand approaches allow testing of the relative accuracy of the stochastic, firm demand, and industry demand methods of demand generation. The approaches also allow the testing of the effect of the value of R^2 on the accuracy of the firm demand and industry demand methods, both within each method and relative to the other two methods.

Of major importance to the testing of these demand approaches was the determination of the environmental patterns of demand which each approach would attempt to replicate (generate). This determination is discussed in the next chapter.

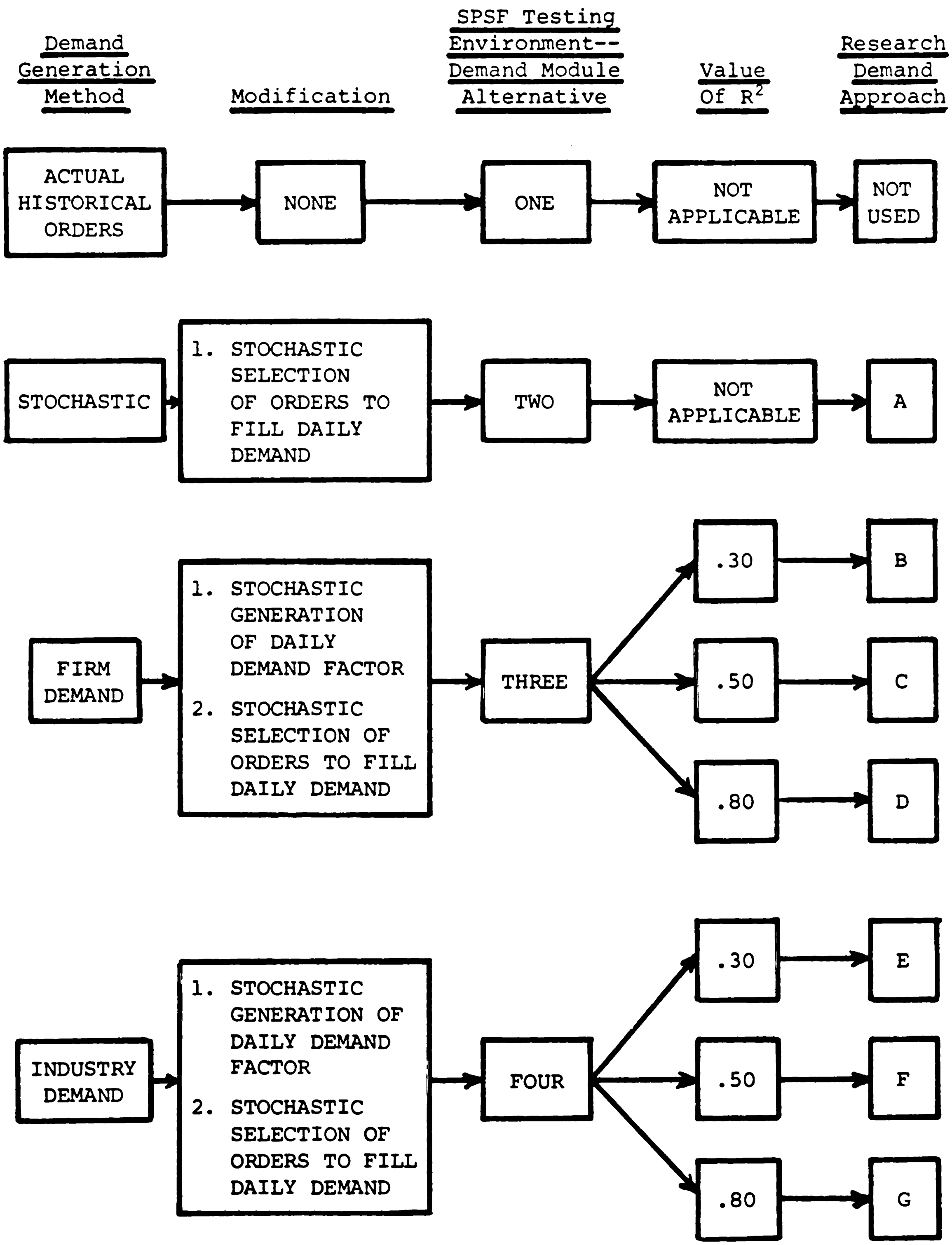

Figure 3-7. Combined Development of Demand Approaches.

CHAPTER III--FOOTNOTES

[1]The initial reporting of the SPSF Testing Environment Research was at the 1976 Transportation and Logistics Educators Conference. See: D. J. Bowersox et al., "Simulated Product Sales Forecasting," in the Proceedings of the 6th Annual Transportation and Logistics Educators Conference (Columbus, Ohio, Transportation and Logistics Research Fund, The Ohio State University, 1976), pp. 189-191. Full reporting and documentation of the basic research will be reported in 1978 by the Michigan State University, Graduate School of Business Administration Research Bureau.

[2]The four forecasting techniques included in the SPSF Testing Environment are reported in R. G. Brown and Richard F. Meyer, "The Fundamental Theorem of Experimental Smoothing," Operations Research 9 (No. 5; September-October 1961): 673-685; P. R. Winters, "Forecasting Sales by Exponentially Weighted Moving Averages," Management Science 6 (No. 3; April 1960): 324-342; D. W. Trigg and A. G. Leach, "Exponentially Smoothing With An Adaptive Response Rate," Operations Research Quarterly 18 (No. 1; March 1967): 53-59; and Stephen D. Roberts and Ruddell Reed, Jr., "The Development of a Self-Adaptive Forecasting Technique," AIIE Transactions 1 (No. 4; December 1969): 314-322.

[3]D. Clay Whybark, "A Comparison of Adaptive Forecasting Techniques," The Logistics and Transportation Review 8 (No. 3; July 1973): 13-26.

[4]Donald Gross and Jack L. Ray, "A General Purpose Forecast Simulator," Management Science 11 (No. 6; April 1965): 119-135.

[5]Philip Kotler, Marketing Decision Making: A Model Building Approach (New York: Holt, Rinehart and Winston, Inc., 1971), p. 97.

[6]Richard Cohen, Statistical Power Analysis for the Behavioral Sciences (New York: Academic Press, Inc., 1969).

CHAPTER IV

DEMAND TEST CONDITIONS

The previous chapter developed the demand generation approaches utilized in this research. This chapter is devoted to an explanation of the environmental conditions, termed demand test conditions, under which the demand approaches were tested and the factors which determined these demand test conditions.

The first section addresses the factors which were considered germane to the development of the demand test conditions. The second section explains the development of the demand test conditions utilized in this research from the relevant factors.

Environmental Factors

Two major factors were considered in the development of the demand test conditions under which the demand approaches were to be tested. The first was the number of products to be used in the generation. This factor is discussed in the next sub-section. The second is the components of the demand patterns to be used. This is discussed in the second sub-section.

Product Number

To test the relative accuracy of the demand approaches developed in the previous chapter, it was actually necessary to only replicate one product. However, the computer cost of simulation is rather high. Therefore, use of more products would cause daily demand to be filled quicker on each day and reduce computer time and cost. The addition of products also added to the complexity of the simulation without really augmenting the research objective of testing the accuracy of the demand approaches. Therefore, it was desirable to reduce the cost of simulation by use of more products but, at the same time, keep the number relatively low to avoid unnecessary complexity.

Since the SPSF Testing Environment allows for the simulation of up to ten products, the choice range was between one and ten products. The determination was made to use five identical products for each demand approach under each demand test condition. The use of five products allowed daily demand to be filled quicker, reducing computer time and cost, and kept the complexity of dealing with a multitude of different products at a minimum.

Demand Patterns

Lippitt[1] mentions four components that constitute a demand pattern over time. These components are depicted in Figure 4-1. The first is level, which can be defined as

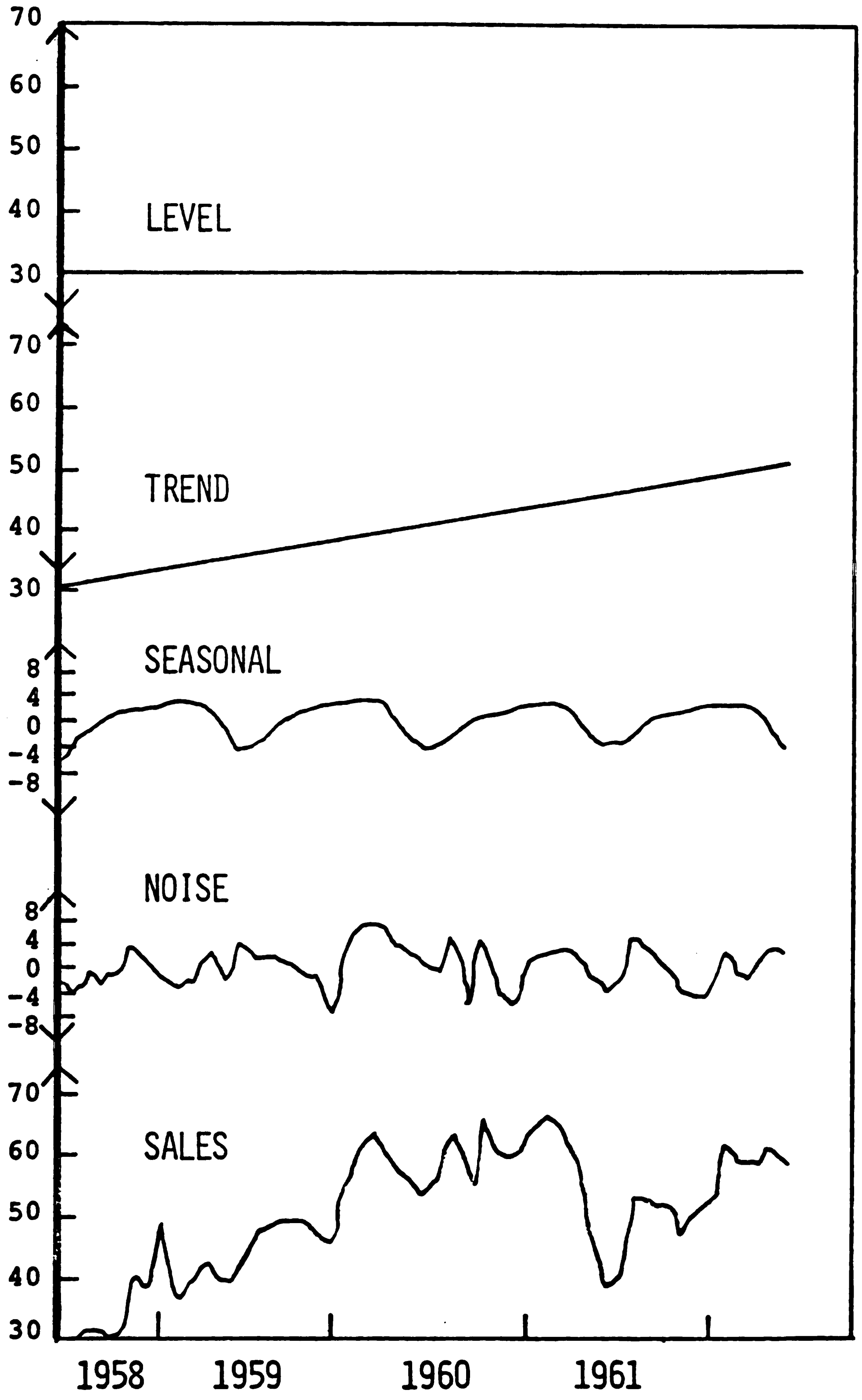

Figure 4-1. Demand Pattern Components.

the point at which the demand pattern started. The second component is trend and can be defined as the increasing or decreasing linear pattern over time. The third pattern is seasonality and represents any repeating cyclical pattern in the demand over time. The last component constitutes any portion of the demand pattern that cannot be explained by the previous three components. This component is termed noise and can be explained by the measure of standard deviation around the other three components.[2] Therefore, the higher the standard deviation, the larger the amount of noise.

Any combination of these components could constitute a demand test condition for this research. Ten such combinations were developed for testing the demand approaches. These ten are discussed in the next section.

Demand Test Conditions

Ten demand test conditions were developed from combinations of the four components of demand patterns discussed in the previous sub-section. These ten conditions represent a cross-section of the range of complexity in demand patterns that could be experienced under actual conditions. Therefore, the results obtained from the testing of accuracy of the demand approaches under each of the ten demand test conditions are generalizable over most demand patterns that a firm may experience.

Each demand test condition was ten periods in length. Each period consisted of twenty days or a total of 200 days of demand for each demand test condition. For all demand test conditions the level of daily demand was set at 750 units for each of the five identical products or 3,750 units of demand overall for each day. Each demand test condition was developed by varying trend, seasonality, and variance around this level.

The first demand test condition, termed Demand Test Condition I, was the simplest demand pattern. It consisted of zero trend and seasonality and low variation over the ten periods. Low variation was defined to be a coefficient of variation[3] of .10 or a standard deviation (σ) of 75 units per product per day. This amounted to a standard deviation over all five products of 375 units per day.

The expected value and standard deviation of daily demand over all ten periods for Demand Test Condition I are given in Table 4-1. The demand pattern is illustrated in Figure 4-2.

Demand Test Condition II also exhibited no trend or seasonality. However, high variation was evidenced in the demand pattern. High variation was defined as twice that of low variation, or a standard deviation of 150 units per product per day. This amounted to a standard deviation of 750 units per day over all five products.

Table 4-1. Demand Test Condition I

Period	Expected Daily Demand	Standard Deviation
1	3,750.0	375.0
2	3,750.0	375.0
3	3,750.0	375.0
4	3,750.0	375.0
5	3,750.0	375.0
6	3,750.0	375.0
7	3,750.0	375.0
8	3,750.0	375.0
9	3,750.0	375.0
10	3,750.0	375.0

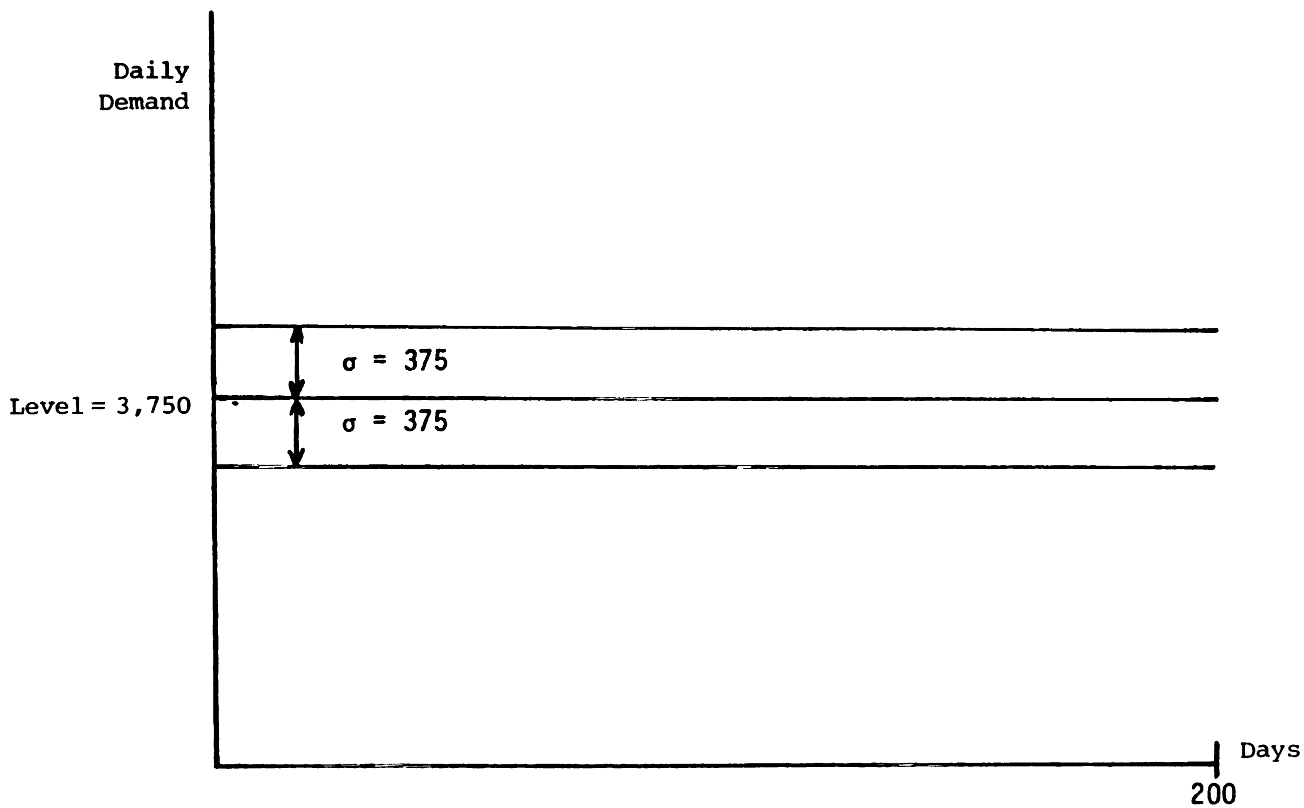

Figure 4-2. Demand Test Condition I.

The expected value and standard deviation of daily demand over all ten periods for Demand Test Condition II are presented in Table 4-2. The demand pattern is illustrated in Figure 4-3.

Demand Test Condition III exhibited no seasonality and the low standard deviation of 375 units per day for all five products. Trend was an increase each period in expected daily demand for each product of 37.5 units, or 187.5 units over all five products. This amounted to a periodic increase in demand over all five products of 5 percent of the level of 3,750 units per day.

The expected value and standard deviation of daily demand over all ten periods for Demand Test Condition III are presented in Table 4-3. The demand pattern is illustrated in Figure 4-4.

Trend for Demand Test Condition IV was identical to that of Demand Test Condition III. No seasonality was exhibited, but variation was set at the high value of standard deviation of 750 units per day over all five products.

The expected value and standard deviation of daily demand over all ten periods for Demand Test Condition IV are presented in Table 4-4. The demand pattern is illustrated in Figure 4-5.

Table 4-2. Demand Test Condition II

Period	Expected Daily Demand	Standard Deviation
1	3,750.0	750.0
2	3,750.0	750.0
3	3,750.0	750.0
4	3,750.0	750.0
5	3,750.0	750.0
6	3,750.0	750.0
7	3,750.0	750.0
8	3,750.0	750.0
9	3,750.0	750.0
10	3,750.0	750.0

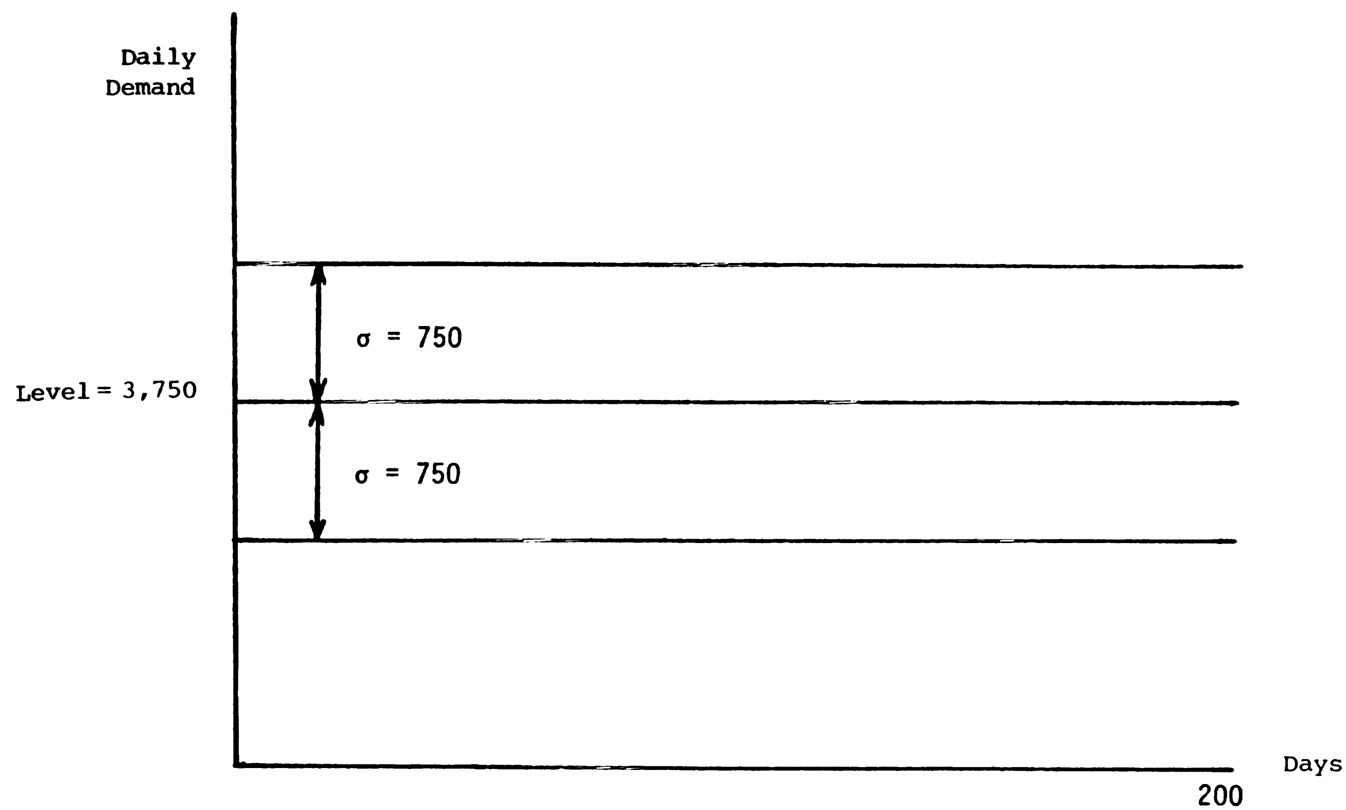

Figure 4-3. Demand Test Condition II.

Table 4-3. Demand Test Condition III

Period	Expected Daily Demand	Standard Deviation
1	3,750.0	375.0
2	3,937.5	375.0
3	4,125.0	375.0
4	4,312.5	375.0
5	4,500.0	375.0
6	4,687.5	375.0
7	4,875.0	375.0
8	5,062.5	375.0
9	5,250.0	375.0
10	5,437.5	375.0

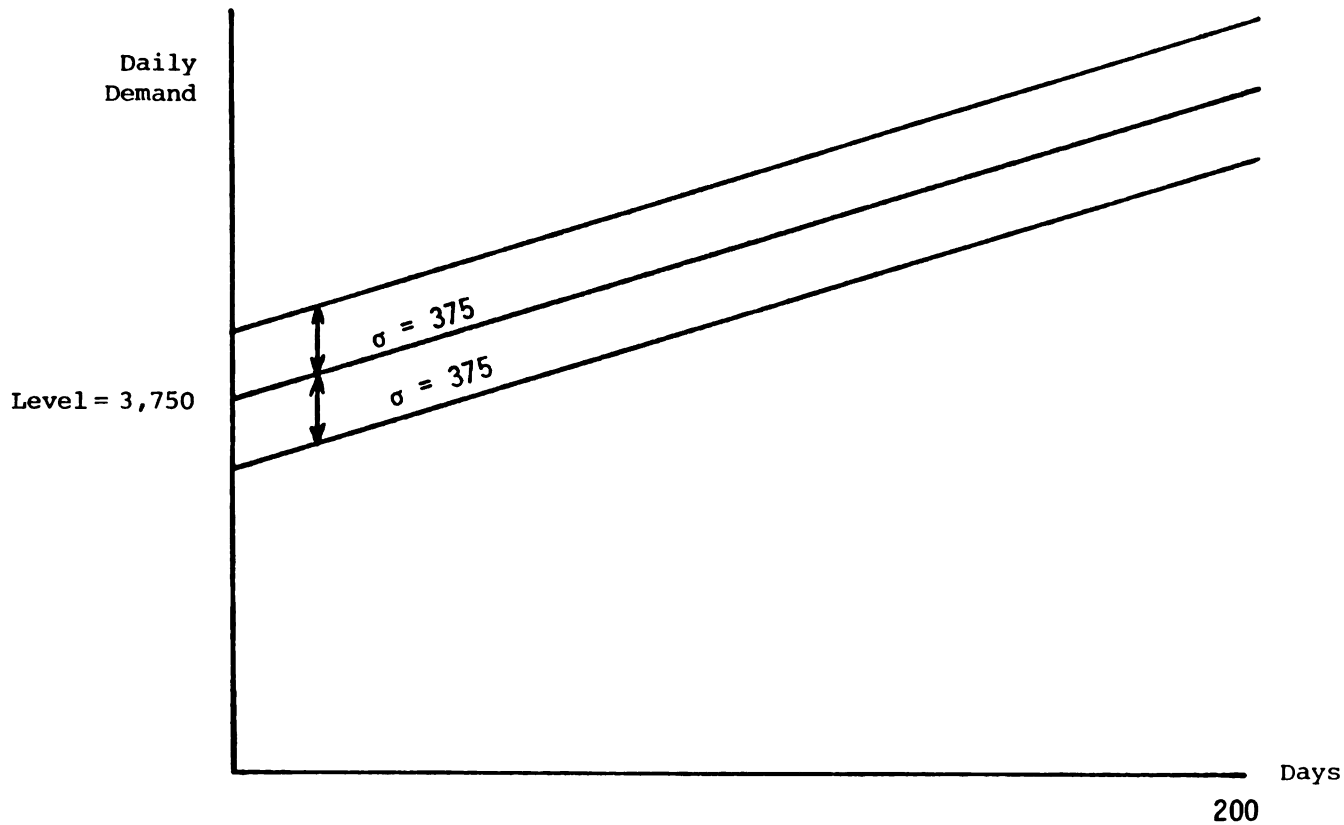

Figure 4-4. Demand Test Condition III

Table 4-4. Demand Test Condition IV

Period	Expected Daily Demand	Standard Deviation
1	3,750.0	750.0
2	3,937.5	750.0
3	4,125.0	750.0
4	4,312.5	750.0
5	4,500.0	750.0
6	4,687.5	750.0
7	4,875.0	750.0
8	5,062.5	750.0
9	5,250.0	750.0
10	5,437.5	750.0

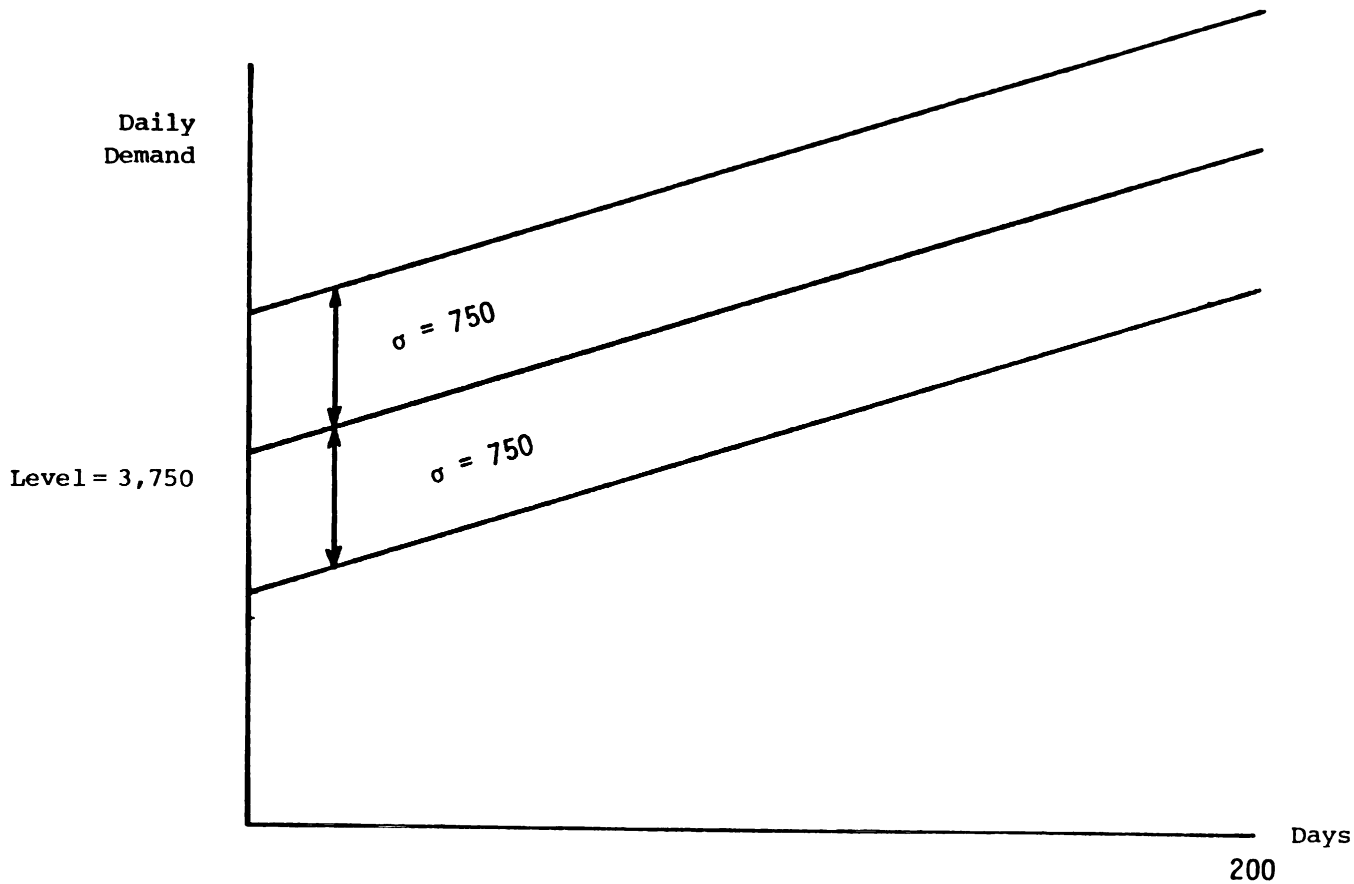

Figure 4-5. Demand Test Condition IV.

Demand Test Condition V exhibited no seasonality and low standard deviation of 375 units per day over all five products. Trend was an increase each period in expected daily demand over all five products of 187.5 units for periods one through five. Expected daily demand over all five products decreased 187.5 units per period for periods six through ten. This represented a trend of positive 5 percent of the level for the first five periods and a trend of negative 5 percent of the level for the last five periods.

The expected value and standard deviation of daily demand over all ten periods for Demand Test Condition V are presented in Table 4-5. The demand pattern is illustrated in Figure 4-6.

Trend for Demand Test Condition VI was identical to that of Demand Test Condition V. No seasonality was exhibited, but variation was at the high value for standard deviation of 750 units over all five products for each day.

The expected value and standard deviation of daily demand over all ten periods for Demand Test Condition VI are presented in Table 4-6. The pattern of demand is illustrated in Figure 4-7.

Table 4-5. Demand Test Condition V

Period	Expected Daily Demand	Standard Deviation
1	3,750.0	375.0
2	3,937.5	375.0
3	4,125.0	375.0
4	4,312.5	375.0
5	4,500.0	375.0
6	4,312.5	375.0
7	4,125.0	375.0
8	3,937.5	375.0
9	3,750.0	375.0
10	3,562.5	375.0

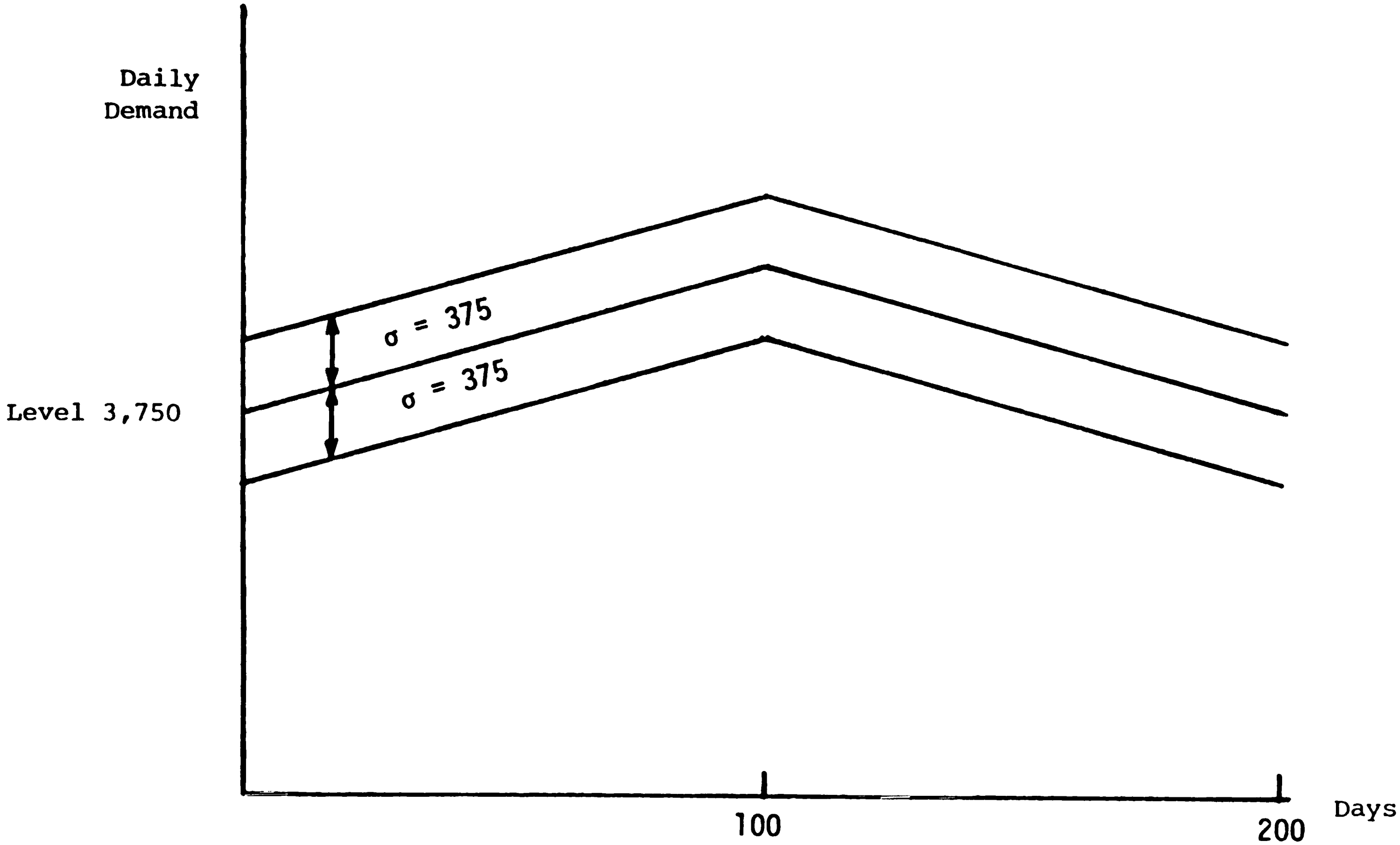

Figure 4-6. Demand Test Condition V.

Table 4-6. Demand Test Condition VI

Period	Expected Daily Demand	Standard Deviation
1	3,750.0	750.0
2	3,937.5	750.0
3	4,125.0	750.0
4	4,312.5	750.0
5	4,500.0	750.0
6	4,312.5	750.0
7	4,125.0	750.0
8	3,937.5	750.0
9	3,750.0	750.0
10	3,562.5	750.0

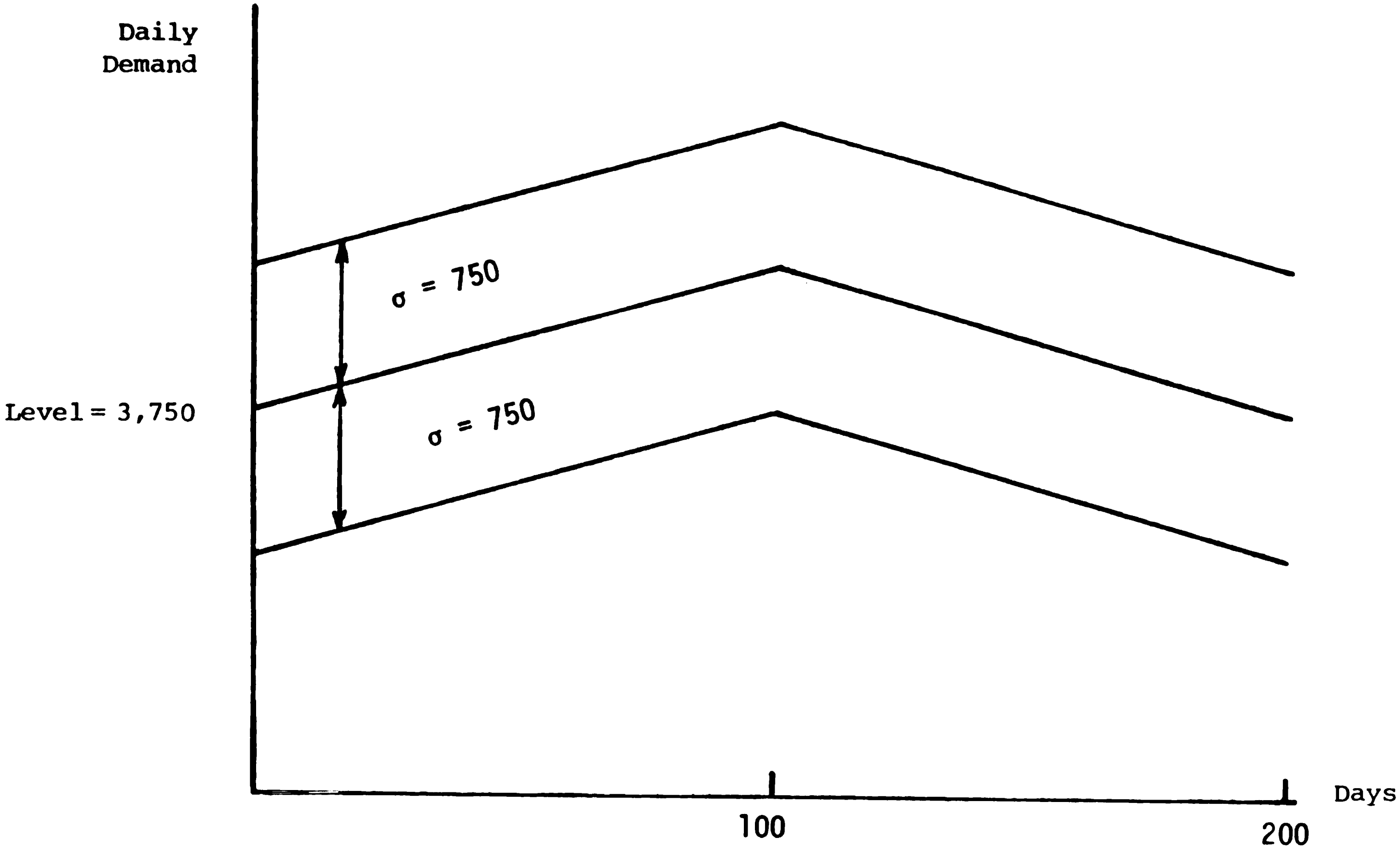

Figure 4-7. Demand Test Condition VI.

Demand Test Condition VII exhibited no trend and low standard deviation of 375 units per day over all five products. A seasonal pattern existed in the ten periods. This was considered a low seasonality pattern and ranged from a high seasonality factor[5] of 1.25 to a low seasonality factor of .75.

The expected daily demand for each period resulting from this seasonal pattern and the standard deviation of daily demand are presented in Table 4-7. The resulting demand pattern is illustrated in Figure 4-8.

Demand Test Condition VIII exhibited the same seasonality pattern as Demand Test Condition VII. No trend was exhibited, but standard deviation was at the high level of 750 units per day over all five products.

The expected value and standard deviation of daily demand are presented in Table 4-8. The demand pattern is illustrated in Figure 4-9.

Demand Test Condition IX exhibited a high seasonality pattern. This pattern ranged from a high seasonality factor of 1.70 to a low seasonality factor of .30. Variation was at the low level with a standard deviation of 375 units per day over all five products. No trend was exhibited.

The expected value and standard deviation of daily demand for all ten periods is given in Table 4-9. Figure 4-10 illustrates this demand pattern.

Table 4.7. Demand Test Condition VII

Period	Seasonality Factor	Expected Daily Demand	Standard Deviation
1	1.00	3,750.0	375.0
2	1.10	4,125.0	375.0
3	1.20	4,500.0	375.0
4	1.25	4,687.5	375.0
5	1.15	4,312.5	375.0
6	1.00	3,750.0	375.0
7	0.90	3,375.0	375.0
8	0.80	3,000.0	375.0
9	0.75	2,812.5	375.0
10	0.85	3,187.5	375.0

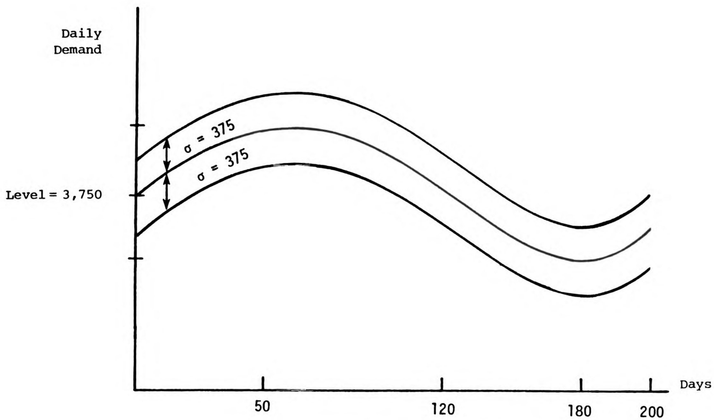

Figure 4-8. Demand Test Condition VII.

Table 4-8. Demand Test Condition VIII

Period	Seasonality Factor	Expected Daily Demand	Standard Deviation
1	1.00	3,750.0	750.0
2	1.10	4.125.0	750.0
3	1.20	4,500.0	750.0
4	1.25	4,687.5	750.0
5	1.15	4,312.5	750.0
6	1.00	3,750.0	750.0
7	0.90	3,375.0	750.0
8	0.80	3,000.0	750.0
9	0.75	2,812.5	750.0
10	0.85	3,187.5	750.0

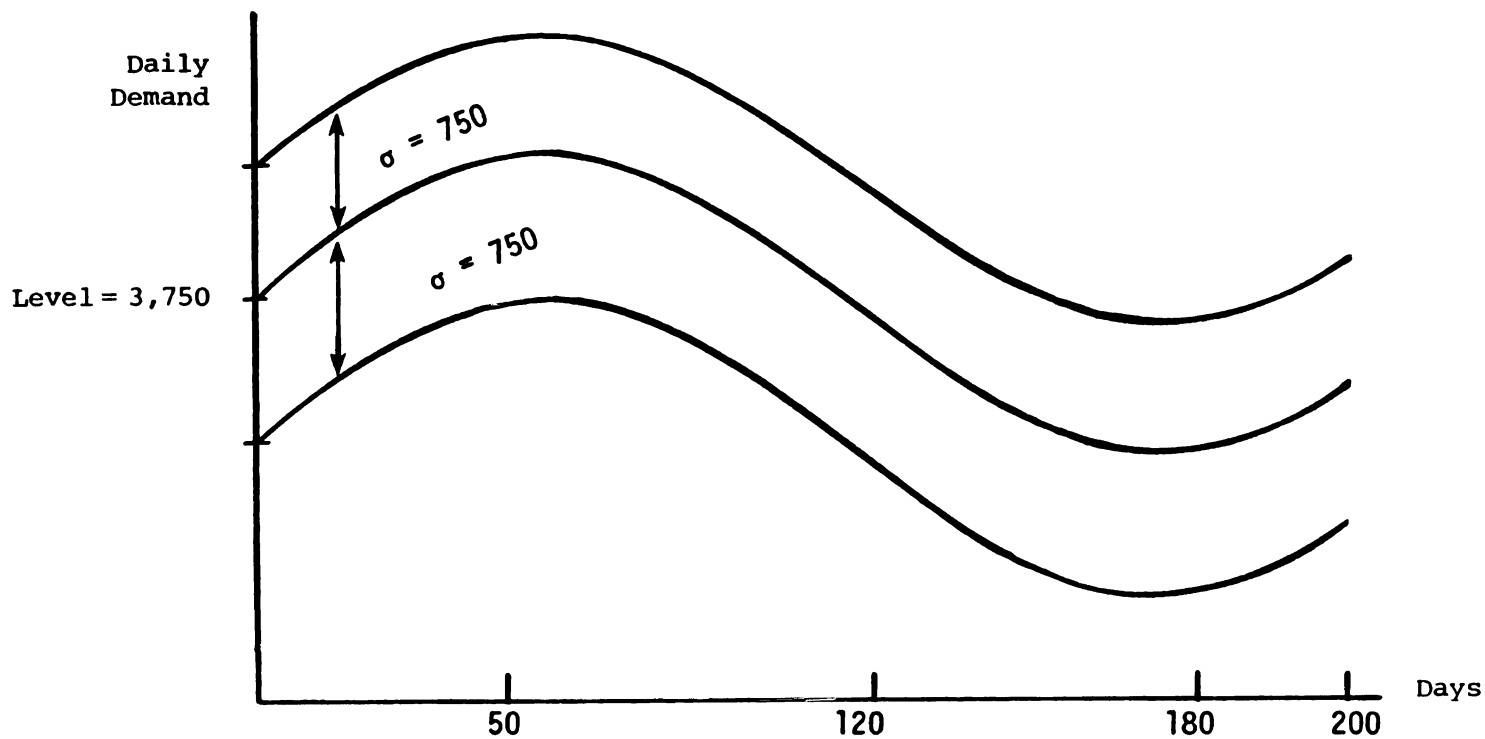

Figure 4-9. Demand Test Condition VIII.

Table 4-9. Demand Test Condition IX

Period	Seasonality Factor	Expected Daily Demand	Standard Deviation
1	1.00	3,750.0	375.0
2	1.20	4,500.0	375.0
3	1.50	5,625.0	375.0
4	1.70	6,375.0	375.0
5	1.35	5,062.5	375.0
6	1.00	3,750.0	375.0
7	0.80	3,000.0	375.0
8	0.50	1,875.0	375.0
9	0.30	1,125.0	375.0
10	0.65	2,437.5	375.0

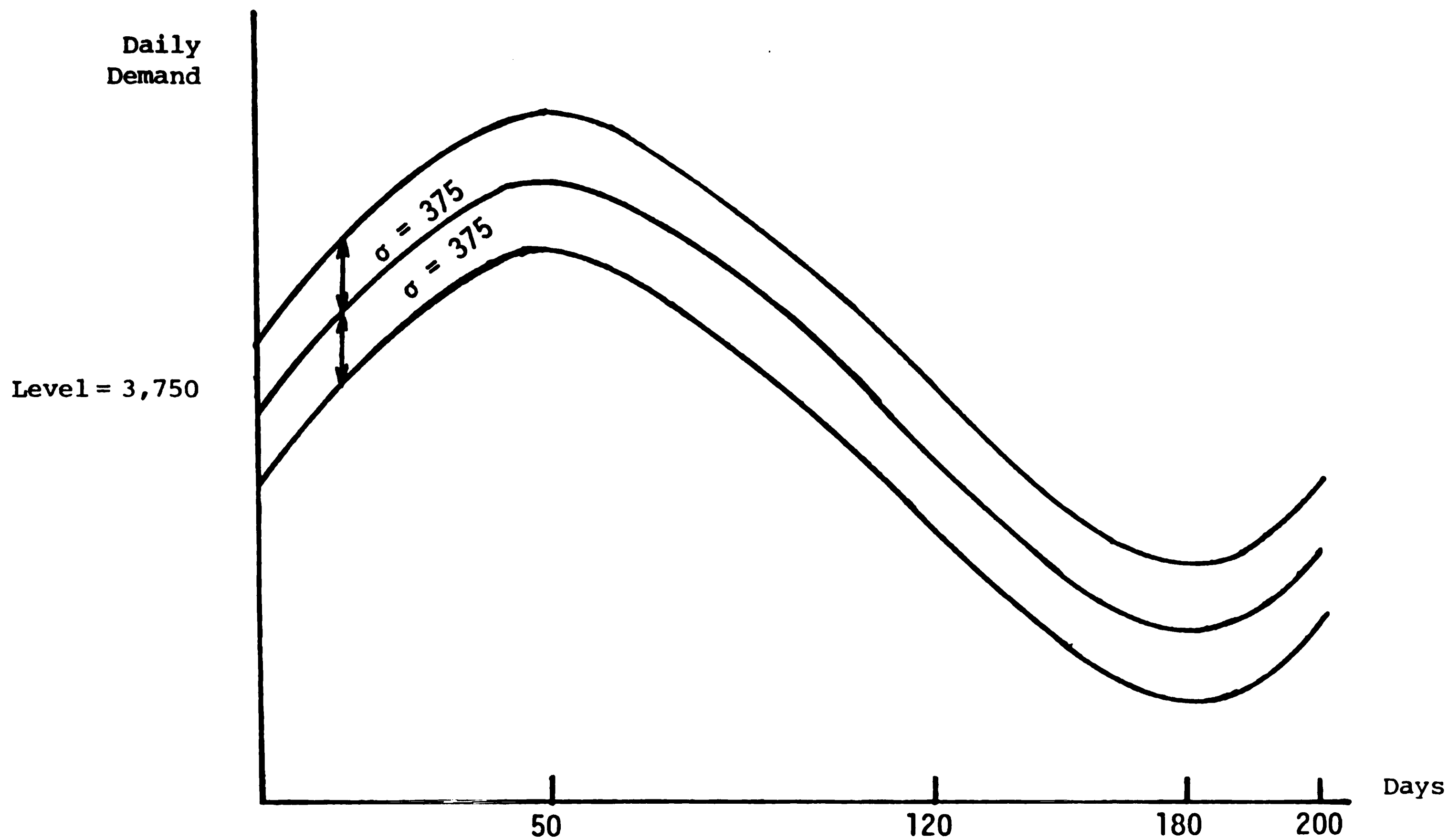

Figure 4-10. Demand Test Condition IX.

Demand Test Condition X is identical to Demand Test Condition IX with respect to the seasonality pattern and lack of trend. However, the variation was set at the high level with a standard deviation of 750 units per day over all five products.

The expected value and standard deviation of daily demand for all ten periods are given in Table 4-10. Figure 4-11 illustrates the demand pattern.

Summary

Ten different demand test conditions were chosen as the environmental conditions under which the accuracy of the demand approaches were to be tested. The first two demand test conditions exhibited no trend or seasonality, but alternated from low and high variation in the demand pattern.

The next two demand test conditions exhibited positive trend and, again, alternated from low to high variation in the demand pattern.

The fifth and sixth demand test conditions exhibited a complete reversal in the direction of the trend midway through the demand pattern. The variation alternated from low to high.

Table 4-10. Demand Test Condition X

Period	Seasonality Factor	Expected Daily Sales	Standard Deviation
1	1.00	3,750.0	750.0
2	1.20	4,500.0	750.0
3	1.50	5,625.0	750.0
4	1.70	6,375.0	750.0
5	1.35	5,062.5	750.0
6	1.00	3,750.0	750.0
7	0.80	3,000.0	750.0
8	0.50	1,875.0	750.0
9	0.30	1,125.0	750.0
10	0.65	2,437.5	750.0

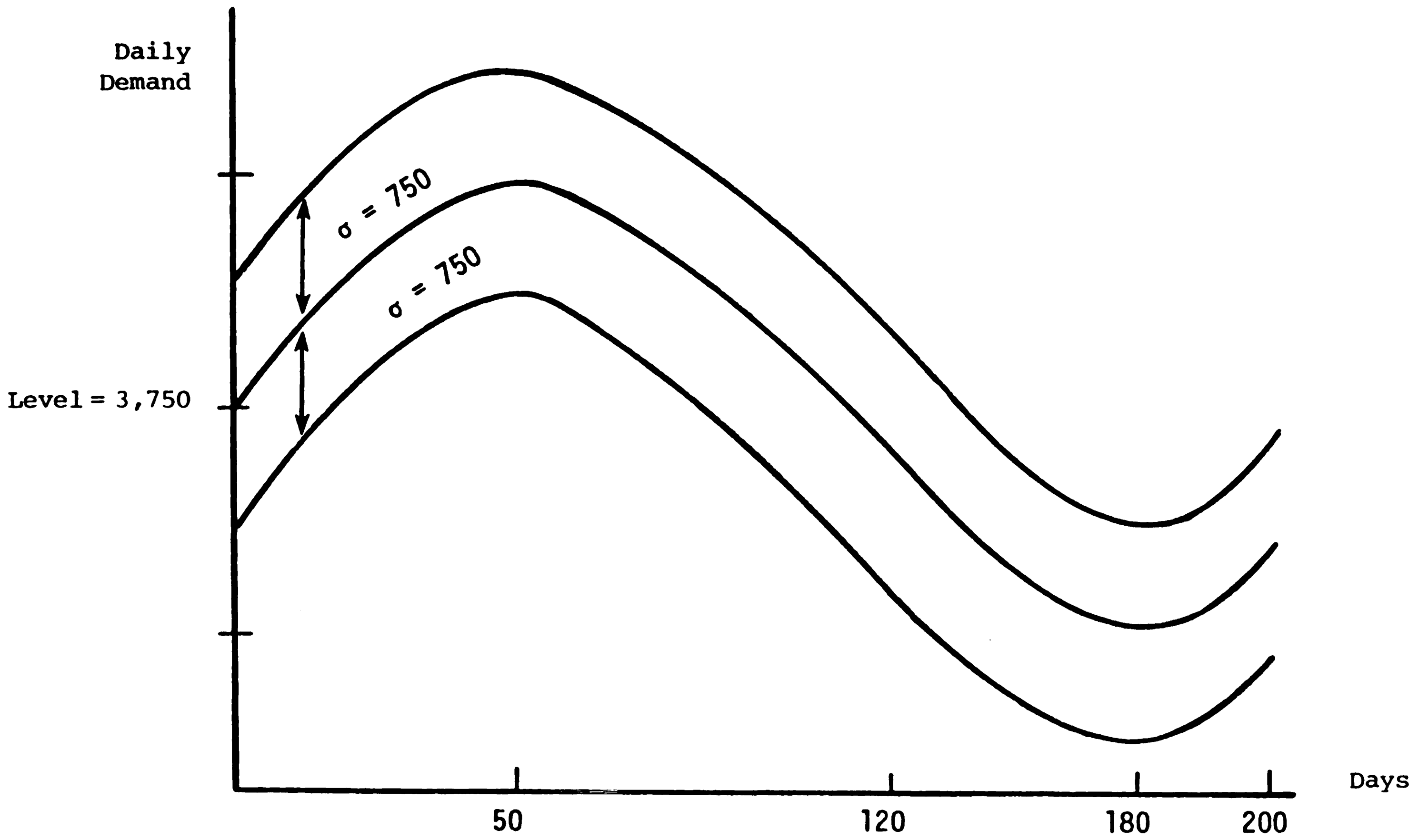

Figure 4-11. Demand Test Condition X.

The last four demand test conditions exhibited two different seasonality patterns with variation alternating from low to high. These ten demand test conditions are summarized in Table 4-11.

Therefore, the relative accuracy of the demand approaches developed in Chapter III were tested under conditions of no trend or seasonality, positive trend, changing trend, low seasonality, and high seasonality. Each of these categories also exhibited low and high variation.

These ten demand test conditions are not exhaustive of all possible combinations of variation, level, trend, and seasonality. However, if all possible combinations had been considered, the list of possible demand test conditions would have been virtually limitless. Therefore, representative trend and seasonality patterns were chosen and combined with the extremes of variation to develop the demand test conditions. In an attempt to isolate the effect of trend and seasonality, these two demand pattern components were not combined in any demand test condition.

The next chapter is devoted to the development of the hypotheses concerning this research and the methodology utilized to test them.

Table 4-11. Demand Test Conditions

Demand Test Condition	Standard Deviation	Trend	Seasonality
I	Low	0	0
II	High	0	0
III	Low	Increasing	0
IV	High	Increasing	0
V	Low	Increasing changing to decreasing	0
VI	High	Increasing changing to decreasing	0
VII	Low	0	Low
VIII	High	0	Low
IX	Low	0	High
X	High	0	High

CHAPTER IV--FOOTNOTES

[1]Vernon G. Lippitt, Statistical Sales Forecasting (New York: Financial Executives Research Foundation, 1969), pp. 167-169.

[2]For a further explanation of standard deviation, see Exhibit I of the Appendix.

[3]For a further explanation of the coefficient of variation, see Exhibit II of the Appendix.

[4]For a further explanation of the seasonality factor, see Exhibit III of the Appendix.

CHAPTER V

HYPOTHESES AND RESEARCH METHODOLOGY

The objective of this research was to measure the accuracy of various approaches to demand generation under certain environmental conditions. The statement of hypotheses and the research methodology required to test these hypotheses are delineated in this chapter. The hypotheses are included in the first section.

The research methodology section includes a description of the simulation runs and the comparisons between these runs that were necessary to test the hypotheses. Further, the response variables and data analysis for each hypothesis are stated.

Hypotheses

The general hypothesis of this research was that, for each demand test condition, one demand approach would be significantly more accurate than the other approaches and that the more accurate approach would not be the same for each demand test condition. The term significantly is used here in the statistical sense. Thus, the hypotheses to be stated relate to the relative accuracy of the demand approaches within each demand test condition and the constancy of this ranking over all demand test conditions.

The hypotheses for each demand test condition of this research were as follows:

H_1: The stochastic process utilized to generate orders from daily demand will generate orders that accurately replicate actual orders.

H_2: One demand approach will be significantly more accurate than all of the other demand approaches.

H_3: Demand Module Alternatives Three and Four produce more accurate replication than Alternative Two only when the value of R^2 is high.

H_4: If Demand Approaches B, C, D, E, F, or G perform more accurately than Demand Approach A, the superior accuracy will not be sufficient to offset the added cost of data gathering inherent in Demand Approaches B through G.

The last hypothesis applied across all demand conditions and was as follows:

H_5: The ranking of demand approaches according to their relative accuracy will remain constant over all demand test conditions.

Research Methodology

This section is divided into two sub-sections. The first describes the simulation runs necessary to test the hypotheses and the second describes the necessary comparisons for testing each hypothesis. The second sub-section also includes the response variables and data analysis for each comparison.

Simulation Runs

For each demand test condition a series of orders was created which constituted daily demand for 200 days or ten periods each twenty days in length. Each demand pattern possessed the characteristics described for the corresponding demand test condition in Chapter IV. For example, the order series created for Demand Test Condition IX constituted daily demand with a pattern over the ten periods that matched the pattern given in Table 4-9 and Figure 4-10.

Once this order stream was created, it was treated as the given demand pattern that was to be replicated. Each demand approach attempted to generate a demand pattern that was identical to this given pattern. Therefore, for each of the ten demand test conditions a given demand pattern and a demand pattern for each of the seven demand approaches was created. Each of these seven demand patterns was compared to the given demand pattern to test the research hypotheses. These demand patterns and the comparative relationships are illustrated in Figure 5-1.

This procedure resulted in ten sets of seven demand patterns or seventy simulation runs. Each set of seven

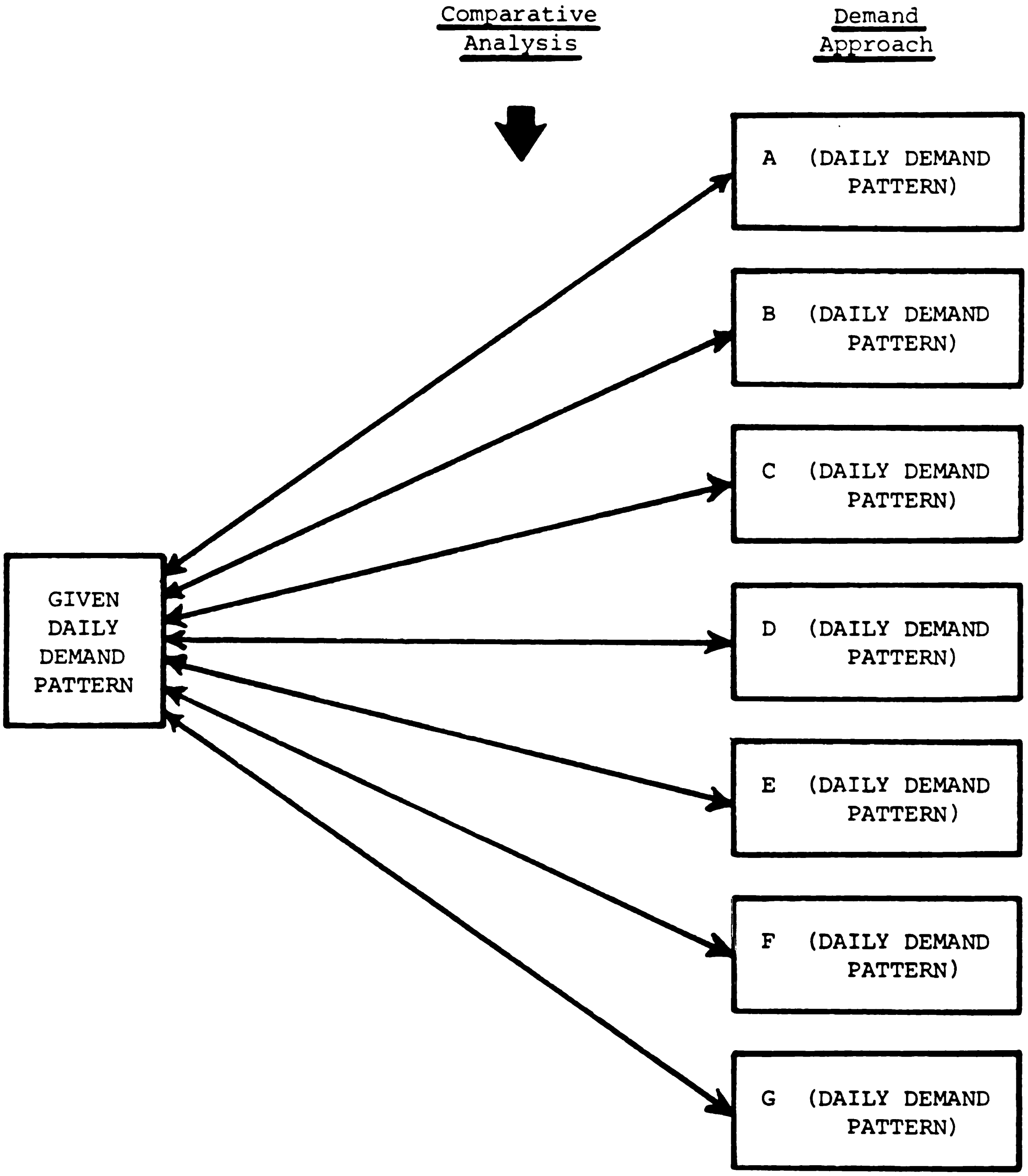

Figure 5-1. Comparative Analysis for Each Demand Test Condition.

demand patterns was compared to the corresponding given demand patterns. These comparisons, the response variables, and the data analysis are discussed in the next sub-section.

Comparative Analysis

To test Hypothesis One it was necessary to determine whether the stochastic process which reduced daily demand to daily orders was accurate. For a clear understanding of the purpose of this stochastic process, the reader should refer back to the process labeled "STOCHASTIC SELECTION OF ORDERS FOR EACH DAY" in Figures 3-2 through 3-4.

This stochastic process is identical in all seven demand approaches for all ten demand test conditions. Therefore, it was necessary to test the accuracy of the process in only one demand test condition and for only one demand approach, rather than all seventy simulation runs. Demand Approach A in Demand Test Condition I was chosen for the analysis simply on the criterion that it was the first run conducted. The response variables chosen for the analysis were the value of product quantity per order and daily demand by product.

The accuracy of the stochastic process was tested by comparing the value of the two response variables for Demand Approach A to the values of the response variables for the demand pattern given for Demand Test Condition I.

If the values of the response variables for Demand Approach A fit--or were not statistically significantly different--the values of the response variables for the given demand pattern, then the stochastic process was deemed accurate.

The t-test of two means was utilized as the statistical test to determine whether the generated response variables fit those of the given demand pattern for each of the five products. The t-test is a statistical test whereby it is hypothesized that two samples came from normal distributions with identical means. The null hypothesis is:

$$H_o: \; M_1 = M_2 \quad \text{or,} \quad M_1 - M_2 = 0$$

where:

M_1 = the mean of the first distribution; and

M_2 = the mean of the second distribution.

The hypothesis is tested by the statistic:

$$\bar{X}_1 - \bar{X}_2$$

where:

$\bar{X}_1$ = the mean of the sample from the first distribution; and

$\bar{X}_2$ = the mean of the sample from the second distribution.

The sampling distribution of the statistic is illustrated in Figure 5-2. The center of this normal distribution is $M_1 - M_2 = 0$ with the standard deviation given by:

$$\hat{\sigma}_{1-2} = \sqrt{\frac{\hat{\sigma}_1^2}{n_1} + \frac{\hat{\sigma}_2^2}{n_2}}$$

where:

$\hat{\sigma}_{1-2}$ = the pooled standard error;

$\hat{\sigma}_1^2$ = the variance of the first sample;

$\hat{\sigma}_2^2$ = the variance of the second sample;

n_1 = the size of the first sample; and

n_2 = the size of the second sample.

The null hypothesis is accepted if the statistic, $\bar{X}_1 - \bar{X}_2$, falls between the critical limits of:

$$CL_L = (M_1 - M_2) - t\ (\hat{\sigma}_{1-2})$$

$$CL_U = (M_1 - M_2) + t\ (\hat{\sigma}_{1-2})$$

where:

CL_L = the lower critical limit;

CL_U = the upper critical limit;

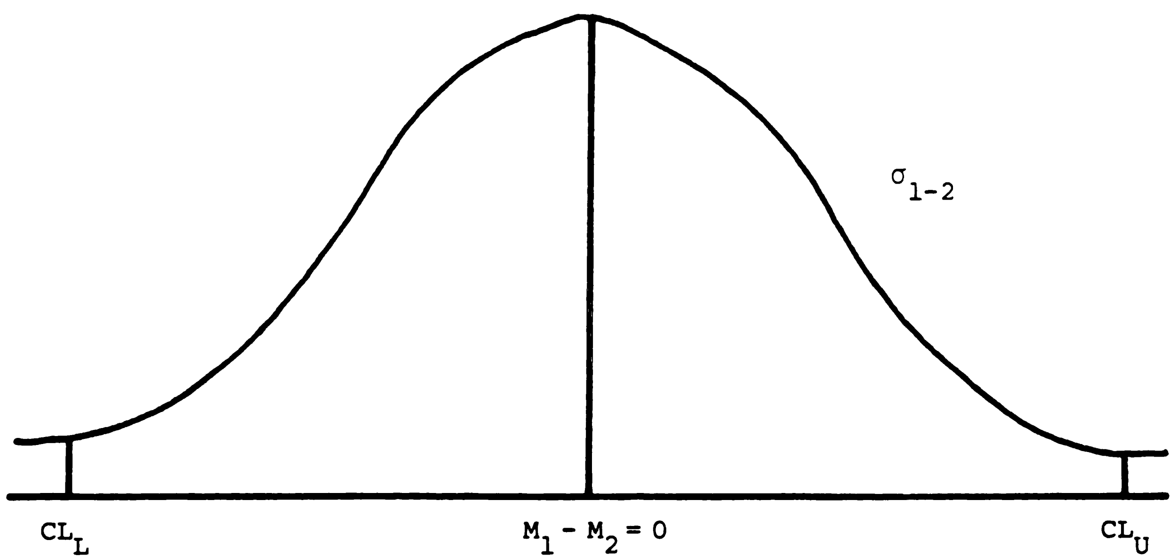

Figure 5-2. Sampling Distribution for t-Test of Two Means.

M_1 = as previously defined;

M_2 = as previously defined;

t = the tabled value for the t statistic corresponding to the level of confidence chosen; and

$\hat{\sigma}_{1-2}$ = as previously defined.

Therefore, if the null hypothesis was accepted, it could be concluded that the stochastic process produced orders that accurately replicated the given orders.

Once this analysis was completed, it was possible to proceed with the testing of Hypothesis Two. To test this hypothesis it was necessary to determine how accurately each demand approach replicated the given demand pattern for each demand test condition.

As previously stated, the stochastic process that derived orders from daily demand was identical for all seven demand approaches. Therefore, after the determination of daily demand, nothing in any of the demand approaches could affect the relative accuracy of that approach. If daily demand for one demand approach more accurately replicated the daily demand given for that demand test condition, the stochastic process which derived orders would not alter that accuracy with respect to the other demand approaches. For this reason daily demand was chosen as the response variable for testing Hypothesis Two.

The frequency with which mean absolute percent error (MAPE) was used in previous research studies to analyze the accuracy of demand generation was noted in Chapter II.[1] For this reason MAPE was selected as the measure to test the accuracy of daily demand for each demand approach compared to the given demand pattern for each demand test condition.

To determine the value of MAPE and the accuracy of daily demand for each demand approach under each demand test condition, the following calculation was performed for each day:

$$APE = \left| \frac{DD_A - DD_G}{DD_G} \times 100 \right|$$

where:

APE = the absolute percent error;

DD_A = the value of daily demand for that day from the demand approach; and

DD_G = the value of daily demand for that day from the given demand pattern.

When this value was calculated for each day of the demand generated by a demand approach in a demand test condition, the mean for the entire 200 days was calculated. This mean was the MAPE value and measured the accuracy with which that demand approach replicated the given pattern.

The procedure was repeated for each demand approach and the value of MAPE recorded. Thus, for each demand test condition a table in the form of Table 5-1 was created. The smallest value for MAPE corresponded to the most accurate demand approach.

A multiple ranking technique[2] was utilized to determine whether the smallest value of MAPE was significantly smaller than the others. Under this technique a confidence interval is placed around each MAPE value in a demand test condition.

This confidence interval is of the form:

$$CL_L = MAPE - Z\ (SD_{MAPE})$$

$$CL_U = MAPE + Z\ (SD_{MAPE})$$

where:

CL_L = the lower limit of the confidence interval;

CL_U = the upper limit of the confidence interval;

MAPE = as previously defined;

Z = value from a standard normal distribution corresponding to the level of confidence chosen; and

SD_{MAPE} = the standard deviation of mean absolute percent error.

The multiple ranking procedure for a demand test condition is illustrated in Figure 5-3.

Table 5-1. Accuracy Measure for Each Demand Test Condition

Demand Approach	CL_L	Accuracy Measure	CL_U
A	CL_{L_A}	$MAPE_A$	CL_{U_A}
B	CL_{L_B}	$MAPE_B$	CL_{U_B}
C	CL_{L_C}	$MAPE_C$	CL_{U_C}
D	CL_{L_D}	$MAPE_D$	CL_{U_D}
E	CL_{L_E}	$MAPE_E$	CL_{U_E}
F	CL_{L_F}	$MAPE_F$	CL_{U_F}
G	CL_{L_G}	$MAPE_G$	CL_{U_G}

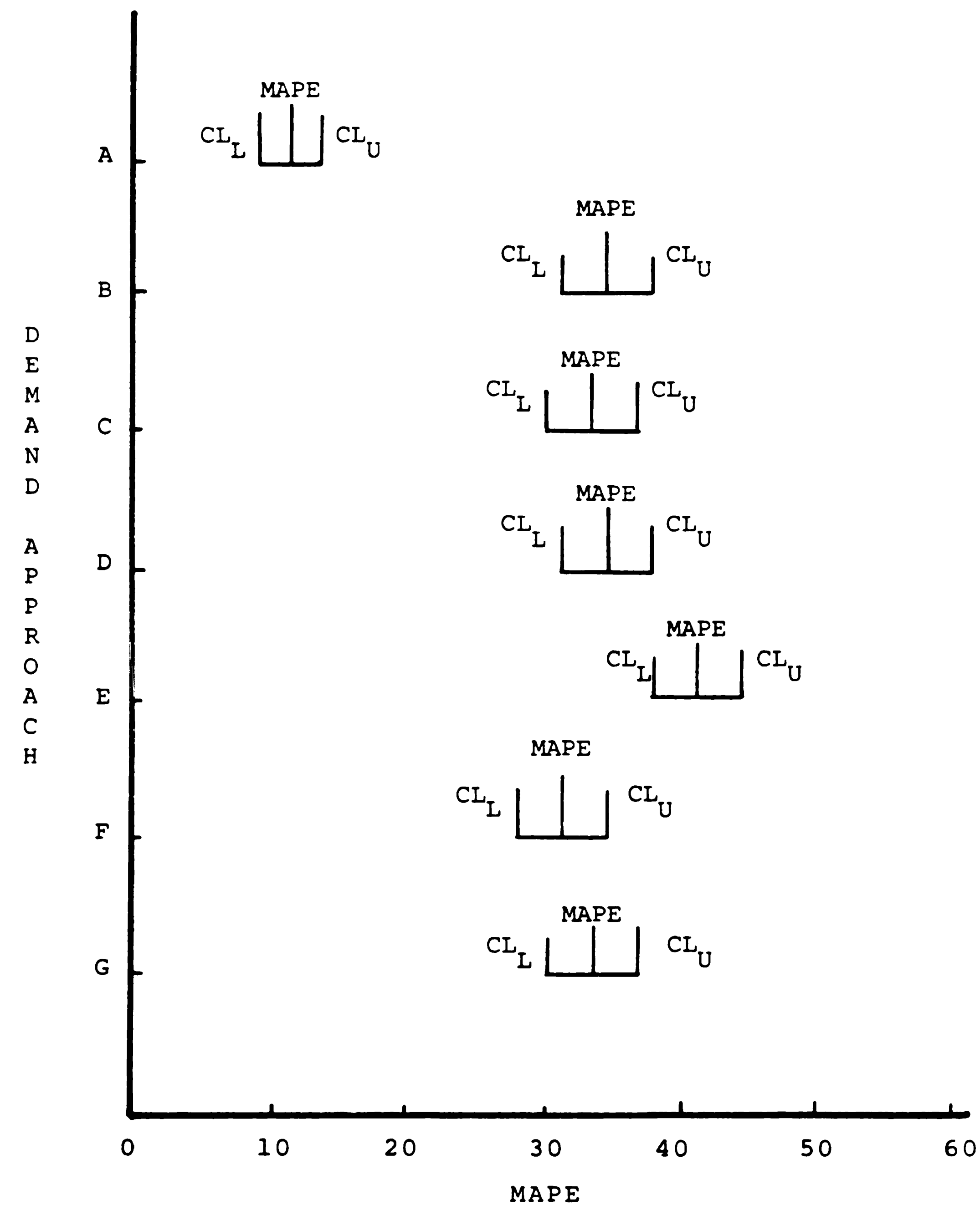

Figure 5-3. Multiple Ranking Procedure.

If the second smallest value of MAPE fell outside of the confidence interval of the smallest value of MAPE, then it could be said that the smallest MAPE was significantly smaller or more accurate than the others. This procedure was repeated for each demand test condition to determine the most accurate demand approach.

The multiple ranking procedure illustrated in Figure 5-3 was utilized to test Hypothesis Three. Again, the closer any value of MAPE was to the vertical zero line to the left of the continuum, the more accurate the corresponding demand approach. Therefore, Hypothesis Three was accepted if the value of MAPE corresponding to either Demand Approaches D or G (high values of R^2) were significantly closer to zero than Demand Approach A and the values of MAPE for Demand Approaches B, C, E, and F were not. This condition would imply the high values of R^2 produce results significantly more accurate than Demand Approach A, but the lower R^2 values were not as accurate as Demand Approach A.

To test Hypothesis Four, it was necessary only to consider those demand test conditions in which one of the demand approaches utilizing Demand Module Alternatives Three or Four proved the most accurate. In these cases it was necessary to determine whether the superior accuracy of this demand approach warranted the added cost.

Since the cost of the simulation runs was almost identical for all demand approaches, any difference in computer cost was negligible. However, considerable additional cost could be incurred in data collection for Demand Module Alternatives Three and Four. This data collection cost would result from research to find independent variables with a correlation to firm demand or industry demand and market share. The larger the value of R^2 required, the more the data collection would cost.

Therefore, to test Hypothesis Four, cost/benefit analysis was conducted in every demand test condition where any of Demand Approaches B through G outperformed Demand Approach A. To accomplish this, an estimate was made of the relative value of the improved accuracy and the cost of data gathering to provide this improved accuracy. If the value exceeded the cost, then the effort was deemed worthwhile. Since this analysis was of a cost/benefit nature, no statistical tests of significance could be performed.

Hypothesis Five was also tested by the Multiple ranking method given in Figure 5-2. If the ranking of each demand approach remained constant over all ten demand test conditions, then this hypothesis was accepted.

Summary

This chapter has presented five hypotheses to be tested. Four of the hypotheses were potentially applicable to each of the ten demand test conditions. The last hypothesis was applicable over all demand test conditions. This created a maximum of forty-one hypotheses to be tested in total. The results of the testing of these hypotheses is presented in the next chapter.

CHAPTER V--FOOTNOTES

[1]Among others: J. Scott Armstrong and James G. Andress, "Exploratory Analysis of Marketing Data: Trees vs. Regression," Journal of Marketing Research 7 (No. 4; November 1970): 487-492; Vithala R. Rao, "Alternative Econometric Models of Sales--Advertising Relationships," Journal of Marketing Research 9 (No. 2; May 1972): 177-181; and Richard Rippe, Maurice Wilkinson, and Donald Morrison, "Industrial Market Forecasting with Anticipation Data," Management Science 22 (No. 6; February 1976): 639-651.

[2]Charles W. Dunnett, "A Multiple Comparison Procedure for Comparing Several Treatments with Control," Journal of the American Statistical Association 50 (No. 272; December 1955): 1096-1121; and Thomas H. Naylor, Kenneth Wertz, and Thomas H. Wonnacott, "Methods for Analyzing Data from Computer Simulation Experiments," Communications of the Association for Computing Machinery 10 (No. 11; November 1967): 703-715.

CHAPTER VI

EXPERIMENTAL RESULTS

The previous chapter presented the hypotheses and the methodology that were conducted to complete this research. This chapter will present the results of this analysis. The chapter is divided into five sections, each of which deals with one of the stated hypotheses.

Hypothesis One

The first hypothesis stated:

H_1: The stochastic process utilized to generate orders from daily demand will generate orders that accurately replicate actual orders.

To test this hypothesis, the t-test of two means was utilized. Under this test the null hypothesis was stated as,

$$H_o: \; M_1 - M_2 = 0$$

and was the center of the sampling distribution of the statistic, $\bar{X}_1 - \bar{X}_2$, where:

M_1 = the mean of the population response variable for the given demand pattern;

M_2 = the mean of the population response variable for Demand Approach A;

$\overline{X}_1$ = the mean of the sample response variable for the given demand pattern; and

$\overline{X}_2$ = the mean of the sample response variable for Demand Approach A.

This hypothesis was tested by comparing the response variables, product quantity per order and daily demand by product, from Demand Approach A under Test Condition I to the response variable for the given demand pattern under Test Condition I. If the null hypothesis was accepted, it was judged that no statistically significant difference existed between the given demand pattern and the demand pattern for Demand Approach A.

Table 6-1 provides a summary of the results of the analysis for product quantity per order at a 5 percent level of significance ($\alpha = .05$). For all five products the value of $\overline{X}_1 - \overline{X}_2$ fell between CL_L and CL_U. Therefore, the quantity per order for Demand Approach A was not statistically significantly different from the quantity per order for the given demand pattern under Demand Test Condition I.

Table 6-2 provides a summary of the results for daily demand by product. Again, the results lead to the conclusion that no statistically significant difference

Table 6-1. Hypothesis One--t-Test of Product Quantity/Order

Product	$\overline{X}_1 - \overline{X}_2$	σ_{1-2}	CL_L	CL_U
One	-0.7650	0.699	-1.3700	+1.3700
Two	+0.0500	0.702	-1.3759	+1.3759
Three	+0.3200	0.628	-1.2309	+1.2309
Four	+0.0400	0.623	-1.2211	+1.2211
Five	-0.1650	0.724	-1.4190	+1.4190

Table 6-2. Hypothesis One--t-Test of Daily Demand by Product

Product	$\overline{X}_1 - \overline{X}_2$	σ_{1-2}	CL_L	CL_U
One	-16.3900	8.932	-17.5067	+17.5067
Two	-14.5200	9.010	-17.6596	+17.6596
Three	-12.4200	8.397	-16.4581	+16.4581
Four	-14.4100	8.576	-16.8090	+16.8090
Five	-15.2300	8.918	-17.4793	+17.4793

exists between daily demand by product for Demand Approach A and the given demand pattern for Demand Test Condition I.

As was explained in the previous chapter, this stochastic process is identical for all simulation runs. Therefore, the results just stated apply not only to Demand Approach A under Demand Test Condition I, but to all seven demand approaches under all ten demand test conditions.

Based on the results of the analysis of the response variables it can be stated that Hypothesis One should be accepted. The stochastic process utilized to generate orders from daily demand generates orders that accurately replicate actual orders.

Hypothesis Two

The second hypothesis stated:

H_2: One demand approach will be significantly more accurate than all the other demand approaches in each demand test condition.

To test this hypothesis each demand test condition was examined individually. Mean absolute percent error (MAPE) was utilized to measure the accuracy of daily demand for each demand approach and multiple ranking was utilized to determine the statistical significance of the accuracy.

Table 6-3 provides a summary of the accuracy of all seven demand approaches under Demand Test Condition I. The column labeled MAPE is the accuracy of each demand approach

Table 6-3. MAPE--Demand Test Condition I

Demand Approach	CL_L	MAPE	CL_U
A	10.919	12.281	13.643
B	34.240	37.507	40.774
C	33.827	36.930	40.033
D	33.827	36.930	40.033
E	41.358	44.396	47.434
F	30.081	33.197	36.313
G	32.268	35.400	38.532

and the columns labeled CL_L and CL_U are the lower and upper limits to the 95 percent confidence interval around the MAPE value.

As was described in the previous chapter, any value outside these confidence limits is statistically significantly different from the MAPE value. For example, the closest MAPE value to Demand Approach A is Demand Approach F. However, the MAPE value for Demand Approach F is outside the confidence limits for Demand Approach A. Therefore, A is significantly more accurate than F and all of the other demand approaches.

This relative accuracy of each demand approach can be more clearly seen through the use of multiple ranking.

An illustration of the multiple ranking for Demand Test Condition I is presented in Figure 6-1. In this illustration the confidence limits for each demand approach are presented. The center value in each confidence interval is the MAPE value. Thus, one demand approach is statistically significantly different from another demand approach if the MAPE value of the former lies outside the confidence interval of the latter.

It can be seen in Figure 6-1 that Demand Approach A is more accurate than all six other demand approaches by a factor of almost three. Thus, for a demand condition with no trend or seasonality and with low variation, the stochastic method represented in Demand Approach A is, by far, the most accurate.

For Demand Test Condition II the values of MAPE, CL_L, and CL_U are presented in Table 6-4. Demand Approach A was the most accurate with a mean absolute percent error of 17.164. This is significantly more accurate than all six other approaches (Figure 6-2). Thus, for a demand condition with no trend or seasonality and a high variance, the stochastic process represented in Demand Approach A is the most accurate.

In fact, observation of Tables 6-5, 6-6, 6-7, 6-8, 6-9, and 6-10 and Figures 6-3, 6-4, 6-5, 6-6, 6-7, and 6-8 all show Demand Approach A significantly more accurate than

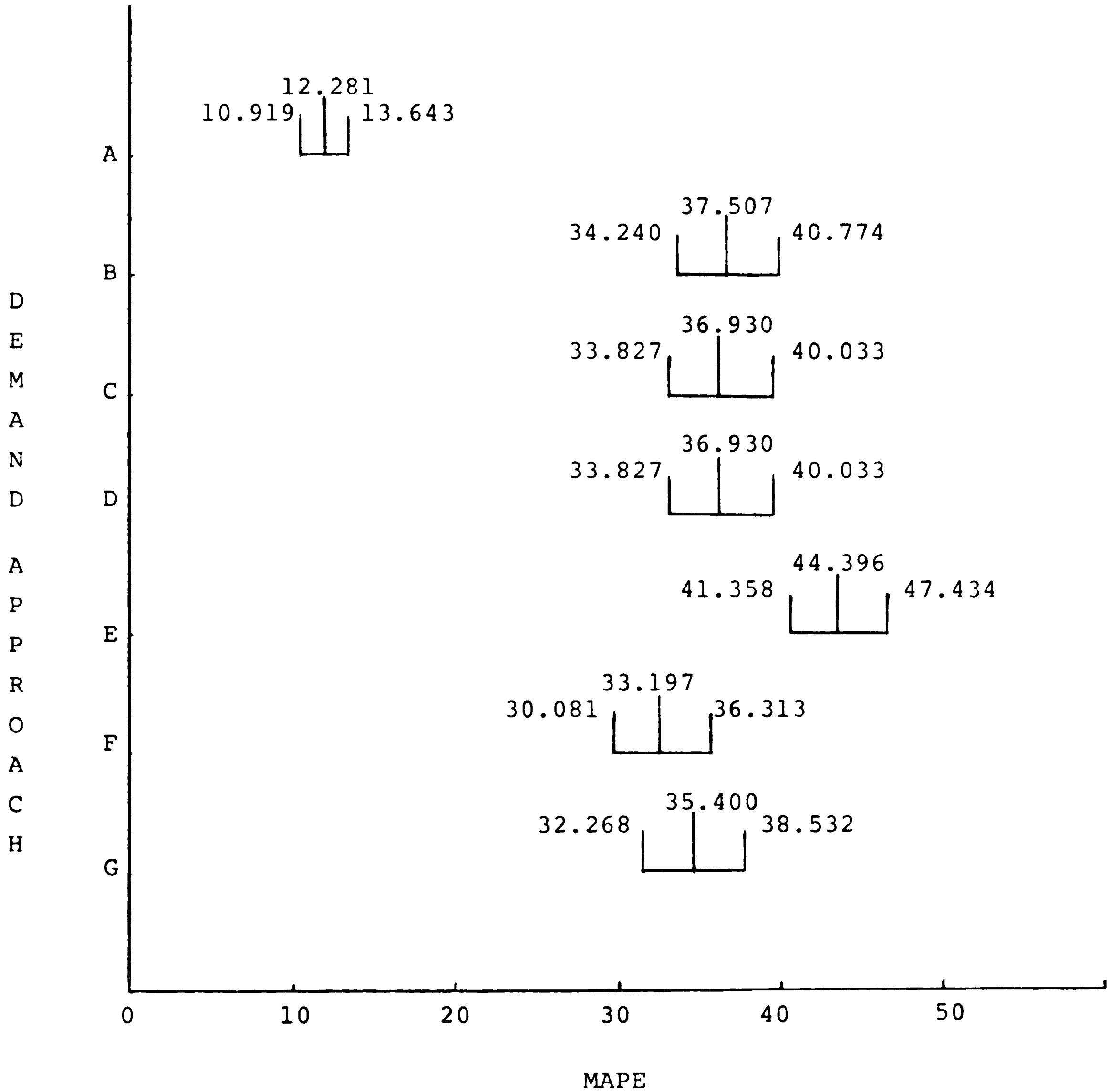

Figure 6-1. Multiple Ranking--Demand Test Condition I.

Table 6-4. MAPE--Demand Test Condition II

Demand Approach	CL_L	MAPE	CL_U
A	15.443	17.164	18.885
B	33.732	36.858	39.984
C	30.989	33.939	36.889
D	29.776	32.740	35.704
E	36.208	39.299	42.390
F	31.074	34.228	37.382
G	31.991	35.421	38.851

any of the other six demand approaches. Therefore, Demand Approach A was most accurate for any demand test condition with or without trend, with either high or low variation, and with or without low seasonality. The simplest method of demand generation, represented in Demand Approach A, was more accurate than the more sophisticated firm demand and industry demand methods in the first eight demand test conditions.

However, these results changed radically for the last two demand test conditions. Table 6-11 and Figure 6-9 summarize the results for all seven demand approaches under Demand Test Condition IX. Under this demand test condition of low variation and high seasonality, Demand Approach A

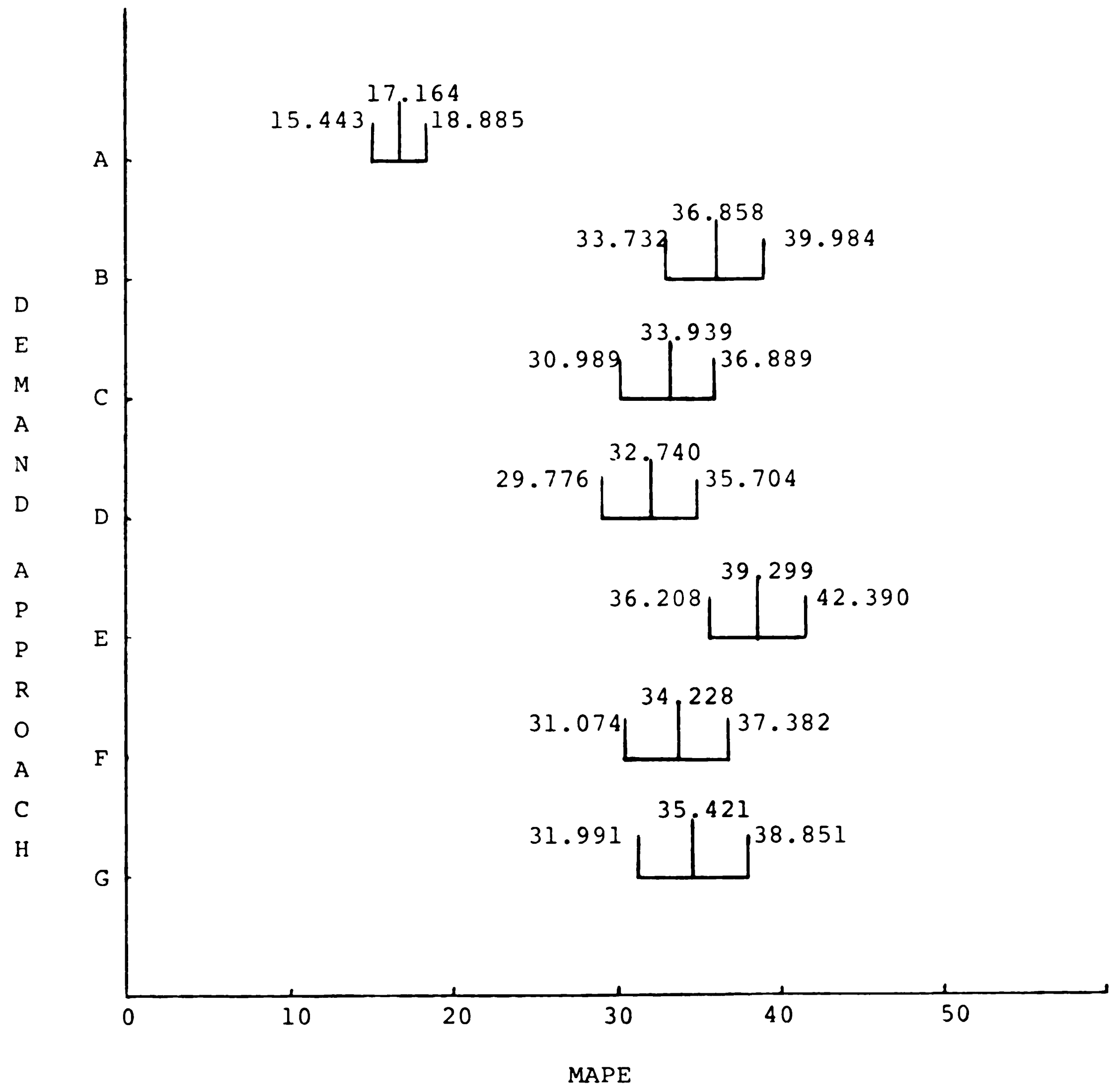

Figure 6-2. Multiple Ranking--Demand Test Condition II.

Table 6-5. MAPE--Demand Test Condition III

Demand Approach	CL_L	MAPE	CL_U
A	10.222	11.547	12.872
B	45.306	48.542	51.778
C	44.413	47.641	50.869
D	36.536	39.719	42.902
E	45.173	48.429	51.685
F	41.583	44.984	48.385
G	37.013	40.173	43.333

Table 6-6. MAPE--Demand Test Condition IV

Demand Approach	CL_L	MAPE	CL_U
A	14.501	16.142	17.783
B	39.396	42.689	45.982
C	33.459	36.928	40.397
D	35.302	38.826	42.350
E	39.218	42.656	46.094
F	43.463	46.738	50.013
G	34.390	37.457	40.524

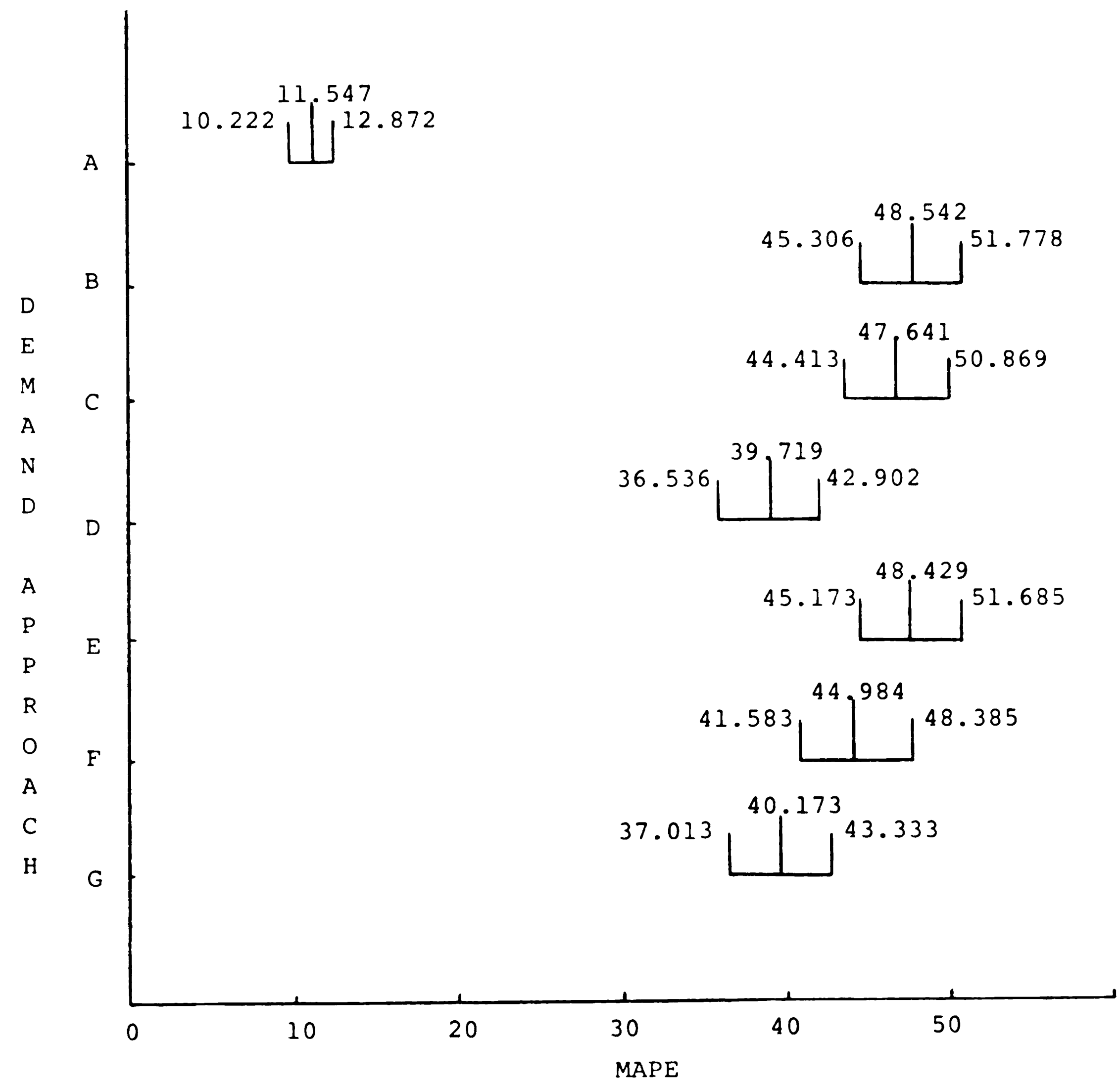

Figure 6-3. Multiple Ranking--Demand Test Condition III.

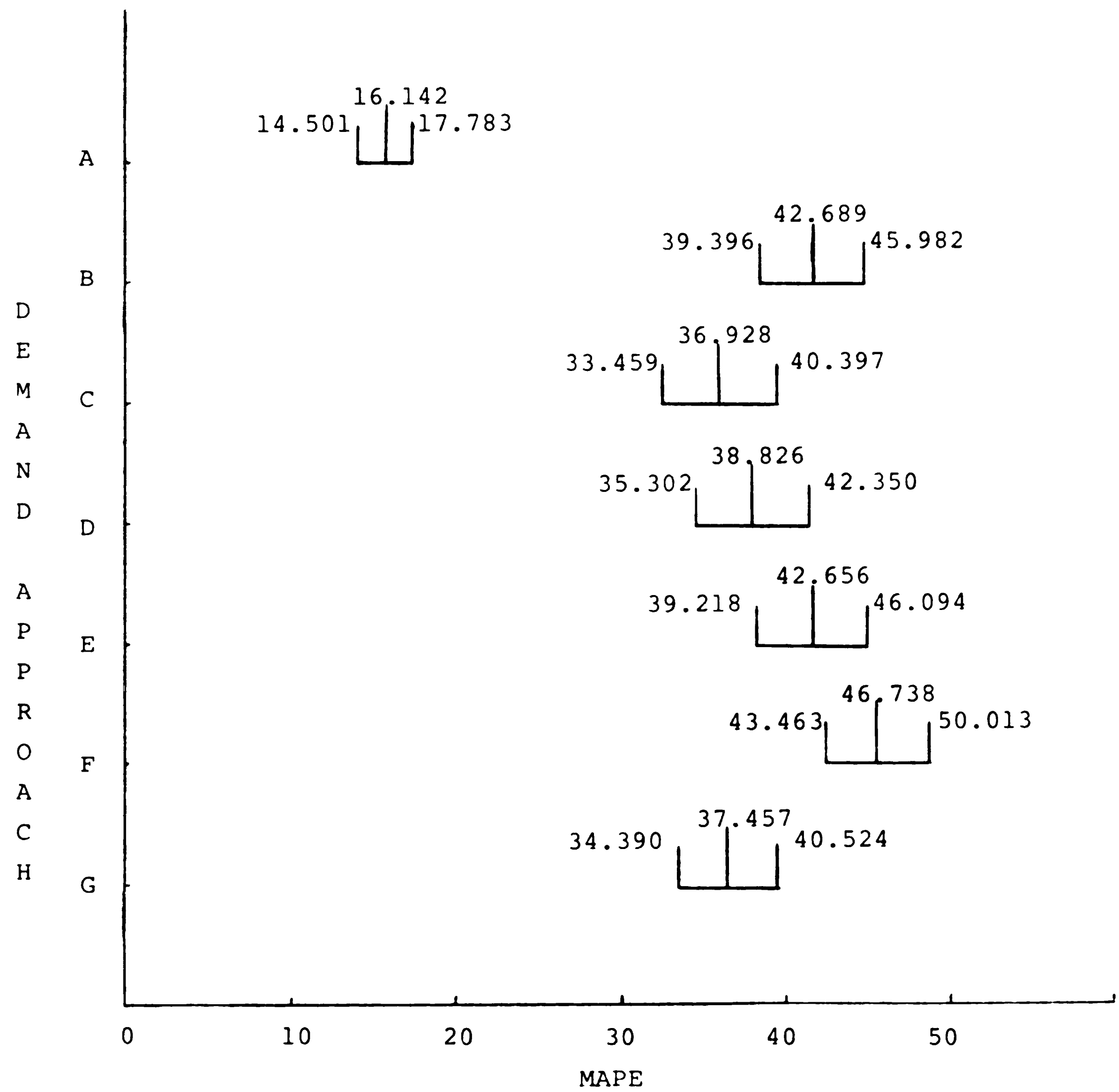

Figure 6-4. Multiple Ranking--Demand Test Condition IV.

Table 6-7. MAPE--Demand Test Condition V

Demand Approach	CL_L	MAPE	CL_U
A	11.057	12.337	13.617
B	47.555	50.689	53.823
C	41.686	44.944	48.202
D	36.209	39.472	42.735
E	46.124	49.150	52.176
F	37.112	40.579	44.046
G	41.784	45.043	48.302

Table 6-8. MAPE--Demand Test Condition VI

Demand Approach	CL_L	MAPE	CL_U
A	14.941	16.746	18.551
B	40.612	43.791	46.970
C	38.048	41.529	45.010
D	31.218	34.560	37.902
E	38.459	41.642	45.143
F	40.171	43.675	47.179
G	36.065	39.473	42.881

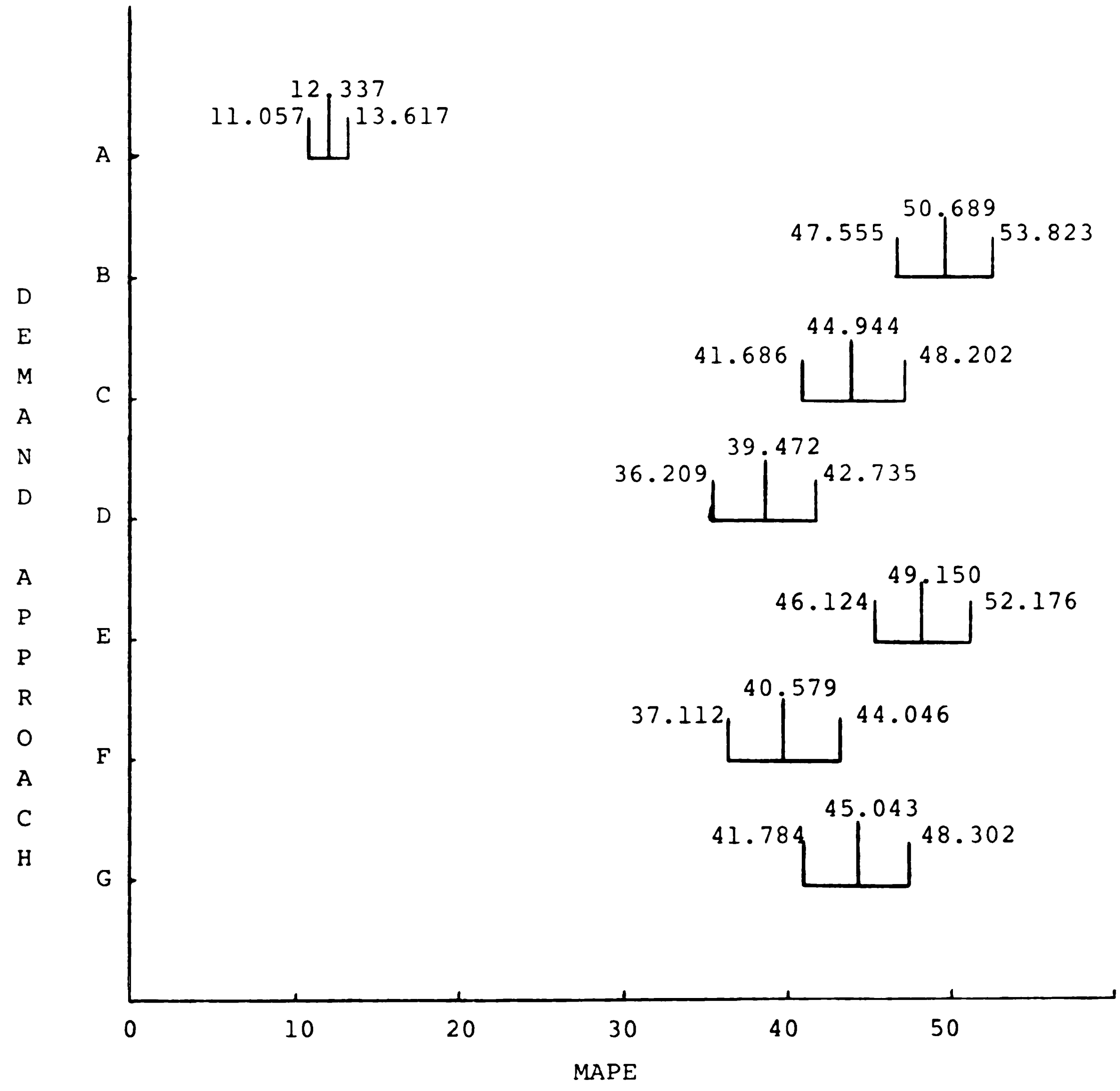

Figure 6-5. Multiple Ranking--Demand Test Condition V.

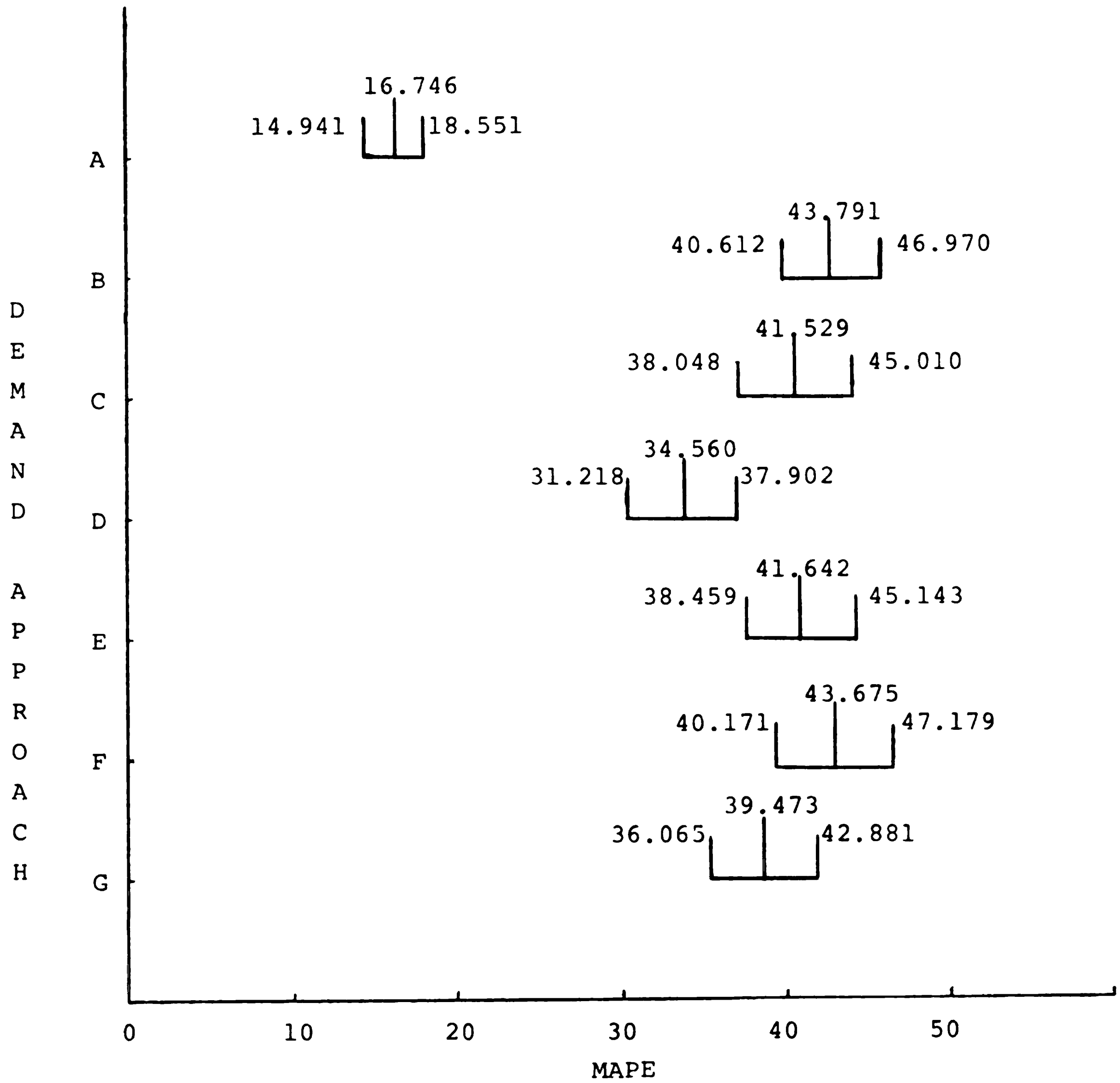

Figure 6-6. Multiple Ranking--Demand Test Condition VI.

Table 6-9. MAPE--Demand Test Condition VII

Demand Approach	CL_L	MAPE	CL_U
A	16.201	18.245	20.289
B	32.284	35.726	39.168
C	32.812	36.220	39.628
D	31.201	34.411	37.621
E	40.218	43.654	47.090
F	29.929	33.030	36.131
G	34.335	37.571	40.807

Table 6-10. MAPE--Demand Test Condition VIII

Demand Approach	CL_L	MAPE	CL_U
A	20.343	22.919	25.494
B	32.722	36.029	39.336
C	35.347	38.606	41.865
D	31.973	35.244	38.515
E	36.418	39.587	42.756
F	35.061	38.232	41.403
G	37.739	41.259	44.779

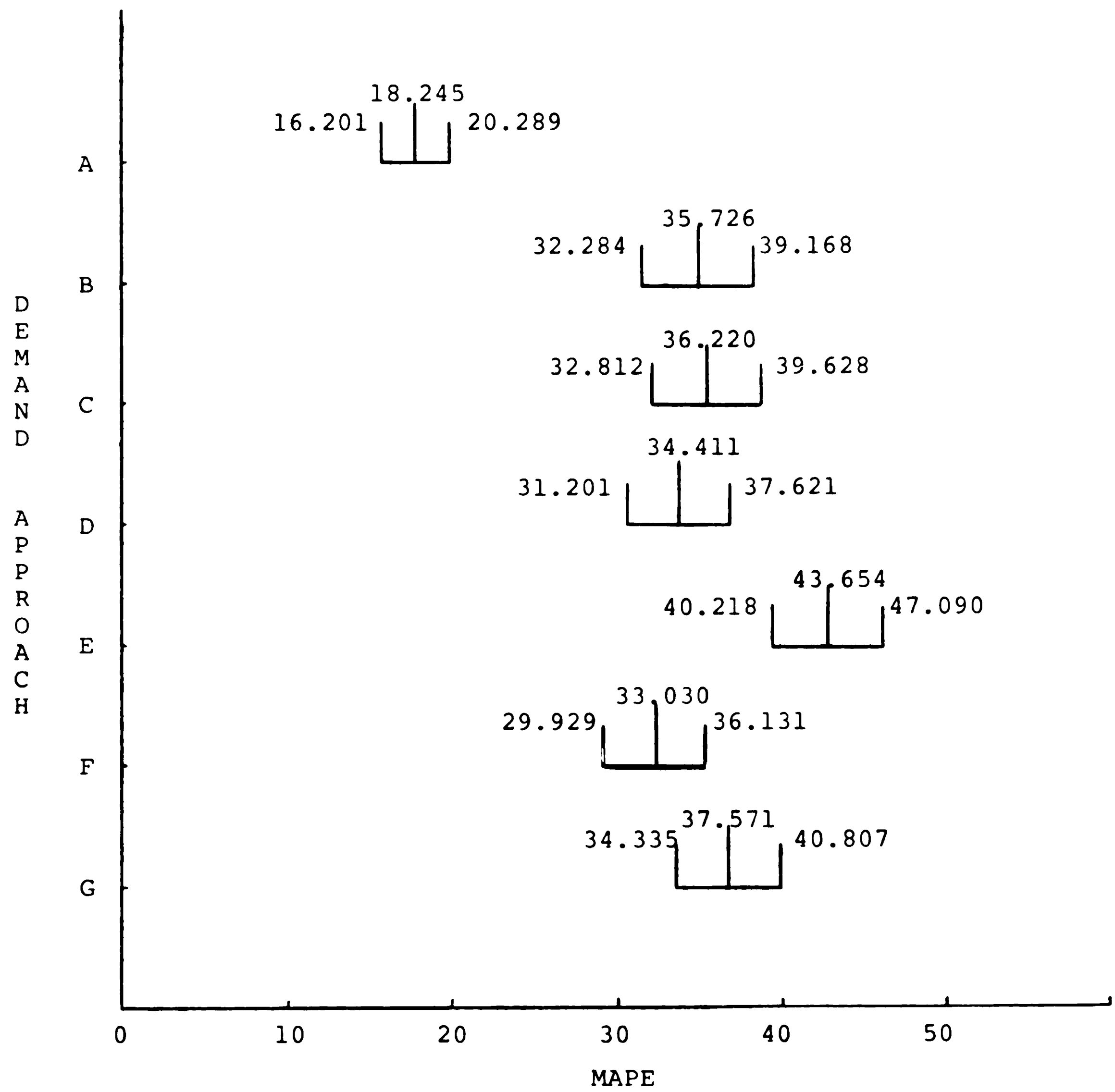

Figure 6-7. Multiple Ranking--Demand Test Condition VII.

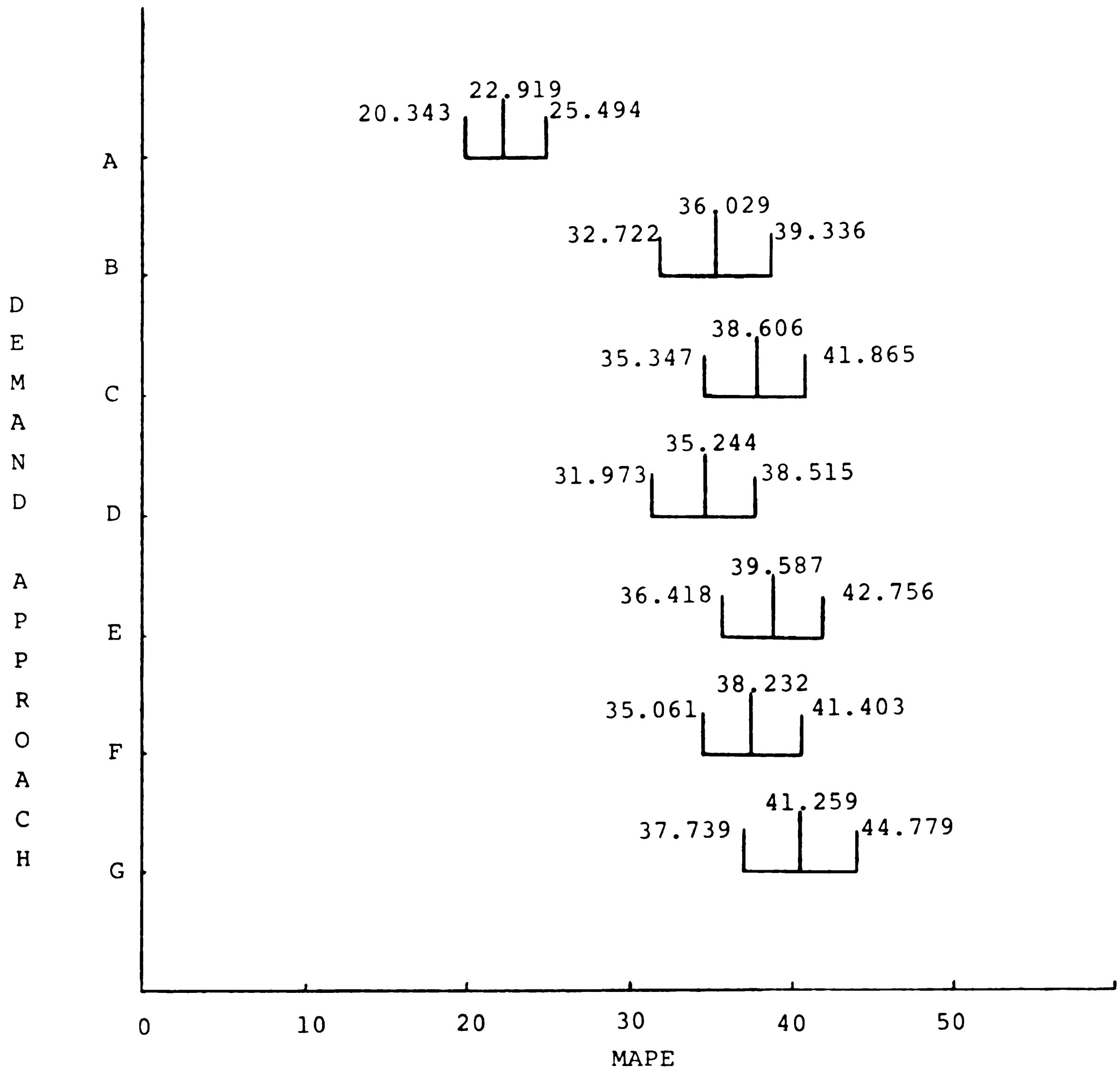

Figure 6-8. Multiple Ranking--Demand Test Condition VIII.

Table 6-11. MAPE--Demand Test Condition IX

Demand Approach	CL_L	MAPE	CL_U
A	46.939	55.814	64.689
B	31.421	34.886	38.351
C	34.802	38.477	42.152
D	33.185	36.954	40.723
E	38.498	42.065	45.632
F	34.095	37.637	41.179
G	34.977	38.570	42.163

was significantly the least accurate of all seven demand approaches.

This condition was also true in Demand Test Condition X. Table 6-12 and Figure 6-10 illustrate this. Therefore, in both demand test conditions exhibiting high seasonality Demand Approach A proved the least accurate.

A possible explanation of this lack of accuracy in Demand Approach A can be seen in Figure 6-11, which illustrates the accuracy of Demand Approach A in each of the ten demand test conditions. It can be seen that before seasonality is introduced (Demand Test Conditions I through VI) the accuracy of Demand Approach A remains relatively constant. However, as more seasonality is introduced in

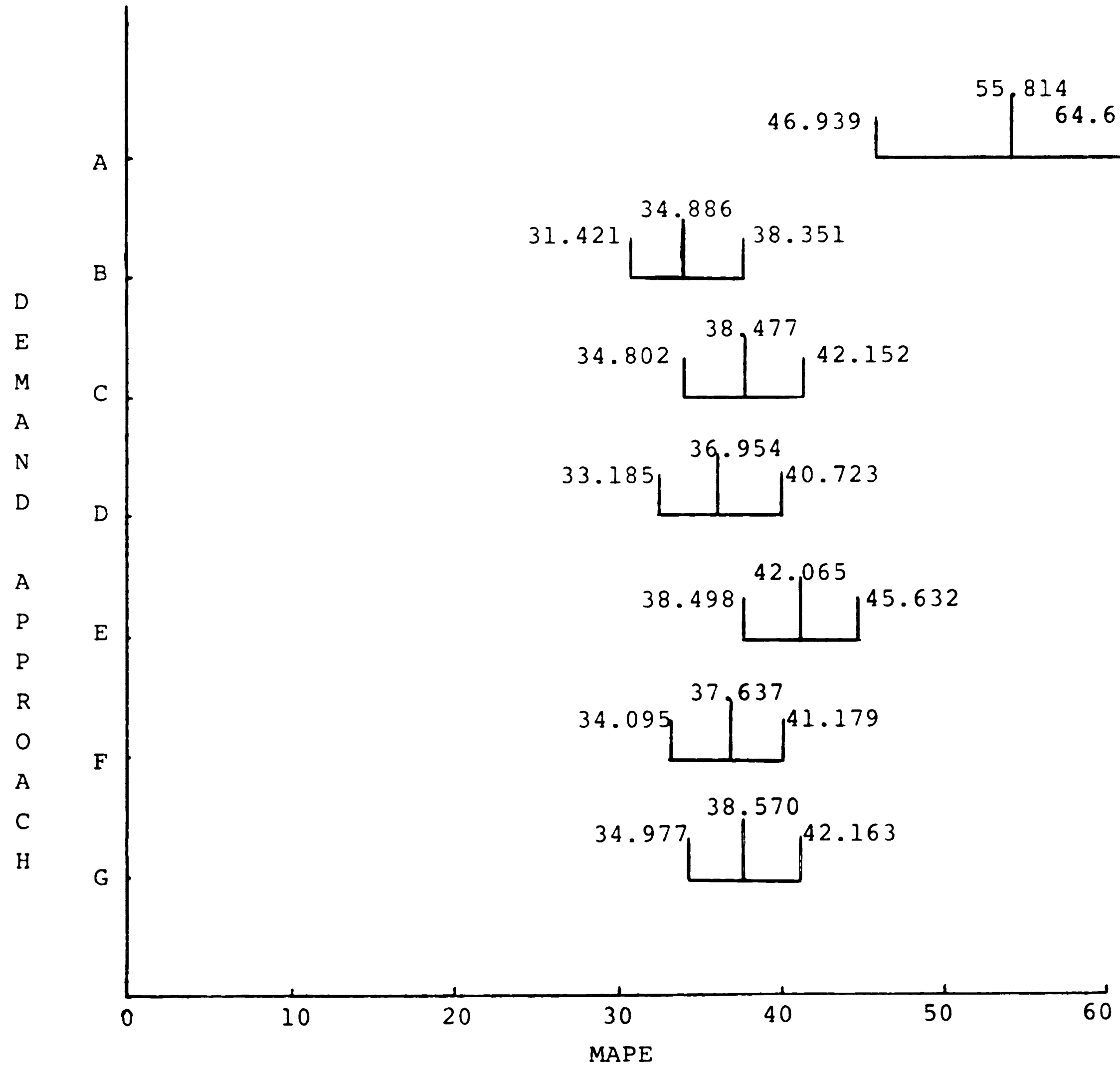

Figure 6-9. Multiple Ranking--Demand Test Condition IX.

Table 6-12. MAPE--Demand Test Condition X

Demand Approach	CL_L	MAPE	CL_U
A	43.476	52.118	60.760
B	32.588	35.820	39.052
C	31.765	35.511	39.257
D	38.079	41.625	45.171
E	33.067	36.276	39.485
F	32.130	35.601	39.072
G	36.636	40.634	44.632

Demand Test Conditions VII through IX, Demand Approach A becomes progressively less accurate. Thus, Demand Approach A provides superior accuracy until the introduction of a large amount of seasonality.

Surprisingly, in all ten demand test conditions, no statistically significant difference appeared to exist between Demand Approaches B through G. Not only was there no difference between the firm demand method, represented by Demand Approaches B through D, and the industry demand method, represented by Demand Approaches E through G, but the values of R^2 had no significant effect.

In terms of Hypothesis Two, Demand Approach A was significantly more accurate than the other demand

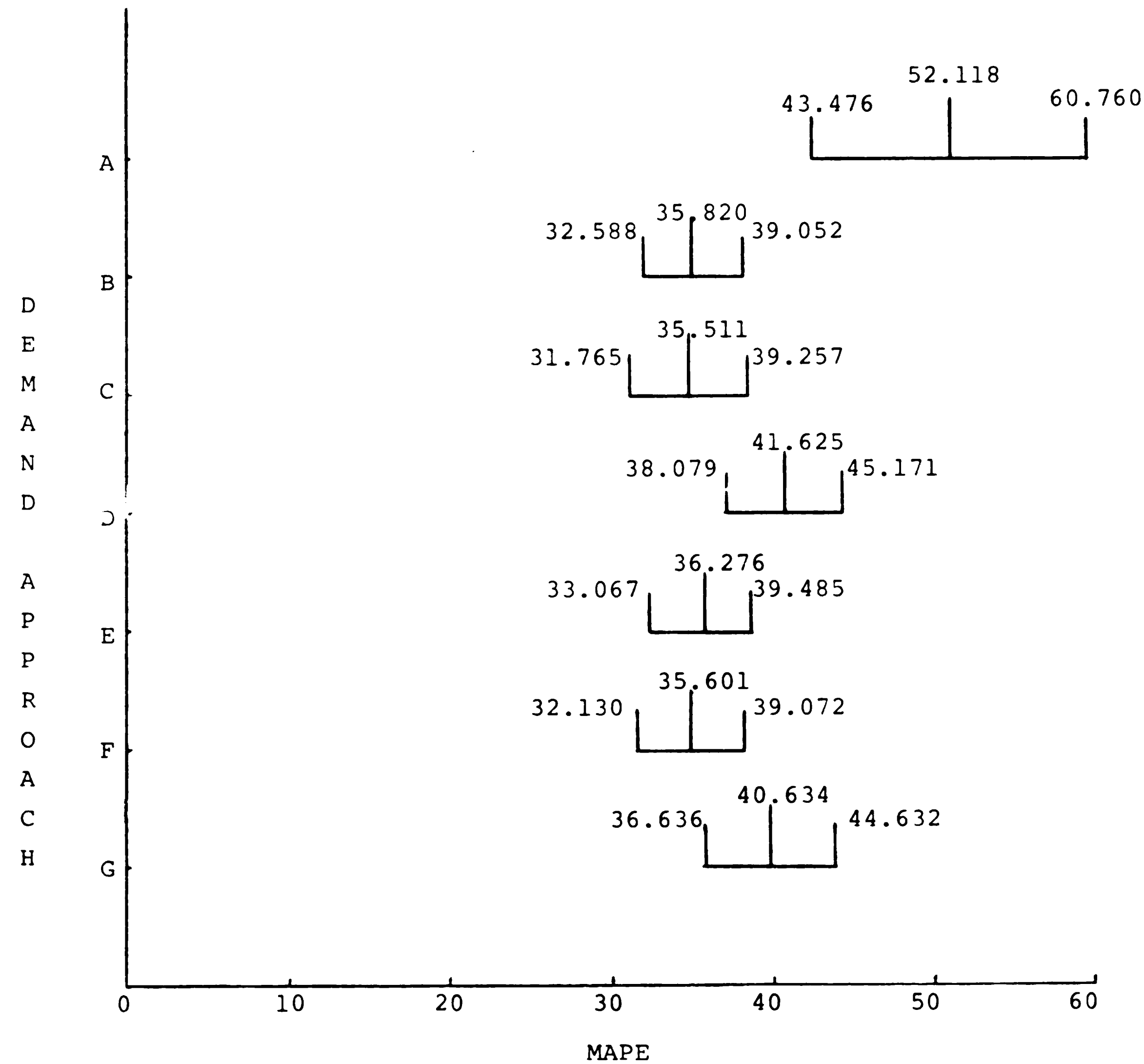

Figure 6-10. Multiple Ranking--Demand Test Condition X.

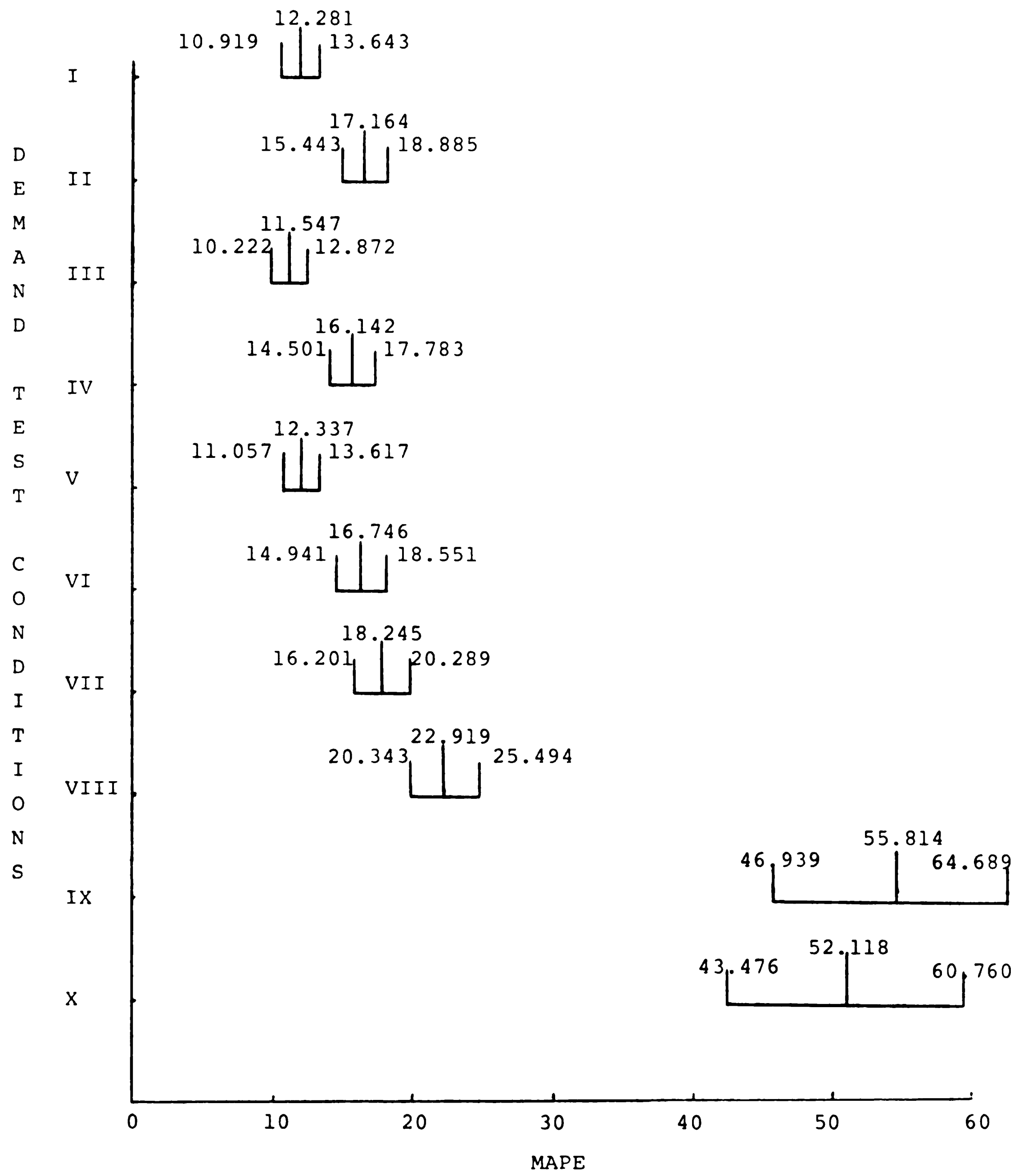

Figure 6-11. Multiple Ranking--Demand Approach A Over All Demand Test Conditions.

approaches for Demand Test Conditions I through VIII. For Demand Test Conditions IX and X the other six demand approaches were significantly more accurate than Demand Approach A, but none of these six was significantly the most accurate.

Hypothesis Three

Hypothesis Three stated:

> H_3: Demand Module Alternatives Three and Four produce more accurate replication than Alternative Two only when the value of R^2 is high.

For this hypothesis to be applicable, either Demand Approach D or G would present more accurate results than Demand Approach A, but Demand Approaches B, C, E, and F would not. In only two demand test conditions was Demand Approach A not the most accurate approach. These two demand conditions are the only two that could be applicable to Hypothesis Three and are the only two analyzed.

Referring again to Figure 6-9, for Demand Test Condition IX, Demand Module Alternatives Three and Four (Demand Approaches B through G) produce more accurate replication than Demand Module Alternative Two (Demand Approach A) regardless of the R^2 value.

The same results can be observed for Demand Test Condition X in Figure 6-10. Thus, in Demand Test Conditions

IX and X, Demand Module Alternatives Three and Four are more accurate than Alternative Two regardless of the R^2 value. Hypothesis Three was rejected in Demand Test Conditions IX and X and was not applicable in Demand Test Conditions I through VIII.

Hypothesis Four

Hypothesis Four stated:

> H_4: If Demand Approaches B, C, D, E, F, or G perform more accurately than Demand Approach A, the superior accuracy will not be significant to offset the added cost of data gathering inherent in Demand Approaches B through G.

Since this hypothesis was constrained to only those demand test conditions where Demand Approach A did not exhibit superior accuracy, only Demand Test Conditions IX and X need be considered. The multiple ranking exhibited in Figure 6-9 provides the analysis for Demand Test Condition IX.

In this demand test condition, as was stated previously, all of the regression type demand approaches are significantly more accurate than Demand Approach A. However, none of these other six approaches is significantly more accurate than the others. This suggests that regardless of whether the firm demand or industry demand method is chosen and regardless of the R^2 value obtained, the accuracy of the regression type approaches is not significantly affected. Thus, a low R^2 value will produce results sufficiently close to high R^2 value results to represent an insignificant difference.

The same results can be observed for Demand Test Condition X in Figure 6-10. Again, all six regression type approaches are significantly more accurate than Demand Approach A, but no significant difference exists between the six.

To develop the regression models inherent to Demand Approaches B through G, various data must be gathered on variables which may correlate well with demand. For example, if a regression model of demand for dishwashers was to be developed, data on such variables as housing starts, apartment starts, disposable income, and population may be gathered as possible input to the regression model.

Much of these data are available on a national basis. However, the demand generation is on a market area basis. Thus, considerable research effort may be necessary to obtain data on such variables as mentioned above on a market area basis.

Once these data are obtained, they must be analyzed with respect to demand. Each variable is analyzed through regression analysis to determine how well it correlates with demand. Variables with a low correlation are discarded. The remaining variables are utilized to develop the regression model which generates demand. The degree to which all of the variables included in the regression model correlate with demand is measured by the value of R^2.

If the value of R^2 is not sufficiently high, the entire process must be repeated. Additional variables must be obtained and analyzed to increase the R^2 value. Thus, the higher the value of R^2 required, the greater the amount of data gathering and regression analysis required. This additional effort creates a higher cost attached to the regression model. Therefore, the cost of data gathering to obtain independent variables that produce as low an R^2 value as .30 can be judged to be relatively low.

Thus, it can be stated that the relatively low cost of data gathering to obtain a low R^2 value will, under conditions of high seasonality, yield results that are as significantly more accurate than the stochastic method as a higher R^2 value. Given that the simulation for which the demand generation is utilized may be the basis for major managerial decisions, the benefit from this improved accuracy could be substantial.

From a cost/benefit perspective, the potentially substantial benefit of utilizing the firm demand or industry demand methods of demand generation would outweigh the low additional cost. In terms of Hypothesis Four, the hypothesis would be rejected for Demand Test Conditions IX and X.

The hypothesis was not applicable to the other eight demand test conditions.

Hypothesis Five

The final hypothesis was tested over all ten demand test conditions and stated:

> H_5: The ranking of demand approaches according to their relative accuracy will remain constant over all demand test conditions.

To test this hypothesis the rank ordering of each demand approach in each demand test condition is summarized in Table 6-13. As can be observed, no set order of accuracy exists throughout all ten demand test conditions. Therefore, Hypothesis Five is rejected.

The only generalizations that can be drawn from this table are those previously determined. Demand Approach A is more accurate than the other six demand approaches in the first eight demand test conditions and the situation is reversed in the last two demand test conditions. Further, no appreciable difference appears to exist between Demand Approaches B through G in any of the demand test conditions.

Table 6-13. Demand Approach Ranking Order

Demand Test Condition	Demand Approach Rank Ordering						
	1	2	3	4	5	6	7
I	A*	F	G	C	D	B*	E
II	A*	D	C	F	G	B	E
III	A*	D	G*	F*	C	E	B
IV	A*	C	G	D	E	B	F
V	A*	D	F	C	G*	E	B
VI	A*	D*	G	C	E	F	B
VII	A*	F	D	B	C	G*	E
VIII	A*	D	B	F	C	E	G
IX	B	D	F	C	G	E*	A
X	C	F	B	E	G	D*	A

*Significantly more accurate than the next Demand Approach.

Summary

Five major hypotheses were stated for this research. Hypothesis One was tested under one demand test condition, Hypothesis Two under all ten demand test conditions, Hypotheses Three and Four each under two, and Hypothesis Five once over all ten demand test conditions. This resulted in a total of sixteen tested research hypotheses.

The results of analysis of these hypotheses found (1) the stochastic process to generate orders from daily demand accurately replicates actual orders; (2) one demand approach was the most accurate for Demand Test Conditions I through VIII, but no demand approach was most accurate in the last two demand test conditions; (3) Demand Module Alternatives Three and Four produce similar accuracy regardless of the R^2 value. Thus, under demand conditions where these alternatives are more accurate, the R^2 value does not affect the greater accuracy; (4) in demand test conditions where regression type approaches were more accurate, the benefit of improved accuracy outweighed the extra cost of data gathering necessitated by these approaches; and (5) no constant rank ordering by accuracy of demand approaches over all ten demand test conditions existed.

CHAPTER VII

CONCLUSIONS

The purpose of this research has been to determine the relative accuracy of methods of demand generation under various environmental conditions. The specific results of the experimental runs were reported in Chapter VI. The purpose of this chapter is to integrate the conclusions drawn from the hypotheses and findings, generalize research findings for future demand generation, and establish the contribution of the research for use in forecasting and analysis of demand factors.

The first section of the chapter reviews the research. The second section relates the findings to acceptance or rejection of the hypotheses. Next, guidelines for improved demand generation and implications of the research are provided. The last two sections evaluate the research limitations and suggest areas for additional investigation.

Research Review

Before the hypotheses are discussed, the design of this research and key terms will be reviewed. Five methods of demand generation were identified from the literature. From these five methods three were selected as applicable to this research. The three are termed the stochastic method, firm demand method, and industry demand method.

The SPSF Testing Environment was utilized to test these methods. The stochastic method was represented by Demand Module Alternative Two of the SPSF Testing Environment, the firm demand method by Demand Module Alternative Three, and the industry demand method by Demand Module Alternative Four.

From these three demand generation methods, seven demand generation approaches were developed. Demand Approach A was the stochastic method. Demand Approach B was the firm demand method with a coefficient of determination, the R^2 value, of .30 in the regression analysis. Demand Approach C was the firm demand method with an R^2 value of .50. Demand Approach D was the firm demand method with an R^2 value of .80. Demand Approaches E, F, and G were the industry demand method with an R^2 value of .30, .50, and .80. For a graphical summary of the development of the demand generation approaches, the reader should refer to Figures 3-5, 3-6, and 3-7.

To evaluate the seven demand approaches, ten environmental conditions were developed. These environmental conditions are termed demand test conditions. For each demand test condition, a 200-day pattern of demand was developed (see Chapter IV for the characteristics of the demand patterns). In each demand test condition all seven demand approaches were utilized in an attempt to replicate the given demand pattern. Therefore, for each demand test condition, a given demand pattern and seven replication patterns (one for each demand approach) were developed. These data were utilized to test the hypotheses discussed in Chapters V and VI.

The next section presents the findings and conclusions of this analysis.

Findings and Conclusions

This section is organized and developed around the research hypotheses.

Hypothesis One

The first hypothesis stated that the stochastic process utilized to generate orders from daily demand would generate orders that replicated actual orders. This hypothesis was tested by the t-test of two means and accepted. Thus, it was concluded that the stochastic process had no effect on the accuracy of any of the demand approaches.

This hypothesis represented a test of internal reliability, or repeatability, of the stochastic process for all simulation runs. Although no generalizable conclusions regarding the overall field of demand generation can be drawn, the acceptance of this hypothesis established the internal reliability necessary for evaluating other research hypotheses.

Hypothesis Two

The second hypothesis was divided into ten research hypotheses. One hypothesis applied to each of the ten demand test conditions. All hypotheses stated that in each demand test condition one demand approach would be significantly more accurate than all others. The hypotheses were tested through the utilization of mean absolute percent error as the measure of accuracy and a multiple ranking test as a measure of significance.

In Demand Test Conditions I through VIII, Demand Approach A, which was the stochastic method, proved to be the most accurate. This method is by far the simplest of the three demand generation methods tested. Therefore, under conditions where seasonality is either at a low level or non-existent, regardless of the existence of trend or the amount of variation, the stochastic method of demand generation is the most accurate of the methods tested. If demand generation for use as a force variable to a simulation model is the only application of concern, the stochastic method should be utilized whenever high seasonality is not evident.

Demand Test Conditions IX and X were subject to high levels of seasonality. Under both of these demand test conditions, all six demand approaches which comprised the firm demand and industry demand methods of demand generation were significantly more accurate than Demand Approach A. In any environmental condition where high seasonality is experienced, it can be concluded that the stochastic method is significantly less accurate than the firm demand or industry demand methods, regardless of the R^2 values obtained. Therefore, the firm demand or industry demand methods would be preferable to the stochastic method whenever high seasonality exists.

However, it must be remembered that the stochastic method has no information value regarding evaluation of factors that affect demand in the market area being simulated and/or for forecasting that demand. The stochastic method operates merely by imputing a probability distribution from which demand is randomly selected each day. No consideration is given to any factors affecting this demand. It is merely a stochastic process. In fact, the values of trend and seasonality must be known beforehand and incorporated into the probability distribution before the stochastic method can be utilized. Since the factors affecting demand are not considered and trend and seasonality must already be known, the method cannot forecast future demand, but only simulate demand patterns. The firm demand and industry demand methods consider various factors which affect demand in the market area. Therefore, the regression model developed to generate demand can also be utilized to analyze the effect of the factors that determined demand. Thus, the model can be utilized to forecast demand. The higher the value of R^2 obtained in the regression model, the more accurate the model will be in forecasting. Therefore, if the model developed for demand generation will also be utilized for forecasting, the stochastic method cannot be used. Either the firm demand or industry demand method must be employed.

In summary, the second hypothesis was accepted for Demand Test Conditions I through VIII with the resultant conclusion that the stochastic method should be utilized for demand generation in any environmental condition where high seasonality is not in evidence. The hypothesis was rejected for Demand Test Condition IX and X with the resultant conclusion that either the firm demand or industry demand method should be utilized for demand generation over the stochastic method in any environmental condition where high seasonality is in evidence.

These conclusions apply only to situations where demand generation is conducted. If forecasting and/or analysis of demand factors is also to be conducted, the conclusions should be adjusted. This adjustment requires the use of the firm demand or industry demand methods over the stochastic method and the use of the highest R^2 value that data gathering cost considerations will allow.

Hypothesis Three

The third hypothesis stated that the firm demand and industry demand methods would produce results more accurate than the stochastic method only when the R^2 value was high. For Demand Test Conditions I through VIII, the stochastic method was more accurate. This rendered the third hypothesis inapplicable in these demand test conditions.

The third hypothesis was applicable in Demand Test Condition IX and X since the firm demand and industry demand methods were more accurate than the stochastic method. However, both methods were more accurate than the stochastic method regardless of the R^2 value obtained. This leads to the conclusion that the R^2 value has no affect on the accuracy of demand generation in either the firm demand or the industry demand methods. Therefore, the third hypothesis was rejected for Demand Test Conditions IX and X. This conclusion is supported in all ten demand test conditions. In all of these test conditions there is no significant difference in accuracy due to different R^2 values.

Therefore, it can be stated that a high R^2 value is of significant value only if the regression model is to be utilized for forecasting and/or analysis of demand factors. In this case, the higher the R^2 value, the more reliable the forecast and/or analysis.

An explanation of this fact can be determined by reviewing the procedure through which the firm demand and industry demand methods are implemented. (The reader is referred back to Figures 3-3 and 3-4 for a graphic representation of both of these methods.) The firm demand method utilizes one regression model to determine firm demand for a particular period. This firm period demand is broken down into daily demand through the stochastic generation of a daily demand factor for each day. From this point the generation of orders is a process identical to that utilized for the stochastic method. The industry demand method is identical to the firm demand method except two regression models are utilized to arrive at firm period demand, one for industry demand and one for market share.

Since the stochastic process for generation of orders from daily demand is identical for all three methods, it can be effectively eliminated as a cause of the dampening of the effect of R^2. Further, the regression models can be eliminated since the use of one model in the firm demand method produces results similar to those from the use of two models in the industry demand method. This leaves only the stochastic process which generates daily demand from period demand. It must be concluded that the stochastic nature of this process has a sufficient dampening effect on accuracy to effectively eliminate any improved accuracy possible from a higher R^2 value. In effect, this dampening of R^2 is the result of compressing the multiple regression analysis into a short range or daily time perspective. The reader should recall from the Literature Review (pp. 26-27) that regression analysis for both the firm demand and the industry demand methods was never for periods of time shorter than one month. In fact, regression analysis is usually categorized as an intermediate or long range method.[1] The stochastic process which generates daily demand factors reduces this monthly demand to daily demand. This represents an attempt to reduce the intermediate or long range method of regression analysis to a short range method. In the process the effect of R^2 on the accuracy is dampened out.

Since this stochastic process is not utilized if the regression model is employed in forecasting, the improved accuracy of a higher R^2 value is not affected. Thus, the higher R^2 value is worthwhile for the purposes of forecasting on an intermediate or long range basis but relatively unimportant for demand generation.

Hypothesis Four

The fourth hypothesis stated that any time the firm demand or industry demand methods were more accurate than the stochastic method, the benefit of the increased accuracy would not be sufficient to outweigh the added data gathering costs. Only Demand Test Conditions IX and X exhibited inferior accuracy for the stochastic method. Therefore, Hypothesis Four was only applicable to these two demand test conditions.

As concluded in Hypothesis Three, in both demand test conditions the firm demand and industry demand methods were more accurate than the stochastic method regardless of the R^2 value. The development of the regression models utilized in the firm demand and industry demand methods incur some cost in the data gathering and analysis. To develop the regression model, various data must be gathered on variables which may correlate well with demand. Much of the necessary data is available on a national basis.

However, the demand generation is on a market area basis. Thus, considerable research effort may be necessary to obtain data on a market area basis.

Once these data are obtained, they must be analyzed with respect to demand. Each variable is analyzed through regression analysis to determine how well it correlates with demand. Variables with a low correlation are discarded. The remaining variables are utilized to develop the regression model which generates demand. The degree to which all of the variables included in the regression model correlate with demand is measured by the R^2 value. If the R^2 value is not sufficiently high, the entire process must be repeated. Additional variables must be obtained and analyzed to increase the R^2 value. Thus, the higher the R^2 value required, the greater the amount of data gathering and regression analysis required. This additional effort attaches a higher cost to the regression model. Therefore, the cost of obtaining the low R^2 value of .30 in Demand Approaches B and E is considerably less than the cost of obtaining the high R^2 value of .80 in Demand Approaches D and G.

Based on the analysis of Hypothesis Three, it was concluded that no significant difference in accuracy existed between any of the regression analysis demand approaches and, therefore, any R^2 value equal to or greater than .30 produces more accurate results than the stochastic method under conditions of high seasonality. This low required value for R^2 substantially limits the possible data gathering costs. Further, the benefits of increased accuracy through the use of the firm demand or industry demand method over the stochastic method can be considerable. The demand generated will be the force variable for a simulation model of the operating system of a firm. Major policy decisions may be based on the analysis of the simulation runs. Given this fact, the accuracy of the demand generation method and consequently, the simulation model could be extremely important. Therefore, the results from testing Hypothesis Four lead to the conclusion that in any condition where high seasonality exists, the use of the firm demand or industry demand method over the stochastic method will normally be justifiable on a cost/benefit basis.

Hypothesis Five

The fifth hypothesis stated that the ranking of demand approaches according to their relative accuracy would remain constant over all demand test conditions. Reference back to Table 6-13 clearly indicates that this hypothesis was rejected. Therefore, no generalizable conclusions can be drawn regarding the rank ordering of the demand approaches or the demand generation methods over demand test conditions. Any conclusion regarding rank ordering must be made specifically for each demand test condition.

However, some interesting conclusions can be drawn from the results of the analysis in Chapter VI. Although the stochastic method offers the potential for much more accurate replication as demonstrated in Demand Test Conditions I through VIII, the accuracy of this method changes drastically under conditions of high seasonality. This is in contrast to the stability exhibited by both the firm demand and industry demand methods. Although not as accurate as the stochastic method, the MAPE values for the firm demand and industry demand methods remained within a range of 26.929 to 50.689 over all ten demand test conditions. This is considerably less than the range of 12.281 to 55.814 for the stochastic method. This combined with the steady decline in accuracy of the stochastic method after seasonality was introduced (Figure 6-11), leads to the conclusion that over all demand test conditions accuracy is more stable with the firm and industry demand methods.

Guidelines and Implications

The conclusions lead to certain guidelines to be followed when conducting demand generation experimentation. In any environmental condition to be replicated that does not exhibit high seasonality, the stochastic method is preferable. This method not only produces the most accurate results under non-seasonal conditions, but it is also the simplest and least expensive method.

For conditions of high seasonality, either the firm demand or industry demand methods should be selected. These methods exhibit superior accuracy in comparison to the stochastic method regardless of the obtained R^2 value. Therefore, only one attempt at data gathering for the regression model should be conducted if demand generation is the only goal. As long as the regression model resulting from this data gathering possesses an R^2 value of greater than .30, no more regression analysis is necessary to improve the accuracy of demand generation.

If the purpose of the research effort in conjunction with demand generation is to analyze of the factors affecting demand and/or demand forecasting, the stochastic method should never be used. This method offers no informational value for forecasting or analysis of demand factors. It is strictly a demand generation method. Either the firm demand or industry demand method should be employed. When either the firm demand or industry demand methods are utilized for demand generation and forecasting, the R^2 value becomes more important. The higher the R^2 value, the more accurate the analysis of demand factors and the forecasting will be. Thus, although R^2 is relatively unimportant to demand generation, the highest value of R^2 allowed by cost considerations should be sought if the model will also perform forecasting and/or analysis of demand factors.

The reader should recall from Hypothesis Three the conclusion that the stochastic process which reduces period demand to daily demand for the firm demand and industry demand methods caused the dampening of the effect of the R^2 value on accuracy. Again, this was due to the attempt to reduce the intermediate or long range regression analysis to a short range method. The use of the firm demand and industry demand methods for short range demand generation did produce superior accuracy in two demand test conditions. However, since the R^2 value is a measure of forecast accuracy, the accuracy for use in forecating and/or analysis of demand factors of either method stops when the effect of R^2 on accuracy stops. Therefore, the firm demand and industry demand methods can be used for short range demand generation, but are of little use for forecasting and/or analysis of demand factors on a short range basis. To utilize these methods for such a purpose, the analysis must be conducted on periods of a month or longer. For short range forecasting such approaches as time series analysis would seem more applicable.[2]

Since the stochastic method proved most accurate in eight of ten environmental conditions, the results imply that in most business situations the stochastic method would be adequate. However, this may not be the case. The fact that the stochastic method was least accurate in cases of high seasonality must be kept in mind. Although high seasonality represented only 20 percent of the demand test conditions, actual business situations where high seasonality exists may represent a much higher percentage. Most firms do experience some form of seasonality. In fact, a recent study of manufacturing, retailing, and wholesaling firms in the United States and Canada found that 41.0 percent of the responding firms experienced high seasonality and 16.4 percent experienced at least moderate seasonality.[3] Therefore, a majority of actual business conditions may fall under the environmental conditions represented in Demand Test Conditions IX and X. This would indicate that in the majority of actual business simulations the firm demand or industry demand methods would prove more accurate than the stochastic method.

This fact has serious implications for future demand generation attempts. Although the firm demand and industry demand methods have proven to be viable methods of demand generation, most previous attempts at demand generation have utilized the stochastic method. Referring back to the Literature Review, the models developed by Balderston and Hoggatt,[4] Gross and Ray,[5] and Whybark[6] all utilized the stochastic method for demand generation. The findings of this research suggest that although the demand generation for these models may be accurate in conditions of low or non-existent seasonality, the models did not utilize the most accurate demand generation methods in conditions which probably represent the majority of actual business demand patterns--high seasonality. Thus, the accuracy of results from demand generation may be less than that which could have been obtained. This lack of accuracy will affect the accuracy and validity of the simulation model for which the demand generation is the force variable. Major policy decisions may be made based on the results of analysis of these simulation runs. Therefore, it could be extremely important to the firm for the simulation model to use the demand generation method which produces the highest obtainable accuracy. The same statement also holds true for general research with simulation models. If the demand generation force variable is less than the obtainable accuracy, the conclusions drawn from more general research with simulation models of a firm could exhibit questionable validity and accuracy.

Future demand generation attempts should keep this finding in mind when selecting the method or methods to use.

If environmental conditions with high seasonality are to be simulated, the firm demand and/or industry demand methods should be included in the simulation model. A logical approach to the use of different methods in different environmental conditions would be to include all three methods. This approach, taken in the SPSF Testing Environment, allows the most appropriate method to be selected for any given simulation. This would afford new simulation models considerably more flexibility than previous models that utilized only the stochastic method.

Limitations of the Research

Any simulation study is constrained to the extent that the simulation model replicates the real world system. The present research is not free of that constraint. However, the SPSF model employed in this research has been subjected to extensive validation tests and has been judged valid.[7]

This particular application of the SPSF model utilized certain simplifying assumptions. First, the Operations Module was limited to a single, infinite inventory location upon which all demand impacted. It is unrealistic to assume any channel of distribution consists of only one location and that location never stocks out. However, the thrust of this research was to evaluate the relative accuracy of various demand generation methods. Thus, the single infinite inventory assumption served to eliminate stockouts, which would have confounded the analysis. For this reason the assumption was justified.

The second simplifying assumption was that the output of the Forecast Module was not utilized. Since the accuracy of forecasting techniques was not the concern of this research, the assumption was justified. A related limitation of this study is the fact that only demand generation models were considered. This ignored the rather large field of forecasting models. However, a simultaneous dissertation was conducted to test various time series forecasting models under different environmental conditions.[8] Further, a large gap seemed to exist in the literature regarding demand generation methods and their accuracy. For these reasons this limitation was justified.

A final limitation of this research concerns the nature of the data analyzed. In each of the demand test conditions, each demand approach attempted to replicate the given demand pattern. These give demand patterns represented not actual but controlled demand data. Therefore, the accuracy of the demand approaches were not necessarily tested in actual situations. However, these controlled demand patterns were designed to be representative of generalizable business demand conditions. It can be argued that actual business data would prove less representative of the generalizable conditions than controlled data created for that purpose. Further, the product and order composition characteristics remained stable over all demand test conditions. To find data which was stable with respect to product and order composition characteristics but exhibited demand patterns for all ten demand test conditions was virtually impossible. Thus, this limitation was not only justifiable, but unavoidable.

Future Research

This research effort has generated a wide range of possible future studies. One promising area for future research would be sensitivity analysis to determine what amount of seasonality and variation cause the stochastic method of demand generation to relinquish its superior accuracy. It was observed in the present research that high seasonality and high variation affected the stochastic method, but a derivation of the affect function and the point where accuracy rapidly decreases was not obtained. It can be observed from Figure 6-11 that the accuracy of the stochastic method begins to fall as variation and seasonality increase (Demand Test Conditions V through X).

However, the large drop in accuracy from Demand Test Conditions VIII to IX discloses little about the rate of accuracy decrease created by seasonality.

Further research could be conducted wherein the amount of seasonality was gradually increased and the accuracy of the stochastic method compared both to itself and the industry and firm demand methods. Thus, the incremental effect of seasonality on the stochastic method and the point where the industry and firm demand methods become more accurate could be observed.

An extremely fruitful area for additional research would be market share studies with actual products. The regression model of market share in the industry demand method can be utilized to evaluate market share for a particular firm and the factors that affect market share. Data over time or across sections of the country could be analyzed to determine the effect on market share. Such factors as price, advertising, product quality, and customer service for the firm in question and the industry competitors could be gathered. This data could be analyzed utilizing the market share equation on page 54. By performing a logarithmic transformation on the data, this equation is expressed in linear rather than fractional form. This linear form of the market share formula can be analyzed through multiple regression analysis to determine the model for market share. Through this model, market share can be forecast for future periods.

In addition, the regression coefficients in the market share model represent elasticities of each of the factor inputs. Thus, the price, advertising, product quality, and customer service elasticities for both the firm and its competitors would be obtainable. This information could assist the manager in determining marketing strategies. The effect on market share of changing any of the factor inputs would be identified. Thus, the marketing manager could view the effect of competitive actions and the most effective counter-moves to meet competitive inroads to market share. For example, if a competitor were to lower price the firm could enter this change into the market share model and analyze its effect on market share. The marketing manager could also try various marketing counter-moves to negate the competitive action. For instance, it may be found that an increase in advertising most effectively countermands the effects of the competitive price move.

Finally, the comparison of different time series and regression analysis models of forecasting would seem a logical progression from this research and the Sims dissertation.[9] Regression analysis has been characterized as a more intermediate or long range model whereas time series forecasting has been termed a short range body of techniques.[10] Time series appears to be more adaptive to rapid changes in demand but regression analysis possesses the advantage of considering environmental factors. It would be interesting to analyze the relative accuracy of both time series and regression analysis under various time settings and environmental conditions. Such conditions as rapid changes in demand, with and without accurate environmental indicators, could be considered. Not only the relative accuracy, but also the cost/benefit impact of each model on a logistical operating system could be evaluated.

CHAPTER VII--FOOTNOTES

[1]Spyros Makridakis and Steven C. Wheelwright, "Forecasting: Issues and Challenges for Marketing Management," Journal of Marketing 41 (No. 4; October 1977): 24-38.

[2]Jeffrey R. Sims, "Simulated Product Sales Forecasting--An Analysis of Forecasting and Operating Discrepancies in the Physical Distribution System" (Ph.D. dissertation, Michigan State University, 1978).

[3]Douglas M. Lambert and John T. Mentzer, Jr. "Report on the Availability of Distribution Cost Information" (Unpublished manuscript, Michigan State University, 1978).

[4]Frederick E. Balderston and Austin C. Hoggatt, Simulation of Market Processes (Berkeley, Calif.: Institute of Business and Economic Research, University of California, 1962), p. 4.

[5]Donald Gross and Jack L. Ray, "A General Purpose Forecast Simulator," Management Science 11 (No. 6, April 1965): 119-135.

[6]D. Clay Whybark, "A Comparison of Adaptive Forecasting Techniques," The Logistics and Transportation Review 8 (No. 3; July 1973): 13-26; and D. Clay Whybark, Testing An Adaptive Inventory Control Model, Herman C. Krannert Graduate School of Industrial Administration Paper No. 289 (Lafayette, Ind.: Purdue University, October 1970), p. 7.

[7]Donald J. Bowersox, David J. Cross, John T. Mentzer, Jr., and Jeffrey R. Sims, Simulated Product Sales Forecasting--Documentation, forthcoming publication in the Fall of 1978 from the Graduate School of Business Administration Research Bureau, Michigan State University.

[8]Sims.

[9]Ibid.

[10]Makridakis and Wheelwright, pp. 24-38.

APPENDIX

SELECTED STATISTICAL CONCEPTS

APPENDIX

EXHIBIT I

STANDARD DEVIATION

The formula for standard deviation for the demand patterns in the demand test conditions is:

$$SD = \sqrt{\frac{\Sigma(X - \overline{X})^2}{N - 1}}$$

where:

- SD = standard deviation;
- X = each observation of demand;
- $\overline{X}$ = the value of demand expected from the measurement of level, trend, and seasonality; and
- N = the number of observations of demand.

EXHIBIT II

COEFFICIENT OF VARIATION

The coefficient of variation is a measure of the amount of variation in data as a fraction of the mean of the data. The formula for coefficient of variation is:

$$CV = \frac{SD}{\bar{X}}$$

where:

CV = the coefficient of variation;

SD = the standard deviation; and

$\bar{X}$ = the mean.

As an example, if the mean of a set of data equalled 3,750 and the standard deviation was 375, then the coefficient of variation would be:

$$CV = \frac{375}{3{,}750} = .10.$$

EXHIBIT III

SEASONALITY FACTOR

A seasonal cycle is composed of a certain number of periods. For instance, twelve months in a year represents twelve periods in a yearly cycle. If no seasonality existed, the fraction of total cycle demand that occurs in any one period would be one divided by the number of periods in the cycle. Each period would have the same demand. Seasonality is the degree to which demand in a period differs from this condition of equality between periods.

The seasonality factor is a measure of this seasonality for each period in a cycle. The formula for the seasonality factor is:

$$SF_i = \frac{PD_i}{CD} \times NP$$

where:

SF_i = the seasonality factor for period i;

PD_i = the demand for period i;

CD = the demand over the entire cycle; and

NP = the number of periods in a cycle.

As an example, if the cycle contained ten periods and the cycle demand was 100,000 units, then the demand for each period would be 10,000 units if no seasonality existed.

However, if demand in Period 4 was 12,500 units, then the seasonality factor for Period 4 would be:

$$SF_4 = \frac{12,500}{100,000} \times 10 = 1.25.$$

Another way of viewing the seasonality factor is to say the period demand of 12,500 units is 1.25 times the demand of 10,000 units expected without seasonality for that period.

BIBLIOGRAPHY

BIBLIOGRAPHY

Books

Amstutz, A. E. Computer Simulation of Competitive Market Response. Cambridge, Mass.: MIT Press, 1967.

Balderston, F. E., and A. C. Hoggatt. Simulation of Market Processes. Berkeley, Cal.: Institute of Business and Economic Research, University of California, 1962.

Bass, Frank M. Mathematical Methods and Models in Marketing. Homewood, Ill.: R. C. Irwin, Inc., 1962.

Bass, Frank M., W. King, and E. A. Pessemier. Applications of the Sciences in Marketing Management. New York: John Wiley & Sons, Inc., 1968.

Bowersox, Donald J. Logistical Management. New York: Macmillan Publishing Co., Inc., 1974.

Christ, Carl F. Econometric Models and Methods. New York: John Wiley & Sons, Inc., 1966.

Cohen, Richard. Statistical Power Analysis for the Behavioral Sciences. New York: Academic Press, Inc.,1969.

Goldberger, Arthur S. Econometric Theory. New York: John Wiley & Sons, Inc., 1964.

Hughes, George David. Demand Analysis for Marketing Decisions. Homewood, Ill.: R. D. Irwin, 1973.

Kotler, Philip. Marketing Decision Making: A Model Building Approach. New York: Holt, Rinehart and Winston, Inc., 1971.

Lippitt, Vernon G. Statistical Sales Forecasting. New York: Financial Executives Research Foundation, 1969.

Massy, William F. "Stochastic Models for Monitoring New Product Introductions." In Applications of the Sciences in Marketing Management. Edited by Frank M. Bass, W. King, and E. A. Pessemier. New York: John Wiley & Sons, Inc., 1968.

Massy, W. F., and R. E. Frank. An Economic Approach to a Decision Model. Cambridge, Mass.: MIT Press, 1971.

Massy, W. F., D. B. Montgomery, and D. G. Morrison. Stochastic Models of Buying Behavior. Cambridge, Mass.: MIT Press, 1970.

Meir, R. C., W. T. Newel, and Harold Pazer. Simulation in Business and Economics. Englewood Cliffs, N.J.: Prentice-Hall, Inc., 1969.

Mills, Harlan D. "A Study in Promotional Competition." In Mathematical Models and Methods in Marketing, pp. 271-288. Edited by Frank M. Bass et al. Homewood, Ill.: Richard D. Irwin, 1961.

Montgomery, D. B., and G. L. Urban. Management Science in Marketing. New York: Prentice-Hall, Inc., 1970.

Naylor, Thomas H. Computer Simulation Experiments with Models of Economic Systems. New York: John Wiley & Sons, 1971.

________. Computer Simulation Techniques. New York: John Wiley & Sons, 1966.

________, ed. Symposium on the Design of Computer Simulation Experiments. Durham, N.C.: Duke University Press, 1969.

Palda, Kristian S. The Measurement of Cumulative Advertising Effects. Englewood Cliffs, N.J.: Prentice-Hall, Inc., 1964.

Preston, Lee E. Studies in a Simulated Market. Berkeley, Calif.: Institute of Business and Economic Research, 1966.

Quetzkow, H., P. Kotler, and R. L. Schultz. Simulation in Social and Administrative Science. Englewood Cliffs, N.J.: Prentice-Hall, Inc., 1972.

Schultz, Henry. The Theory and Measurement of Demand. Chicago: The University of Chicago Press, 1958.

Shannon, Robert E. Systems Simulation--The Art and Science. New York: Prentice-Hall, Inc., 1975.

Urban, Glen L. "An On-Line Technique for Estimating and Analyzing Complex Models." In Changing Market Systems, pp. 322-327. Edited by Reed Moyer. Chicago: American Marketing Association, 1968.

Wald, Herman, and L. Jureen. _Demand Analysis_. New York: John Wiley & Sons, Inc., 1953.

Warner, B. T. _A Model for Total Marketing in Computers in Advertising_. London: The Institute of Practitioners of Advertising.

Articles, Periodicals, and Papers

Aaker, David A. "Using Buyer Behavior Models to Improve Marketing Decisions." _Journal of Marketing_ 34 (No. 3; July 1970): 52-57.

Amstutz, A. E., and H. Claycamp. "Simulation Techniques in the Analysis of Marketing Strategy." MIT Working Paper, 1966, pp. 208-266.

Armstrong, J. Scott, and James G. Andress. "Exploratory Analysis of Marketing Data: Trees vs. Regression." _Journal of Marketing Research_ 7 (No. 7; November 1970): 487-492.

Assael, Henry. "Segmenting Markets by Response Elasticity." _Journal of Advertising Research_ 16 (No. 2; April 1976): 27-35.

Balachandran, V. "Comment on Solving the 'Marketing Mix' Problem Using Geometric Programming." _Management Science_ 21 (No. 10; June 1975): 1204-1205.

Balachandran, V., and Dennis H. Gensch. "Solving the 'Marketing Mix' Problem Using Geometric Programming." _Management Science_ 21 (No. 2; October 1974): 160-171.

Bass, Frank M. "A New Product Growth Model for Consumer Durables." _Management Science_ 15 (No. 5; January 1969): 215-227.

________. "A Simultaneous Equation Regression Study of Advertising and Sales of Cigarettes." _Journal of Marketing Research_ 6 (No. 3; August 1969): 291-300.

Bass, Frank M., Abel Jeuland, and Gordon P. Wright. "Equilibrium Stochastic Choice and Market Penetration Theories: Derivations and Comparisons." _Management Science_ 22 (No. 1; June 1976): 1051-1063.

Bass, Frank M., and Leonard J. Parsons. "Simultaneous-Equation Regression Analysis of Sales and Advertising." Applied Economics 1 (March 1969): 103-124.

Beckwith, Neil E. "Multivariate Analysis of Sales Responses of Competing Brands to Advertising." Journal of Marketing Research 9 (No. 1; May 1962): 168-176.

________. "Concerning the Logistical Consistency of Multivariate Market Share Models." Journal of Marketing Research 10 (No. 3; August 1973): 341-344.

Bell, David E., et al. "A Market Share Theorem." Journal of Marketing Research 12 (No. 2; May 1975): 136-141.

Blattberg, Robert C., and Subrata K. Sen. "Market Segments and Stochastic Brand Choice Models." Journal of Marketing Research 13 (No. 1; February 1976): 34-35.

Bowersox, Donald J., David J. Closs, John T. Mentzer, Jr., and Jeffrey R. Sims. "Simulated Product Sales Forecasting: Present Status and Future Potential," Proceedings of the Seventh Annual Transportation and Logistics Educators Conference. Transportation and Logistics Research Fund, The Ohio State University, Columbus, Ohio, 1976, pp. 27-30.

Bowersox, Donald J., David J. Closs, John T. Mentzer, Jr., and Jeffrey R. Sims. "Short Range Product Sales Forecasting," Proceedings of the Fourteenth Annual National Council of Physical Distribution Managers, 1976, pp. 193-216.

Bryout, J. W. "A Simulation Model of Retailer Behavior." Operational Research Quarterly 26 (No. 1; April 1975): 133.

Buzzell, Robert D., and Michael J. Baker. "Sales Effectiveness of Automobile Advertising." Journal of Advertising Research 12 (No. 3; June 1972): 3-8.

Clarke, Darral G. "Sales-Advertising Cross-Elasticities and Advertising Competiton." Journal of Marketing Research 10 (No. 3; August 1973): 250-261.

Claycamp, Henry J., and Luscien E. Liddy. "Prediction of New Product Performance: An Analytical Approach." Journal of Marketing Research 6 (No. 4; November 1969): 414-420.

Cowey, A., and D. Green. "A Marketing Model for a Price Promoted Consumer Good--A Case Study." Operational Research Quarterly 26 (No. 1; March 1975): 3.

Ehrenberg, A. S. C. "Models of Fact: Examples from Marketing." Management Science 16 (No. 7; March 1970): 435-445.

Ehrenberg, A. S. C., and P. Charlton. "An Analysis of Simulated Brand Choice." Journal of Advertising Research 13 (No. 1; February 1973): 21-33.

Elton, Martin, and Jonathan Rosenhead. "Micro Simulation of Markets." Operational Research Quarterly 22 (No. 2; June 1971): 117.

Emshoff, James R., and Alan Mercer. "Aggregate Models of Consumer Purchases." Journal of Royal Statistical Society, Series A General, 133 (Part 1; 1970): 14-32.

Emshoff, James R., and Alan Mercer. "A Marketing Model for Sales to Consumers." Operational Research Quarterly 18 (No. 3; September 1967): 257.

Eskin, Gerald J., and Penny H. Baron. "Effects of Price and Advertising in Test-Market Experiments." Journal of Marketing Research 14 (No. 4; November 1977): 449-509.

Ezzati, Ali. "Forecasting Market Shares of Alternative Home-Heating Units by Markov Process Using Transition Probabilities Estimated from Aggregate Time Series Data." Management Science 21 (No. 4; December 1974): 462-473.

Frank, Ronald E. "Predicting New Product Segments." Journal of Advertising Research 12 (No. 3; June 1972): 9-13.

Gross, Donald, and Jack Ray. "A General Purpose Forecast Simulator." Management Science 9 (No. 8; April 1965): 119-135.

Guerts, M. D., and I. B. Ibrahim. "Comparing the Box-Jenkins Approach with the Exponentially Smoothed Forecasting Model Application to Hawaii Tourists." Journal of Marketing Research 12 (No. 2; May 1975): 182.

Horsky, Dan. "Market Share Response to Advertising: An Example of Theory Testing." Journal of Marketing Research 14 (No. 1; February 1977): 10-21.

Houston, Franklin S., and Doyle L. Weiss. "An Analysis of Competitive Market Behavior." Journal of Marketing Research 11 (No. 2; May 1974): 151.

Howry, E. P., and L. R. Klein. "Dynamic Properties of Non-Linear Econometric Models." International Economics Review 13 (No. 3; October 1972): 599-618.

Jones, J. Morgan. "A Dual Effect Model of Brand Choice." Journal of Marketing Research 7 (No. 4; November 1970): 458-464.

Kinberg, Yoram, and Ambar G. Rao. "Stochastic Models of a Price Promotion." Management Science 21 (No. 8; April 1975): 897-907.

Kinberg, Yoram, Ambar G. Rao, and Melvin F. Shakun. "A Mathematical Model for Price Promotions." Management Science 20 (No. 6; February 1974): 948-959.

Kitchener, Alan, and David Rowland. "Models of Consumer Product Market." Operational Research Quarterly 22 (No. 1; March 1971): 67.

Kotler, Philip. "Competitive Strategies for New Product Marketing Over the Life Cycle." Management Science 12 (No. 4; December 1965): 104-119.

________. "Mathematical Models of Individual Buyer Behavior." Behavioral Science 13 (No. 4; July 1968): 274-287.

________. "The Competitive Marketing Simulator--A New Management Tool." California Management Review, Spring 1965, p. 49.

________. "The Use of Mathematical Models in Marketing." Journal of Marketing 27 (No. 4; October 1963): 31-41.

Krishnan, K. S., and Shiv K. Gupta. "Mathematical Model for a Duopolistic Market." Management Science 13 (No. 7; March 1967): 568-583.

Kuehn, Donald A., and Doyle L. Weiss. "Marketing Analysis Training Exercise." Behavioral Science 10 (No. 1; January 1965): 51-67.

Lambin, Jean-Jacques. "Optimal Allocation of Competitive Marketing Efforts: An Empirical Study." Journal of Business 43 (October 1970): 468-484.

________. "A Computer On-Line Marketing Mix Model." Journal of Marketing Research 9 (No. 2; May 1972): 119-126.

________. "What Is the Real Impact of Advertising?" Harvard Business Review 53 (No. 3; May-June 1975): 139-147.

Lavington, Michael R. "A Practical Micro-Simulation Model for Consumer Marketing." Operational Research Quarterly 21 (No. 1; March 1970): 25.

Lawrence, R. J. "Models of Consumer Purchasing Behavior." Applied Statistics 15 (November 1966): 216-233.

Lipstein, Benjamin. "Modeling and New Product Birth." Journal of Advertising Research 10 (No. 5; October 1970): 3-11.

Little, John D. C. "BRANDAID II." Sloan School of Management. Working Paper, Cambridge, Mass.: MIT, 1973, pp. 687-693.

________. "BRANDAID: A Marketing-Mix Model, Part 1: Structure." Operations Research 23 (No. 4; July-August 1975): 628-655.

________. "BRANDAID: A Marketing-Mix Model, Part 2: Implementation, Calibration, and Cast Study." Operations Research 23 (No. 4; July-August 1975): 656-673.

MacLachlan, Douglaus L. "Models of Intermediate Market Response." Journal of Marketing Research 9 (No. 4; November 1972): 378.

Makridakis, Spyros, and Steven C. Wheelwright. "Forecasting: Issues and Challenges for Marketing Management." Journal of Marketing 41 (No. 4; October 1977): 24-38.

Massy, William F. "Forecasting the Demand for New Convenience Products." Journal of Marketing Research 6 (No. 4; November 1969): 405-412.

________. "Order and Homogeneity of Family Specific Brand-Switching Processes." Journal of Marketing Research 3 (No. 1; February 1966): 48.

Massy, William F., and R. E. Frank. "The Study of Consumer Purchase Sequences Using Factor Analysis and Simulation." Proceedings Annual Meeting of the Business and Economics Section of the American Statistical Association, Chicago, 28-30 December 1964.

Massy, William F., and D. G. Morrison. "Comments on Ehrenberg's Appraisal of Brand Switching Models." Journal of Marketing Research 5 (No. 2; May 1968): 225-229.

McCann, John M. "Market Segment Response to the Marketing Decision Variables." Journal of Marketing Research 11 (No. 4; November 1974): 339-412.

McGuire, Timothy W., and Doyle L. Weiss. "Logically Consistent Market Share Models II." Journal of Marketing Research 13 (No. 3; August 1976): 296-302.

Merars, A. "Application of Operational Research in Marketing." Operational Research Quarterly 17 (1966): 235-252.

Morrison, Donald G. "Interpurchase Time and Brand Loyalty." Journal of Marketing Research 3 (No. 3; August 1966): 289.

Naert, Phillipe A., and A. Bultez. "Logically Consistent Market Share Models." Journal of Marketing Research 10 (No. 3; August 1973): 334-340.

Nakanishi, M., and L. G. Cooper. "Parameter Estimation of a Multiplicative Competitive Interactive Model-Least Squares Approach." Journal of Marketing Research 11 (No. 3; August 1974): 303-311.

Nelson, C. R. "The Prediction Performance of the FRB-MIT-Model of the U.S. Economy." American Economic Review 62 (No. 5; December 1972): 902-917.

Norton, W. E. "Forecasting with a Macroeconomic Model." Economic Research 48 (No. 121; March 1972): 116-122.

Parsons, Leonard J. "An Econometric Analysis of Advertising, Retail Availability, and Sales of a New Brand." Management Science 20 (No. 6; February 1974): 938-947.

Parsons, Leonard J., and Walter A. Henry. "Comparison of Time Series Data Using Spectral Analysis." Journal of Marketing Research, November 1972, p. 391.

Rao, Vithala R. "Alternative Econometric Models of Sales-Advertising Relationships." Journal of Marketing Research 9 (No. 2; May 1972): 171-181.

Rippe, Richard, Maurice Wilkinson, and Donald Morrison. "Industrial Forecasting with Anticipations Data." Management Science 22 (No. 6; February 1976): 639-651.

Rosenhead, J. V. "Experimental Simulation of a Social System." Operational Research Quarterly 19 (No. 3; September 1968): 289-298.

Schultz, Randall L. "Market Measurement and Planning with a Simultaneous Equation Model." Journal of Marketing Research 8 (No. 2; May 1971): 153-164.

________. "Studies of Airline Demand-Review." Transportation Journal 11 (Summer 1972): 48-62.

Schultz, Randall L., and Joe A. Dodson. "A Normative Model for Marketing Planning." Simulation and Games 5 (No. 4; December 1974).

Sexton, Donald E., Jr. "Estimating Marketing Policy Effects on Sales of a Frequently Purchased Product." Journal of Marketing Research 7 (No. 3; August 1970): 338-347.

________. "Cluster Analytic Approach to Market Response Functions." Journal of Marketing Research 11 (No. 1; February 1974): 109.

Shakun, Melvin. "A Dynamic Model for Competitive Marketing in Coupled Markets." Management Science 12 (No. 12; August 1966): 525-530.

Stansell, Stanley R., and Ronald P. Wilder. "Lagged Effects of Annual Advertising Budgets." Journal of Advertising Research 16 (No. 5; October 1976): 35-40.

Stern, R. N. "Market Behavior in a Simulated Society." Simulation and Games 5 (No. 4; December 1974): 347.

Urban, Glen L. "A Mathematical Modeling Approach to Product Line Decisions." Journal of Marketing Research 6 (No. 1; February 1969): 40-47.

________. "A New Product Analysis and Decision Model." Management Science 14 (No. 8; April 1968): 490-517.

________. "Sprinter Mod-II--A Model for the Analysis of New Frequently Purchased Consumer Products." Operations Research 18 (No. 5; September-October 1970): 805-854.

Urban, Glen L., and Richard Karash. "Evolutionary Model Building." Journal of Marketing Research 8 (No. 1; February 1971): 62-66.

Ward, Ronald W. "Measuring Advertising Decay." Journal of Advertising 16 (No. 4; August 1976): 37-41.

Weinberg, Charles B. "Dynamic Correction in Marketing Planning Models." Management Science 22 (No. 6; February 1976): 677-687.

Weiss, Doyle L. "Determinants of Market Share." Journal of Marketing Research 5 (No. 3; August 1968): 290-295.

Whybark, D. Clay. "A Comparison of Adaptive Forecasting Techniques." The Logistics and Transportation Review 8 (No. 3; July 1973): 13-26.

________. "Testing an Adaptive Inventory Control Model." Working Paper No. 289, Purdue University, Lafayette, Indiana, October 1970.

Wildt, Albert R. "Estimating Models of Seasonal Market Response Using Dummy Variables." Journal of Marketing Research 14 (No. 1; Feburary 1977): 34-41.

________. "Multifirm Analysis of Competition Decision Variables." Journal of Marketing Research, February 1974, p. 50.

Woodside, Arch G., and James D. Clokey. "Multi-Attribute/ Multi-Brand Models." Journal of Advertising Research 14 (No. 5; October 1974): 33-40.

Zellner, Arnold. "An Efficient Method for Estimating Seemingly Unrelated Regression and Tests for Aggregation Bias." Journal of American Statistical Association 57 (June 1962): 348-368.

Unpublished Material

Bowersox, Donald J., David J. Closs, John T. Mentzer, Jr., and Jeffrey R. Sims. Simulated Product Sales Forecasting--Documentation. Forthcoming publication in the Fall of 1978 from the Graduate School of Business Administration Research Bureau, Michigan State University.

Camp, Robert. "The Effect of Variable Lead Times on Logistics Systems." Ph.D. dissertation, Pennsylvania State University, 1973.

Houston, Frank S. "Competitive Brand Behavior: An Analysis of Market Share Retention, Relative Advertising in Aggregate Demand Models." Ph.D. dissertation, Purdue University, 1972.

Lambert, Douglas M., and John T. Mentzer, Jr. "Report on the Availability of Distribution Cost Information." Manuscript, Michigan State University, 1978.

MacLachlan, Douglaus L. "Market Response Demand Models: A Comparison of Variable Markov and Distributed-Lag Approaches." Ph.D. dissertation, University of California, 1971.

Nakanishi, Masao. "A Model of Market Reactions to New Products." Ph.D. dissertation, University of California, Los Angeles, 1968.

Sims, Jeffrey R. "Simulated Product Sales Forecasting--An Analysis of Forecasting and Operating Discrepancies in the Physical Distribution System." Ph.D. dissertation, Michigan State University, 1978.

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

Wagenheim, George D. "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.