A SIMULATED SALES FORECASTING MODEL: A BUILD-UP APPROACH

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FRED WILLIAM MORGAN, JR.
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This is to certify that the

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presented by

Fred William Morgan, Jr.

has been accepted towards fulfillment
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Donald J Bowersox
Major professor

Date July 21, 1972

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ABSTRACT

A SIMULATED SALES FORECASTING MODEL:
A BUILD-UP APPROACH

By

Fred William Morgan, Jr.

Business firms have long been frustrated in their attempts to evaluate their forecasting capabilities prior to anticipated sales becoming actual sales. This dissertation is a presentation of a way to deal with this measurement problem. This is accomplished by devising both a forecasting archetype and an approach for tailoring the forecasting model to meet specific needs.

Three traditional bases for categorizing forecasting models are:

1. The length of the forecasting period
2. The level of the forecast
3. The technique utilized.

Forecasting periods shorter than one year can be arbitrarily defined as short-term, while periods lengthier than one

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The objective of this research is to build and to implement a model with flexibility along the three dimensions of prediction interval, level of detail, and technique. Each of these dimensions was studied thoroughly. The prediction interval and level of detail were treated as aspects of the planning horizon for forecasting. Since forecasts are critical inputs to the planning process, the planning horizon influences both of these dimensions. Long-term planning requires aggregate forecasts for lengthier time periods. Short-term forecasts are more detailed and cover smaller time intervals. The emphasis of this study was arbitrarily placed on a short-term (one year) time span.

To aid in the selection of the appropriate forecasting technique, a set of guidelines was developed. This set includes the following: (1) cost, (2) level of detail, (3) accuracy, (4) turning points, (5) market factors, (6) input requirements, (7) planning horizon, (8) timing,

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Several techniques were explored, including (1) factor listing, (2) jury of executive opinion, (3) sales force composite, (4) users' expectations, (5) moving average, (6) exponential smoothing, (7) time series analysis, and (8) regression and correlation analysis. A comparison of these techniques with respect to the set of guidelines revealed that exponential smoothing was the most appropriate short-term forecasting method.

The need for a flexible forecasting model was discovered as a result of a research project at the Graduate School of Business at Michigan State University to develop a viable long-range planning model for physical distribution systems. The model, referred to as the Long-Range Environmental Planning Simulator (LREPS), includes (1) the basic components of the physical distribution system, (2) a strategic planning horizon, and (3) the sequential decision problem. The model is modular in nature and, since its initial uses, has been extended to cover broader classes of manufacturing firm and public sector planning.

LREPS provides the framework for the forecasting model and a way to validate the forecasting model's capability under controlled conditions. Several hypothesized actual sales patterns, each the result of different marketing plans and environmental conditions, can be simulated with LREPS. Based on physical distribution costs and forecasting accuracy, management can determine the most appropriate forecasting technique, prediction interval, and level of detail needed to anticipate these sales patterns. Assuming given external conditions, management can adopt a market plan and know which forecasting system is most useful.

The research objective, the construction and implementation of a flexible short-term forecasting model for use in conjunction with LREPS, has been achieved. An industrial sponsor supplied sample data for the development of a specific model.

Five values for the exponential smoothing constant (0.01, 0.05, 0.10, 0.30, 0.50) and for the prediction interval (1 wk., 2 wks., 1 mo., 2 mos., 3 mos.) were examined. Each of these two variables was associated with variable physical distribution costs through regression analysis. The t statistic revealed several statistically significant correlations. Alternative levels of detail were compared using the F statistic. Based on statistical evidence, the following recommendations were made:

1. Smoothing constant values in the 0.01 to 0.10 range are appropriate.

2. Prediction intervals from one to two weeks are appropriate.

3. Product forecasts are as accurate as product-region forecasts.

The relationship between forecasting accuracy (an index composed of the relative forecasting variance and Theil's inequality coefficient) and variable physical distribution cost was measured using Spearman's rank correlation coefficient. A statistically significant direct relationship was observed.

LREPS provides several measures of system service achievement, one of which is the percent of case units backordered. Percent backorders was regressed against variable physical distribution cost. The relationship was an inverse one and was significant at the .01 level, based on the t statistic. Since service and percent backorders are inversely related, service and cost proved to be directly related.

The computer experimentation provides a general way to adapt this build-up forecasting model for use by any firm selling products in different market segments.

The forecasting technique, the prediction interval, and the level of detail should be manipulated to optimize the firm's objective. The LREPS model facilitates this manipulation by allowing the firm to input alternative simulated actual sales for testing different forecasting models.

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Several individuals and groups deserve recognition for their contributions, both direct and indirect, to this research. The industrial sponsor of LREPS, Johnson and Johnson Domestic Operating Company, is gratefully acknowledged. The research team, headed by Dr. Donald J. Bowersox, faculty advisor, and composed of several doctoral students, must be thanked. Team members were Dr. O. Keith Helferich, Dr. Edward J. Marien, Dr. V. K. Prasad, Dr. Michael Lawrence, Dr. Peter Gilmour, and Richard Rogers.

The dissertation committee consisted of Dr. Donald J. Bowersox, Dr. Richard J. Lewis, and Dr. Donald A. Taylor, all Professors of Marketing and Transportation at Michigan State University, and Dr. O. Keith Helferich, Systems Research Incorporated, Lansing, Michigan.

Dr. Bowersox, committee chairman and academic advisor, has guided me since the outset of my doctoral program. He gave me the opportunity to participate in the LREPS project and kept me focused on the research objectives of this dissertation.

Dr. Lewis' knowledge of forecasting techniques and statistical analysis was of great value in the development of the technical aspects of this research. His constant encouragement enabled me to persevere to the end.

Dr. Taylor, as department chairman, has been a steadying influence throughout my academic career. This is in addition to his valuable comments and suggestions regarding this work.

Dr. Helferich spent many hours explaining the intricacies of the LREPS model and informing me of the latest model sophistications. His suggestions led to many improvements in the forecasting model.

Additional support in the form of computer time and guidance was provided by Systems Research Incorporated. Without this assistance this study would have been extended by several months and hundreds of dollars.

To Gerald Brown, who provided the computer programming expertise for this research, I am indebted. His good humor as I continually changed by programming requirements should not be unrecognized.

The professional typing assistance provided by Mrs. Jo McKenzie is greatly appreciated. She remained patient despite my missed deadlines.

Finally, I wish to thank my wife, Karen, and son, Todd, for their patience and support throughout the duration of this research and my doctoral program.

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CHAPTER I

INTRODUCTION

Statement of Purpose

The determination of sales volumes for future time is mandatory for assessing a company's prospects. The sales forecast is the core of management's planning effort. However, even firms with the most sophisticated forecasting systems cannot evaluate their forecasting capabilities until anticipated sales become actual sales. The overall purpose of this research is to develop a way to deal with this measurement problem. This is accomplished by devising both a forecasting archetype and an approach for tailoring the forecasting model to meet specific needs.

Three traditional bases for categorizing forecasting models are:

1. The length of the forecasting period
2. The level of the forecast
3. The technique utilized.

Forecasting periods shorter than one year can be arbitrarily defined as short-term, while periods lengthier than one year are long-term in nature. The level of the forecast could be the economy, the industry, or the firm. Within the firm are product, product group, region, and product-region levels. Techniques can be described as either mathematical or nonmathematical with managerial judgment playing a vital role in either case.

To set the stage for the propositions which follow, a definition of a sales forecast is needed. The following definition that the American Marketing Association prescribes is used:[1]

> Sales Forecast--An estimate of sales in dollars or physical units for a specified future period under a proposed marketing plan or program and under an assumed set of economic and other forces outside the unit for which the forecast is made. The forecast may be for a specified item of merchandise or for an entire line.
>
> Comment--Two sets of factors are involved in making a Sales Forecast: (1) those forces outside the control of the firm for which the forecast is made that are likely to influence its sales, and (2) changes in the marketing methods or practices of the firm that are likely to affect its sales.
>
> In the course of planning future activities, the management of a given firm may make several forecasts, each consisting of an estimate of probable sales if a given marketing plan is adopted or a given set of outside forces prevails. The estimated effects that several marketing plans may have on Sales and Profits may be compared in the process of arriving at that marketing program which will, in the opinion of the officials of the company, be best designed to promote its welfare.

The following comments about the usefulness of forecasting provide an alternative viewpoint:[2]

> Once established, the sales forecase becomes the basis for marketing and other plans in the company, with the volume of sales forecast, in a sense, as a built-in goal. As a chemical company executive puts it, "When sales are forecast at a certain level, the entire operation--production, marketing support, sales manpower, etc.--is geared to that level of activity." This leads some to argue that the forecast is to a considerable extent self-fulfilling, so that any later comparison of actual sales with the forecast value may be a better gauge of marketing accomplishment than of forecasting accuracy.
>
> The spokesman for a large office equipment company feels strongly about this point. "I do not consider what we do 'forecasting,'" he asserts. "We are setting targets, self-fulfilling prophecies. One only forecasts events over which he has no control. This distinction needs far more emphasis than it is typically given."

The American Marketing Association's definition provides considerable direction for this research. First, several forecasts, each resulting from a different set of environmental conditions and marketing plans, should be prepared. Next, the forecasting period should be specified because different length periods are possible. Finally, the forecast could be made for an individual product or for the entire product line.

The executives' comments imply that a gauge for comparing forecasts with actual sales helps to evaluate forecasting accuracy and to measure marketing effectiveness.

Situation Analysis

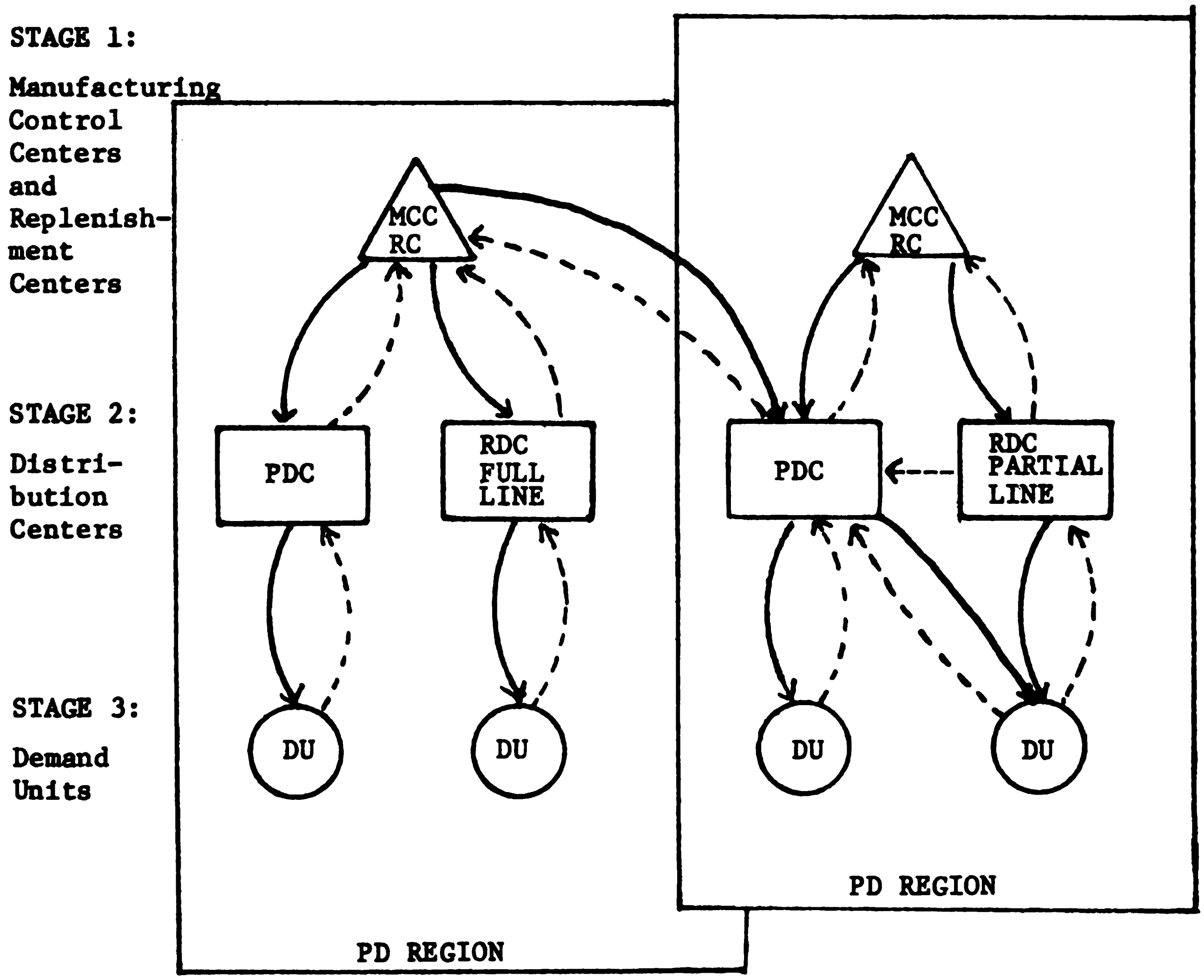
Computer simulation can incorporate the desired forecasting model features into a single comprehensive model. Simulation permits a more realistic and complex model for solving business problems than those possible through the application of analytical techniques.[3,4]

While a generalized simulation of the firm is not yet available, the physical distribution system has been modeled successfully. The integrated physical distribution network has been conceptualized as consisting of fixed facilities, transportation capability, inventory allocations, communication, and unitization.[5]

An overview of the typical physical distribution system appears in Figure 1.1. There are three stages of activities: (1) the Manufacturing Control Center (MCC) stage at which products are produced and inventoried at the Replenishment Center (RC), (2) the Distribution Center (DC) stage at which products are located adjacent to the marketplace, and (3) the customer demand stage, identified in Figure 1.1 as the Demand Unit (DU) stage. Demand units consist of the geographic customer groupings because the inclusion of individual customers as DU's is prohibitively costly and time-consuming. For this application DU's are defined as ZIP Sectional Centers, although counties,

FIGURE 1.1[1]

STAGES OF THE PHYSICAL DISTRIBUTION NETWORK



-------------INFORMATION FLOW ——————————PRODUCT FLOW

REGION...THE REGION IS DEFINED BY THE ASSIGNMENT OF RDCS AND DUS TO A PDC.
MCC......EACH MANUFACTURING CENTER PRODUCES A PARTIAL LINE.
RC.......REPLENISHMENT CENTERS STOCK ONLY PRODUCTS MANUFACTURED AT COINCIDENT MCC.
RDC......REMOTE DISTRIBUTION CENTER, FULL OR PARTIAL LINE.
PDC......PRIMARY DISTRIBUTION CENTER, EACH PDC IS FULL LINE AND SUPPLIES ALL PRODUCTS TO DUS ASSIGNED TO THE PDC REGION; PRODUCT CATEGORIES NOT STOCKED AT THE PARTIAL LINE RDCS IN THE REGION ARE ALSO SHIPPED BY THE PDC.
DU.......THE DEMAND UNIT CONSISTS OF ZIP SECTIONAL CENTER(S).

[1]D. J. Bowersox, et al., Dynamic Simulation of Physical Distribution Systems, Monograph (East Lansing, Michigan: Division of Research, Michigan State University, Forthcoming).

Standard Metropolitan Statistical Areas, Economic Trading Areas, and REA modified grid blocks were also given consideration.[6]

The distribution center stage includes four levels: (1) Primary Distribution Centers (PDC), which handle a full line of products and have the potential to serve all the DU's in a defined region of the total market area; (2) Remote Distribution Centers-Full Line (RDC-F), which handle all products; (3) Remote Distribution Centers-Partial Line (RDC-P), which handle only a portion of the product line; and (4) Consolidated Shipping Points (CSP), RDC-P's which handle no products, but function as points at which the demand of several DU's is agglomerated and served by a PDC. PDC's are capable of serving the same DU's served by RDC-P's; however, PDC's cannot serve the DU's served by RDC-F's.

A computerized model, encompassing all of the aforementioned components and activities, has been developed.[7,8] This model is entitled Long-Range Environmental Planning Simulator (LREPS). It is capable of simulating changes in the firm's physical distribution system, such as the addition of distribution centers or the rearrangement of communication linkages.

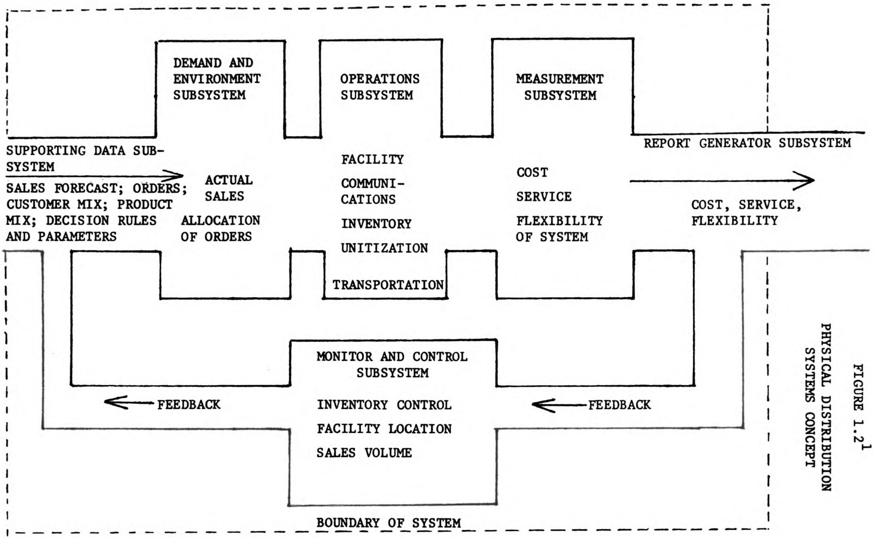
The conceptual model can be most easily understood by examining Figure 1.2, which illustrates the major model components. The Demand and Environment Subsystem (D&E) focuses on testing for changes in the customer and product mix and in order characteristics. The D&E also provides the sales level and the basis for allocating sales among DU's. The Operations Subsystem (OPS) processes orders through the major physical distribution activities. The Measurement Subsystem (MEAS) develops the criteria for evaluating alternative distribution system configurations. The Monitor and Control Subsystem (M&C) is the model supervisor and the controller section of LREPS in which feedback from past activities can dynamically affect current policy decisions. Exogenous data are inputted through the Supporting Data Subsystem which audits, reduces, and formats information into usable terms. Finally, model output is converted into managerial reports by the Report Generator Subsystem.

Figure 1.2 reveals the importance of the sales pattern as a critical input to LREPS. One of the unique features of LREPS is the treatment of sales volumes and patterns. Several activities carried out within the Supporting Data Subsystem relate to the preparation of sales data.

The first step is a detailed analysis of sales

FIGURE 1.2[1]

PHYSICAL DISTRIBUTION SYSTEMS CONCEPT



[1]D. J. Bowersox, _et al._, _Dynamic Simulation of Physical Distribution Systems_, Monorgraph (East Lansing, Michigan: Division of Research, Michigan State University, Forthcoming).

invoices. All invoices for several years can be analyzed, but statistical sampling can significantly reduce this number. Sample invoices are arrayed in matrix form. Invoices are randomly selected from the matrix, and each line entry on the invoices is compared with the list of tracked products (those included in LREPS as being representative of the entire product line). If the line entry matches a tracked product, then it is included as a line entry on a simulated invoice. The entry consists of product order dollars, weight, cube, and cases. Order summaries, including total order dollars, weight, cube, cases, and lines, are accumulated for all products. The simulated invoices representing the tracked products and customer types comprise the Order File Generator, from which orders are selected to fill simulated demand requirements.

Multiple customer types with different order characteristics (e.g., different average order dollars, weight, etc.) can be simulated. New customers with hypothetical order characteristics are also permitted. New products can be modeled by assuming values for the average and standard deviation of cases per order and dollars, weight, and cube per case. The distribution of lines per order can also be varied.

LREPS requires a data stream representing simulated actual daily sales. The pattern is arbitrary. It can be a simple linear trend, an oscillating function, or even a random function. Daily sales are allocated to 390 domestic DU's (derived from ZIP Codes) based on weighted indexes. The indexes are constructed by correlating regional sales with one or more independent variables. For example, if population were the only independent variable selected, then each index would be the ratio of the DU's population to the total U.S. population.

Orders are randomly selected from the Order File Generator until their total sales equals simulated actual daily sales. Detailed records are maintained for the tracked products for inventory control and system costing purposes. The results for the tracked products are extrapolated to represent the entire product line.

Research Problem

A specific research problem can now be formulated. The LREPS model facilitates the inputting of many sales patterns, each representing the effects of a different combination of marketing and environmental factors. The use of several forecasting levels is possible with LREPS, the most detailed being the product-DU level. Since one day is the smallest discrete event processed within LREPS, one week has been arbi

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has been arbitrarily defined as the shortest forecast interval; however, any longer interval is permissible. Different forecasting techniques can be applied to different products or regions. Finally, accuracy measurement formulae can easily be incorporated into LREPS. Every desirable feature of a forecasting model noted earlier can be handled within the LREPS structure.

The objective of this research is to build and to implement a model with flexibility along the three dimensions of forecasting technique, time interval, and detail, utilizing the unique allocative capability of the LREPS Order File Generator. The result is a build-up (from detailed to aggregate levels) forecasting mechanism. Emphasis is arbitrarily placed on a short-term (one year) time span.

LREPS provides the framework for the forecasting model and a way to validate the forecasting model's capability under controlled conditions. Several hypothesized actual sales patterns, each the result of different marketing plans and environmental conditions, can be simulated with the LREPS Order File Generator. Based on physical distribution costs and forecasting accuracy, management can determine the most appropriate forecasting technique, prediction interval, and level of detail needed to anticipate these sales

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these sales patterns. Assuming given external conditions, management can adopt a marketing plan and know which forecasting system is most useful.

To accomplish this objective, two research phases have been carried out. In the first phase the three dimensions of the forecasting model are studied, and a generalized forecasting mechanism is constructed. To guide the initial portion of this research and to lay a foundation for later computer experimentation, these questions were formulated:

1. What are the criteria for selecting the most useful forecasting system? How should a short-term (one year) forecasting mechanism be chosen? Although each firm is in a somewhat unique situation, perhaps certain guidelines could prove to be universally applicable.
2. What is the current "state of the art" of forecasting? What techniques are presently available for use in predicting sales volumes? Will the shortened time period (one year) decrease the number of alternatives?
3. What are the criteria for evaluating forecasting accuracy?

The second research phase is an example of an application of the generalized forecasting model, used in conjunction with LREPS. Computer experimentation is used to determine levels for the smoothing constant (parameter of the simple exponential smoothing model, the chosen forecasting technique), the time interval, and the level of forecasting detail. The effects on physical distribution costs and forecasting accuracy of varying these three dimensions are subjected to statistical analyses.

Both smoothing constant values and prediction interval values can be associated with physical distribution costs and forecasting accuracy by using regression and correlation analysis. The t statistic is used to test for significance of the relationships. The appropriate level of detail can be determined by comparing forecasting variances for alternative levels through the use of the F test. By specifying design constraints (e.g., minimized physical distribution costs or forecasting accuracy), management specifies the levels of the dimensions of the forecasting model.

Additional experimentation associating physical distribution costs and service is presented to illustrate a specific use for the detailed, short-term forecasting model.

Organization of Thesis

This dissertation consists of eight chapters. After the introductory chapter, Chapter II provides an overview of sales forecasting. The planning horizon covered by the forecast is discussed, as are the many uses for sales forecasts. A set of guidelines to aid in the selection of the forecasting technique is presented.

Chapter III details the various forecasting techniques along with a comparison of these alternatives. A forecasting technique to be used in conjunction with LREPS is chosen, using the selection criteria developed in the previous chapter.

Measures of forecasting accuracy are explored in Chapter IV. Both quantitative and qualitative approaches are dealt with in detail. In addition, an evaluative process is covered which differs somewhat from conventional statistical error analysis.

Chapter V delineates the research methodology followed in the computer experimentation. The research hypotheses are devised in testable form.

The first set of computer experiments is described in Chapter VI. At this stage the predictive equations, the build-up function, and the prediction interval are studied. The final version of the applied, short-term forecasting

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The second group of experiments, those relating the cost and service of physical distribution, are presented in Chapter VII. A comparison of experimental results with the traditional concept is offered.

Finally, Chapter VIII summarizes the previous findings to suggest a generalized approach to simulated sales forecasting. The implications for longer-term forecasting are discussed. Areas for future study which have been uncovered by this work are also outlined.

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CHAPTER I--FOOTNOTES

[1]Marketing Definitions: A Glossary of Marketing Terms (Chicago: The American Marketing Association, 1960), p. 22.

[2]Sales Forecasting Practices: An Appraisal, Experiences in Marketing Management, No. 25 (New York: The National Industrial Conference Board, 1970), p. 34.

[3]P. Gilmour, Development of a Dynamic Simulation Model for Planning Physical Distribution Systems: Validation (unpublished doctoral dissertation, Michigan State University, 1971).

[4]For a discussion of the usefulness of simulation in the analysis of business problems, see O. K. Helferich, Development of a Dynamic Simulation Model for Planning Physical Distribution Systems: Formulation of the Mathematical Model (unpublished doctoral dissertation, Michigan State University, 1970).

[5]D. J. Bowersox, E. W. Smykay, and B. J. LaLonde, Physical Distribution Management (New York: The Macmillan Company, 1968), Ch. 5.

[6]Helferich, pp. 112-121.

[7]Helferich.

[8]E. J. Marien, Development of a Dynamic Simulation Model for Planning Physical Distribution Systems: Formulation of the Computer Model (unpublished doctoral dissertation, Michigan State University, 1970).

CHAPTER II

OVERVIEW OF SALES FORECASTING

Introduction

As firms continue to adopt and to practice the marketing concept, anticipation of the future becomes critical. Prompt reaction to diagnosed needs indicates that the marketing concept has been implemented. The diagnosis, or the anticipation, provides the information base upon which marketing plans are constructed.

Many companies formalize this anticipatory process and call it "planning." The planning process includes objectives and strategies, policies, and detailed plans designed to achieve these objectives. Further, planning is operationalized through an organization which implements decisions and reviews performance to set the stage for another planning cycle.[1]

A primary component of planning is the sales forecast. The sales forecast is a vital link in the circuitous forecast-marketing activity-results (sales)-forecast, etc. relationship. Without the forecast, levels of marketing activity cannot be meaningfully determined. Conversely, not knowing the sales that result from a given level of marketing effort, the marketer can't develop a sound forecast. This circular process can "explode" by compounding the inaccurate forecast, or it can be "fine-tuned" by discovering the nature of the marketing-output relationship.

It is apparent that the objective of sales forecasting is to reduce the uncertainty which enshrouds management decision making.[2] The amounts of product sales in the different market segments obviously cannot be known exactly. The purpose of sales forecasting is to reduce the range within which sales will lie. So sales forecasting deals with probabilities, averages, variations, and confidence intervals.

An important aspect of any probabilistic process, such as sales forecasting, is the error of the estimate. (See Chapter IV for a detailed discussion of error analysis.) Anytime the future is evaluated, a certain amount of error is bound to be present under nondeterministic conditions. Error can arise from two different sources, depending on which is utilized: extrapolating historic data and estimating future business conditions. These are the two types of limiting approaches to forecasting. Using only historic data, or intrinsic factors, the foreca

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the forecaster assumes a continuation of past relationships and conditions. On the other hand, new variables and functions can be developed from extrinsic factors which take into account a supposed restructuring of traditional relationships.[3]

No matter which perspective is adopted, the timeliness of the forecast is an important consideration. In order to be a forecast, the estimate must be made before-the-fact. The estimate must be available soon enough to guide management as it develops plans for the forecasted period. As a result, the feedback mechanism must operate smoothly and precisely. Data must be available for analysis as soon as they become "history."

Planning Horizon for Forecasting

The forecasted planning horizon can be studied from two standpoints. First, it can be viewed from strictly a time-oriented perspective. Over how long a period is the firm forecasting? Is it a month, a year, or several years?[4] The other viewpoint refers to the scope or level of the forecast. Is the forecast made at the product, firm, industry, or even the national level?

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Forecasting Frequency

The frequency of the sales forecast is examined first. There are actually three subsets to this area of investigation. The specific time period for which forecast data are prepared is one area. Next is the frequency of preparation and revision of forecast data. The remaining subset is the longer-term period for which these shorter-term forecasts are collected.

A recent survey of 161 companies revealed that the most popular forecast period is one month. Table 2.1 highlights the responses collected from the reporting companies. The range of time periods which were mentioned includes day, week, month, quarter, half-year, and year.

As might be expected, the frequency of sales forecast preparations varies considerably from the time period for which forecasts are compiled. Table 2.2 presents the data on frequency of preparation. Forecasts are, however, revised between major preparations. This contention is supported by comparing Tables 2.2 and 2.3.

As noted in Chapter I, this research is aimed at short-term (one year and less) estimations; however, to complete this phase of the analysis, the length of the longer-term forecasting period should be presented. Table 2.4 summarizes the answers provided by the surveyed firms.

TABLE 2.1.--Shortest Time Breakdown Used for Sales Forecasts[1]

Time Period Breakdown	Percentage of Forecasts[2]		
	All Companies Reporting	Manufacturing Companies Reporting	Service Companies Reporting
Month	52%	55%	43%
Quarter	21	23	13
Year	22	17	40
Other[3]	5	5	4
Total	100%	100%	100%

Note: Based on information from 161 reporting companies--132 manufacturers and 29 service firms (insurance, banking, transportation, utilities).

[1]Sales Forecasting Practices: An Appraisal, Experiences in Marketing Management, No. 25 (New York: The National Industrial Conference Board, 1970), p. 23.

[2]Percentages are for forecasts made at all levels of product detail.

[3]Includes day, week, half-year.

TABLE 2.2.--Frequency of Sales Forecast Preparation[1]

Time Period Breakdown	Percentage of Forecasts[2]		
	All Companies Reporting	Manufacturing Companies Reporting	Service Companies Reporting
Annually	58%	53%	76%
Semiannually	4	3	11
Quarterly	20	22	9
Monthly	14	17	2
Other[3]	4	5	2
Total	100%	100%	100%

Note: Based on information from 161 reporting companies--132 manufacturers and 29 service firms (insurance, banking, transportation, utilities).

[1] Sales Forecasting Practices: An Appraisal, Experiences in Marketing Management, No. 25 (New York: The National Industrial Conference Board, 1970), p. 21.

[2] Percentages are for forecasts made at all levels of product detail.

[3] Includes "as needed," bimonthly, weekly, seasonally, biennially, and irregularly.

TABLE 2.3.--Frequency of Sales Forecast Revision[1]

Time Period Breakdown	Percentage of Forecasts[2]		
	All Companies Reporting	Manufacturing Companies Reporting	Service Companies Reporting
Monthly	24%	28%	0%
Quarterly	29	30	28
Semiannually	12	12	12
Annually	20	16	42
As needed	7	6	10
Other[3]	8	8	8
Total	100%	100%	100%

Note: Based on information from 161 reporting companies--132 manufacturers and 29 service firms (insurance, banking, transportation, utilities).

[1]Sales Forecasting Practices: An Appraisal, Experience in Marketing Management, No. 25 (New York: The National Industrial Conference Board, 1970), p. 22.

[2]Percentages are for forecasts made at all levels of product detail.

[3]Includes daily, weekly, bimonthly, and a few irregularly timed revisions.

TABLE 2.4.--Longest Period Ahead for Which Forecasts Are Regularly Prepared[1]

Longest Period	Percentage of Forecasts[2] All Manufacturing Companies Reporting	All Service Companies Reporting
Less than one year	12%	4%
One year	36	35
Between one and five years	19	11
Five years	28	33
Over five years	5	17
Other[3]	-[a]	0
Total	100%	100%

Note: Based on information from 161 reporting companies--132 manufacturers and 29 service firms (insurance, banking, transportation, utilities).

[1]Sales Forecasting Practices: An Appraisal, Experiences in Marketing Management, No. 25 (New York: The National Industrial Conference Board, 1970), p. 24.

[2]Percentages are for forecasts made at all levels of product detail.

[3]Includes irregular intervals (e.g., "life of product"); "skip" intervals (e.g., "next three years and the fifth"); and other indeterminate periods (e.g., "through the next season").

[a]Less than 1%.

The previous data indicate that the prediction period, revision frequency, and overall planning range vary considerably. Because of this variation, forecasts are generally classified as short-term (operating) or long-term (planning) in nature. The dividing line between these two extremes is not a sharply defined one. Often this margin is defined as the area of intermediate forecasts. A long-term forecast for one firm may be a short-term estimate for some other company, depending on several conditions which are discussed later.

Operating forecasts guide the company in its day-to-day or week-to-week functioning. Of particular relevance to this research are the effects of forecasts on inventories, distribution service capabilities, and distribution costs. Considerable detail is required for these operating forecasts to be useful. For example, product forecasts, or at least product group forecasts, would be necessary to maintain the inventory control system.

Long-range forecasts emphasize general tendencies in the sales pattern. These estimates are used as overall guides for the establishment of policy and the direction of corporate effort. Capital investment might be based on long-range sales expectations. The level of detail isn't necessarily as demanding for long-term forecasts. The general purpose of these estimates doesn't require a product-territory breakdown.

A convenient scheme for classifying forecasts could be based on a period of one year. If the scope of the forecast is one year or less, it could be defined as short-term in nature. If the forecast is for several years, it is a long-range estimate. To hedge slightly would be to define the range for intermediate forecasting as going from one to three years. The classificatory criterion is strictly arbitrary.

One rule to aid in the selection of the prediction interval has been outlined: the purpose of the forecast (operating vs. planning). A general set of guidelines can be suggested:[5,6,7,8]

1. Purpose of the forecast
2. Degree of accuracy desired
3. Characteristics of the time series
4. Availability of forecasting techniques
5. Fiscal year of firm.

The first guideline has already been covered in sufficient detail. The desired degree of accuracy refers to a general relationship between the length of the forecast period and the accuracy of the forecast. An accepted belief is that accuracy decreases as the time interval increases. This seems to be reasonable because the distant future is usually more unclear than the near future. The validity of this hypothesized relationship is explored during the experimental phases of the research.

Equally important as the level of accuracy are the basic characteristics of the time series. In other words, what is the expected volatility of sales over future time paths? A pattern indicating a smooth, regular change over time between periods of high and low sales may allow a relatively lengthy prediction period. Conversely, an erratic pattern may necessitate a shorter interval. Many factors could affect the regularity of sales. These include the nature of the product, geographic location of the market, and the rate of innovation, to name only three.

The availability of forecasting techniques is a "state of the art" limitation. As technology, primarily computers, advances, problems of data storage and manipulation are being overcome to a substantial degree. Excepting long-term trend analysis, long-range forecasting isn't reliable because of the limitations of current forecasting techniques.[9] Numerous authors have reported attempts to forecast the business cycle with varying degrees of success.[10,11,12] Until executives understand the inherent relationships of the business cycle, long-range forecasting will remain underdeveloped; furthermore, prediction intervals will necessarily remain short.

Finally, the corporate fiscal year imposes restrictions on the forecasting interval. Financial statements, tax returns, and budgets are generally prepared to conform to the fiscal time period. Since forecasting is such an integral part of budgeting, it is logical that the forecast would parallel the fiscal year.[13,14] Perhaps periods shorter than the fiscal period might be forecasted, but these forecasts could be aggregated to yield the forecast for the fiscal year.

Forecasting Level

The different levels of forecasting are typically classified as the economy, the industry, and the firm. Within the firm it is possible to reach an even more detailed level, such as by product, by geographic region (based on sales territories, supply locations, or some grid system) or by customer type. As firms become larger and look for new markets, perhaps the economy level will become a subset of a global forecast.

The implication of this treatment of forecasting levels is, so far, that proper forecasting technique entails a general-to-specific direction. In other words, the first forecast should be a general economic analysis, perhaps with an estimate of gross national product or disposable personal income. Knowing the forecast for general business conditions and the relative importance of the industry to the economy, a firm can develop the industry forecast. This is the "pot" for which competitors in an industry vie. Relative marketing effort determines what percentage of industry sales a given company captures. Beyond this, the marketing effort for a given product in a certain geographic area determines that product's sales in the area.

It is the contention here that the build-up approach is just as reasonable and logical an approach to forecasting as the aforementioned breakdown method. The build-up technique is essentially the opposite of the breakdown approach. Instead of going from general-to-specific, the build-up method emphasizes a reverse flow. The overall forecast is the result of consolidating many smaller, more detailed ones.

Several reasons can be suggested in support of the build-up approach. They are as follows:

1. The computer has significantly reduced the data storage and computational barriers to build-up forecasting.

2. Geographic segments may differ substantially

in terms of buying behavior.

3. Different products may exhibit dissimilar sales patterns over time.

4. Relative marketing effort may have a greater impact on sales than general business conditions.

As noted in Chapter I, the electronic computer is characterized by processing speed and data storage capacity. The nature of build-up forecasting calls for a large data bank. For example, a geographic-product class reference system, such as the one in LREPS, requires input data for each forecasting cell. In addition, predictive equations and parameters must be built for each cell, although certain cells may utilize the same equations. The critical role of the computer becomes evident. Without the data storage capacity the essential inputs could not be organized, and without the computing speed the forecasts would be prohibitively expensive and untimely.

For many reasons people in different parts of the country may react in unique ways to the firm's marketing effort. For this research the reasons aren't as important as providing a mechanism which allows the inclusion of contrasting behavior. If these segments weren't analyzed separately, the overall forecast might be reasonable; however, offsetting errors might hide the individual mistakes

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As with geographic variance, individual products can exhibit greatly differing sales patterns. A prediction formula for each product may be in order. Accuracy at the product level is especially important in terms of inventory management. Offsetting errors by product could result in a virtually ineffective system of inventory controls.

Perhaps the foremost reason for using the build-up approach is that it deals directly with the effect of the marketing plan. The breakdown method treats the marketing variables after considering general economic factors. Often times the firm in question may be only insignificantly affected by the level of national prosperity. In such cases, relative marketing effort may hold the key to sales volume. The build-up approach facilitates such an analysis by beginning with a detailed, segment-by-segment forecast.

Uses for Sales Forecasts

Earlier the distinction between long- and short-term forecasting was described, as was the purpose of these projections. The value to top management of sales estimates for distant time periods was noted. The forecast is a fundamental input to the long-range planning process, and the long-range plan provides the framework for short-term operations

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operations.[15] Since this research is primarily concerned with developing a short-term forecasting device, the uses discussed here relate to this time span.

The simplest way to appreciate the multiplicity of uses for forecasts is to examine a typical firm's organization chart. Nearly every branch or department requires a sales estimate as a guide to its operation. The emphasis here is on marketing's utilization of the forecast, but other uses are covered for completeness. A listing of the many company areas interested in the sales forecast would include the following:

1. Production
    a. output
    b. materials procurement
2. Engineering
3. Research
4. Personnel
5. Finance
    a. budgeting
    b. pricing
6. Marketing
    a. promotion
    b. pricing
    c. sales budgeting
    d. sales service
    e. distribution--includes inventories, transportation, communications, unitization, and facility location.

Economies in the production process are attained via high-volume production runs. Applying the systems concept, management realizes that minimizing production costs doesn't necessarily imply maximizing company profits. One means of emphasizing this message to production management is through the sales forecast. Fluctuating seasonal production requires trading off among production economies, storage costs, and other firm expenses. An important use of the sales forecast is to provide production managers with a gauge for planning and controlling output.[16] The forecast becomes the basis for assigning plant capacity, anticipating work force needs, and sequencing the delivery and storage of supplies and input materials.

A common use for the sales forecast by the engineering department would be in the scheduling of machinery repair and plant maintenance.[17] The sales forecast guides the production schedule which, in turn, can be used by engineering to arrange upkeep work during minimal production periods.

Anticipating the sales volume of a new product is a most difficult and critical undertaking, yet too often this is not done. A textbook application of the marketing concept would entail discerning an unsatisfied need as the first step in new product planning. But if the technical staff develops the product in the laboratory, independent of market needs, the sales forecast might be overlooked. This should not be the case. Regardless of the source of the innovation or its "newness," the sales forecast offers a rational assessment of potential.

The very nature of the personnel function implies a need for estimates of future sales. Determining the size of the work force, especially that proportion classified as a variable productive force, is dependent upon the volume of output. Again the sales forecast is a vital information requirement.

Another area inherently affected by the sales forecast is finance. Preparing corporate budgets and, with the help of department personnel, the departmental budgets, financial executives must know the anticipated sales volumes. A considerable amount of detailed forecasting is required to generate adequate budgets, especially for individual products or product groups. Long-term financial planning utilizes forecasts also, but this area is outside the limits of this research.

Marketing relies on correct forecasts as much as, if not more than, any other department. Often times promotional expenditures are planned on the basis of revenues. (The validity of this allocative sequence is not questioned ere.) Marketing and finance collaborate to set selling rices. The price is a function of market conditions and tandard costs, to list only the two most important factors. n estimate of volume is necessary to determine cost levels nd to validate market conditions. This is a circular rocess since sales depend on price and vice versa.

The sales manager needs the forecast to set terri- orial and product sales quotas and targets. The expected olume in each territory helps the manager allocate personnel n an equitable basis. Regional estimates aid in the estab- ishment of service branches by benchmarking the areas of oncentrated sales effort.

Distribution is another marketing area for which he sales forecast is an essential input. The impact of he forecast on inventories is readily observable from the tandard formula for the economical order quantity. If nly a constant cost of ordering (A) and annual carrying harge (i) are assumed, then the order quantity which inimizes cost is

$$Y = \sqrt{\frac{2AS}{i}}$$

here S is annual sales units. Adding more cost elements omplicates the formula, but the same cost minimization roblem remains. The problem seems simple enough. Yet an naccurate estimate for S makes the entire operation

superfluous. Without an accurate estimate for sales, the analysis reduces to a test of mathematical dexterity.

The other elements of the distribution system are influenced by the sales forecast more on a joint basis, rather than individually. This is a manifestation of the systems concept. An accurate forecast can reduce the number and size of inventories in the distribution system. The number of inventories is synonymous with facility locations. Facility location points can be reduced to the level where total distribution costs, also including transportation, communications, and unitization, are minimized. Without precise forecasts transportation and communications costs may be lowered because of the many, large inventory placements. The overall effect may be to incur nonoptimum system costs, due primarily to exorbitant inventory cost. Forecasting accuracy allows management to minimize the sum of all costs with a greater degree of confidence in the results.

Criteria for Technique Selection

Several points have been covered which can be listed in a set of criteria for guiding the selection of a sales forecasting mechanism. Other considerations have not yet been covered explicitly, but they merit inclusion in the ist which follows:[18,19]

1. Cost
2. Level of detail
3. Accuracy
4. Turning points
5. Market factors
6. Inputs
7. Planning horizon
8. Timing
9. Rigor
10. Clarity.

There is the temptation to beg the issue by leclaring that all companies are different and so to con-lude that this list is not useful. On the contrary, these en factors are independent of the firm being analyzed. very company should be able to appraise itself with espect to each factor. Contradictory objectives may be lluminated by such an analysis; nevertheless, these riteria help to focus on feasible forecasting methods.

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Cost is the expense associated with the functioning f the sales forecasting mechanism. This category includes he computer or clerical cost to operate the model, the cost to gather and format the data, and the cost to analyze and to prepare reports. By now the interdependence of these criteria should be apparent. Detail and accuracy, for example, are attained at a specific cost. Changing either of these will result in a different cost. Management must decide if the given forecast is the best for a reasonable cost level. If not, either the forecasting method can be changed, or the present approach can be analyzed for potential improvement.

Level of Detail

The level of detail refers to the intrafirm forecasting level. Is a forecast going to be developed for each product in each sales region? Or will a selected sample of products be tracked over time, as in the initial LREPS model? The importance of detail for operating forecasts has already been pointed out. Of course, if every product is forecast for each tiny geographical segment, accuracy is lost. There seems to be a level of detail beyond which sales volume is so small and erratic that forecasting accuracy is decreased.

Accuracy

Accuracy is an after-the-fact concept. Certain forecasting techniques may logically seem to be more useful in a given situation, but only by comparing performance with estimates can the forecast be evaluated. Management must continually monitor the forecasting mechanism for accuracy readings. (See Chapter IV for suggested accuracy measurement approaches.) Standards and tolerances can be set, based on managerial experience and judgment. If the forecasted data don't satisfy these conditions, a review is in order to pinpoint the causes. Diminished levels of accuracy can be blamed on erroneous assessments about certain of the other selection criteria. For example, the geographic grid system may define too many small regions with very little sales activity.

Turning Points

Foreseeing turning points could be considered as yet another form of accuracy measurement. However, it can be argued that most forecasting techniques are reasonably precise from a statistical viewpoint. The real test of the tool is whether or not it predicts turning points in the time path of sales.[20] This is particularly important for long-term forecasting. On a shorter time span, adjustments can be made for directional changes in sales patterns. For lengthy forecasts a shift in direction after a few months renders useless the remainder of the analysis based on the fo

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Market Factors

A number of market factors can be proffered which have an impact on the selection of a sales forecasting technique. The most important of these are (1) the diversity of the product line, (2) the number of marketing channels, (3) the degree of product "newness," and (4) the geographic market size.

Companies which have been acquiring subsidiaries or have been expanding into new markets have broad, and oftentimes unrelated, product lines. Unlike products are often affected by different factors, so the forecasting system must be more complex to deal with this divergence. Some products may be relatively easy to forecast, while others require a detailed technical analysis. The more diverse the company's product offerings, the more complex and burdensome the forecasting mechanism becomes.

The length, as well as the type, of the marketing channel influences the choice of the forecasting scheme. The company selling directly to the final consumer has only its own and its competitors' marketing strategies to assess. As the channels become lengthier, the marketing strategies of the

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of the intermediaries have a greater impact on the forecast. Also, the same product may be sold through different types of channels. For example, appliances may be sold under a firm's private label as well as through national retailers. Although the physical products are identical, the assumption that the same factors affect sales or that the same forecasting techniques are applicable for both products may be invalid.

An obvious problem in estimating the sales of a new product is the absence of historical data. Today, however, many so-called new items are merely variations on old themes or designs. Forecasts for these older or similar products can be modified to reflect the supposed advantages of the new product. A truly new development, such as a technological innovation, is a project for the marketing research department.[21]

If a firm sells certain products nationally and others regionally, then a regional approach to developing estimates seems reasonable. A product's sales may be affected by different factors in different parts of the country, again suggesting localized forecasting.

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Input Requirements

Inputs are of three types: data, human, and hardware. Data input refers to the "numbers," or informational requirements, of the forecasting model. The human category can be further broken down based on the task to be performed or the skills brought to bear on the problem. The ability to recognize and to choose among data source alternatives is needed, and mastery of the intricacies of the forecasting techniques is also important. Someone must perform the manipulative task of formatting the input data. Finally, interpretive skills are basic to proper utilization of the forecasted results. The last category, hardware, refers to devices such as computers which replace humans to perform the tedious, repetitive, and time-consuming computational processes.

It is difficult to say which of the three input types is the most important. A weakness in any one category may result in an unreliable forecast. Data are available from many locations. A firm with a good record-keeping system can rely on this internal source for much historical data. Statistical sampling can reduce considerably the data bank required to operate the forecasting mechanism. At the same time, data can be collected by a direct research program or by dealing with research agencies or public sources o

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sources of information, such as the government. A joint analysis of intra- and extrafirm data could provide insight into the future of sales patterns. Data associations might even be recognized which lead to correlation analysis.

The human element is an integral part of the forecasting process. A wide spectrum of know-how is required. Broad level guidance for choosing the model based on data availability is a must. This suggests a combination of technical competence and managerial judgment. At a slightly lower level, at least in terms of decision-making, is the capacity to extract the needed data from the massive corporate and public banks of information and to format it usefully. This is especially important in view of the increased reliance on electronic data processing equipment.

Ultimately, the forecast must be used; a forecast is not a goal in itself. The many uses for sales forecasts already mentioned in this chapter are evidence of this. Management at several levels will have access to the forecasted results. They should be aware of the weaknesses in the other factors, the data and the technique used. They should be told the degree of confidence which can be placed in the forecast.

Planning Horizon

The planning horizon has been detailed very thoroughly previously. Long-term or planning forecasts dictate gross forecasting approaches which sum but don't report explicitly all geographic and product estimates. Conversely, short-term or operating forecasts suggest this detailed reporting.

The specific forecast interval, such as a week or a month, affects the selection of the technique, as does the frequency of preparation of forecasts. Oft-repeated, short-term forecasts necessitate a model which is inexpensive to use. This implies a relatively small data base and an algorithm which iterates quickly. Forecasts for a year or more can be more sophisticated in terms of formulae and data needs if they aren't generated frequently.

Timing

No forecast, regardless of its precision or detail, is useful unless it is available on a timely basis--that is, available for use when needed. The speed with which a forecast can be generated, given the input, should be as fast as is economically feasible. Computers have resolved this problem considerably; however, less sophisticated or smaller firms may rely on mechanical or manual calculation.

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For these companies speed is very much a consideration.

If new input data are necessary for each forecast, such as with correlation and regression analysis, the timing of the availability of this information is critical. The input series should precede or "lead" the forecasted series. This enables the firm to use current data to forecast the future.

Rigor

Rigor refers to both the objectivity of the forecasting model and its technical assumptions. Subjective evaluation of the forecast is certainly permissible, but it is reserved for the users of the forecast. The model should not be designed to yield forecasts which match management's preconceived notions. The model should be an unbiased manifestation of fact, professionally constructed by capable personnel.

All of the quantitative forecasting methods are based on certain inherent assumptions, not always explicitly mentioned. Any forecasting method is weakened if it does not satisfy these assumptions about the data, sales patterns, etc. The more powerful methods have more rigorous sets of assumptions, but they yield more reliable output if these assumptions are met. Forecasting is analogous to statisti

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statistical testing. Nonparametric tests allow the researcher to test hypotheses. If the data conform to the requirements of certain parametric tests, then the researcher has more powerful tools at his disposal.

Clarity

This final guidelines draws on nearly all of the preceding criteria for its substance. A useful forecast must be understandable in terms of the technique used, the weaknesses of the forecast, the physical presentation of the data, and the preforecast research and analysis. A manager who merely receives a host of numbers referring to products and regions and time periods is in no position to make use of this data. On the other hand, every manager needn't be well versed in all of the technical facets of forecasting. For the manager perhaps physical layout is the most important factor. Hopefully, among the team members required to complete the forecasting process from start to finish will be people capable of answering any questions that management might ask.

Summary

This chapter has introduced the broad considerations of sales forecasting. The role of sales forecasting as a key element of the planning process should be evident.

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Both long- and short-range planning utilize the forecast. The length of the planning horizon is, therefore, a major concern of the firm. The impact of this variable planning period on sales forecasting is manifested in terms of the period length and detail of the forecast.

The several examples of the uses for forecasts serve to illustrate the company-wide value of these estimates. Virtually every department in the firm can make use of the sales forecast.

Finally, another perspective, that of a firm about to select a forecasting mechanism or evaluate the present one, suggests a set of guidelines to aid in the selection or evaluation. This universal list represents the major factors that a firm should consider.

With this overview of sales forecasting as a common starting point, a detailed discussion about and comparison of the various techniques for forecasting is meaningful. This presentation is found in Chapter III. Further, the importance of forecasting accuracy can now be better understood. Methods of error analysis are discussed in Chapter IV.

CHAPTER II--FOOTNOTES

[1] G. A. Steiner, Top Management Planning (New York: The Macmillan Company, 1969), p. 7.

[2] L. G. Erickson and R. J. Lewis, forthcoming publication (New York: McGraw-Hill, Inc., 1972), ch. 7.

[3] Management Operating System: Forecasting, Materials Planning and Inventory Management--General (White Plains, N.Y.: International Business Machines Corporation), p. 1.

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[6] Forecasting Sales, Studies in Business Policy, No. 106 (New York: The National Industrial Conference Board, 1964), pp. 7-8.

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[14]Erickson and Lewis, ch. 7.

[15]Steiner, pp. 211-212.

[16]Forecasting Sales, p. 4.

[17]Ibid., p. 5.

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[19]B. R. Copeland, Sales Forecasting for the Individual Business Enterprise (Ann Arbor, Michigan: University Microfilms, 1967), pp. 41-49.

[20]Erickson and Lewis, ch. 7.

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CHAPTER III

SALES FORECASTING TECHNIQUES

Introduction

This chapter presents an analysis of the various ways, both mathematical and nonmathematical, to forecast sales. The techniques covered are those that have been systemetized through usage. Individual guessing based on hunches, for example, is not included. Only those methods which can be reduced to a series of logical steps are discussed. The advantages and disadvantages of each technique are also presented. Next, the various techniques are compared with each other. The objective is to select the most appropriate technique for use in later experimentation.

Presentation of Techniques

Although considerable space is allotted to sales forecasting in most marketing texts, the basic forecasting techniques have not changed significantly in recent years. An occasional new application is mentioned, and perhaps small technical dimensions are added from time to time.

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However, the methods remain virtually unchanged.

Two general approaches to sales forecasting are popular. These are the build-up and the breakdown approaches. The build-up approach is characterized by qualitative or nonmathematical estimating, while the break-down approach can be either qualitative or quantitative.

Nonmathematical Forecasting

Four nonmathematical techniques are common:

1. Factor listing
2. Jury of executive opinion
3. Sales force composite
4. Users' expectations.

The overall approach in each instance is qualitative; however, this is not to say that these approaches are not structured. For example, in the sales force composite method each salesman may contribute his estimate based on a very thorough analysis.

Factor Listing.--The factor listing approach is the simplest of the qualitative approaches. It involves the development of a list of factors or events which have an effect on sales. Those factors which would increase sales are denoted accordingly, as are those lowering sales. Then the list is evaluated in one or both of two ways. First, the number of positive factors is compared with the number of negative ones. If there are more positive factors, then sales are expected to increase in the future. As might be suspected by now, a majority of negative factors would lead to a forecasted decline.

The second possibility is to assign weights, as well as a positive or negative sign, to each factor. A weighted total can then be computed by multiplying weights and signs and summing the results. Again, a positive score suggests a sales increase, while a negative total foretells a decline. The relative change expected might be available from the magnitude of the total score.

Obviously this technique, though structured, is unsophisticated.[1] It relies on the compilation of a thorough list of factors. Without such a list the approach is trivial. Considerable expertise on the part of the compiler of the list is required. In addition, the arbitrary assignment of weights under the second scoring possibility is subject to criticism. Simply by manipulating the weighting values, management can change both the sign and magnitude of the total score.

Jury of Executive Opinion.--This approach to sales forecasting has been practiced for many years by companies. So in spite of its simplicity, it's one of the oldest techniques available and in use.[2] It involves a combining or grouping of the estimates supplied by a cross-section of a company's executives. One writer has glamorized the process by subdividing it into the following three variations:[3]

1. An originating committee approach
2. A reviewing committee approach
3. A presidential survey approach.

The originating committee compiles the tentative forecast, as well as revised and final versions. If the committee also happens to be the budget committee, it can grant final approval of the sales forecast as the sales budget.

A reviewing committee does not prepare the initial forecast. Instead, this first draft is submitted to the reviewing committee for examination and revision. Ultimately, the reviewing committee approves a final forecast and submits it to the person or persons who have the authority to approve the forecast as the budget. It is possible that this authority is vested in the reviewing committee itself; hence, no further evaluation is necessary.

The presidential survey is similar to the originating committee approach in that several executives develop and submit forecasts. The executives don't meet as a group. The forecasts are reviewed by the chief operating officer, wh

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who eventually develops the finalized forecast. In this way the estimates of those the president considers to be the most pragmatic can be weighted more heavily; however, this technique stifles group discussion and relies on the skills of the president, who may not be the most qualified forecaster in the firm.

The jury of executive opinion method offers several advantages and disadvantages.[4,5,6,7,8] First, on the plus side, the approach can be implemented quickly. By specifying regular due dates for the projections, the committee or the president can routinize the process. Second, detailed or complex statistics may not be mandatory. Executives may rely on their many years of experience to develop their forecasts. Next, balance is achieved by drawing on many different departments throughout the company. Production, finance, marketing, and others may all be invited to participate, resulting in forecasts as seen from several vantage points.

Another benefit of the jury method is that it is "data free." That is, the jury approach doesn't require a data bank beyond that which is stored in the executives' memories. This method might be especially valuable for new firms, new products, or new markets for existing products. Finally, this technique supposedly synthesizes the most cu

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current information available. Alert managers are aware of the latest happenings within their departments, and marketers should be cognizant of market trends. The result should be an up-to-date, relevant forecast.

Considerable negative criticism has been aimed at the jury method of forecasting. The most obvious one is that personal biases and opinions are given considerable recognition. Guesswork, rather than fact-finding, may characterize this scheme. It has been suggested that many executives are in no position to assay potential market performance. Second, should highly paid and skilled executives be bothered with developing these estimates, particularly the operating forecasts? Couldn't their time be better spent on other tasks?

Another disadvantage is that the ultimate forecast is an average. The accuracy of an average of opinions is highly suspect. Fourth, since it is an average, the forecast cannot be traced to any one individual. Responsibility for the projections is dispersed throughout the firm. If there is a disparity between actual and forecasted sales, anyone can ease the pressure placed on him by simply blaming someone else.

Fifth, to get any kind of local, product line, or weekly forecast is nearly impossible. This would occupy an inordinate proportion of the executives' time. Management must settle for aggregate forecasts. Lastly, the inertia of committees may slow down the forecasting process. Several confident men in positions of power, each with a different opinion, provide the fodder for controversy and indecision.

Sales Force Composite.--The sales force composite method involves gathering data from either salesmen or sales managers. The former approach has been described as a "grass-roots" one because it represents the forecasts of the men closest to the markets.[9] Each salesman is asked to estimate future sales within his territory.[10] Often estimates are submitted for each product for which the salesman is responsible.

The National Industrial Conference Board, in a recent summary, cited many advantages of the sales force composite method:[11]

1. Uses specialized knowledge of men closest to the market.

2. Places responsibility for the forecast in the hands of those who must produce the results.

3. Gives sales force greater confidence in quotas developed from these forecasts.

4. Tends to give results greater stability because of the magnitude of the sample.

5. Lends itself to the easy development of product, territory, customer, or salesmen breakdowns.

The same source, however, also notes a number of disadvantages. These are as follows:[12]

1. Salesmen are poor estimators, often being either more optimistic or more pessimistic than conditions warrant.

2. If estimates are used as a basis for setting quotas, salesmen are inclined to understate the demand in order to make the goal easier to achieve.

3. Salesmen are often unaware of the broad economic patterns shaping future sales and are thus incapable of forecasting trends for extended periods.

4. Since sales forecasting is a subsidiary function of the sales force, sufficient time may not be made available for it.

5. Requires an extensive expenditure of time by executives and sales force.

6. Elaborate schemes are sometimes necessary to keep estimates realistic and free from bias.

By bypassing the salesmen and utilizing the specialized knowledge of the sales managers, a company can overcome many of the aforementioned shortcomings. These managers view the need for adequate and realistic sales forecasts from a management perspective. They realize the need for constant monitoring and updating of the forecast. Considerable time should be saved by freeing salesmen from the forecasting tasks for which they are likely ill-equipped.[13] A serious drawback of basing the forecast on sales management's estimates is the loss of the localized knowledge of the salesmen; however, managers might consult with their salesmen prior to formulating the forecast.

Users' Expectations.--Advocates of the users' expectations method propose that actual and potential customers are the best sources of information upon which to base an estimate. Of course, anytime a survey or questionnaire is used, problems of accurate representation of the population are encountered. Anticipating a poor rate of response, forecasters might poll an extremely large sample. If the population is small, it might be enumerated completely and researched.

As was the case earlier, arguments can be made by those favoring and those opposing this approach to forecasting.[14,15] First, the users' expectations method is based on information obtained directly from the users who, taken together, make up the firm's market. Second, the company can learn, maybe only subjectively, the thoughts underlying the intentions of buyers. Next, indirect sources, middlemen, are eliminated by going to the customer. The level of detail is under the control of the forecaster. Fourth, new product sales or new markets can be estimated when other methods are inapplicable.

Also, the notion of a survey seems logical because buyers are worthy of consideration. Other methods overlook

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this basic fact. Industrial buyers often plan ahead and buy periodically. Perhaps this personal contact will make known facts not discernable from other approaches, such as when a buyer plans to shift to another supplier. Last of all, the users' expectations method can serve as a cross-check on the results of another way of forecasting.

Objections to this approach have been raised. As noted, diverse markets with many products and users do not lend themselves, except at the expenditure of much time and money, to a survey approach. The reliability of users has to be considered. Uninformed or uncooperative buyers can seriously hamper the research. Third, any forecast based on expectations is a function of those expectations. If for some reason buyers' expectations are altered, the old forecast would be immediately outdated.

A survey approach is necessarily time-consuming. Pretesting of the questionnaire is almost mandatory. Considerable manpower is required to contact personally each respondent in the sample. The alternative is to rely on the lower return rate of voluntarily completed mail surveys. If there are any middlemen, they can exert considerable influence on the buying practices of purchasers. These intermediaries should be polled in a separate interview for completeness.

This concludes the study of the nonmathematical approaches to sales forecasting. These judgmental approaches may not be appealing to the trained statistician; nevertheless, they provide the means for the less technically trained forecaster to complete his assigned task.

Mathematical Forecasting

The mathematical techniques for forecasting which are covered here are the following:

1. Moving average
2. Exponential smoothing
3. Time series analysis
4. Regression and correlation analysis.

For each of the above quantitative approaches, a specific numeric or logical decision rule or process is executed to generate the forecasted value. There is nothing inherently superior about a quantitative technique as compared to a qualitative one, despite the aura of infallibility which seems to surround the former.

Moving Average.--Again, the starting point is the simplest of the alternatives. The term "moving average" is precisely definitive of the nature of this technique. The forecast is calculated by averaging sales for the most recent n time periods. As the data for another period

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become available, the average is recalculated, again for the last n periods. So the moving average technique consists of adding to the total the latest period's data and deleting the data from n+1 periods in the past. This total is then divided by n to achieve the forecasted value.

If t denotes the most recent time period and S(t) represents sales in period t, then the current moving average value is MA(t). Expressed symbolically, this relationship is

$$MA(t) = \frac{S(t) + S(t-1) + \cdots + S(t-n+1)}{n}$$

where n is the number of time periods.

Obviously the moving average value is easy to compute, especially once the initial value is obtained. The mechanics of the process can easily be programmed for use on an electronic computer.[16] Also, the technique is easily understood, so the problem of training personnel in its use is a minimal one.

Unfortunately, there are several limitations which cannot be overlooked. An inherent assumption of the moving average method is that the future will be, for the most part, an unweighted and lagged extension of the past. If this trend can be validated for a given product, then perhaps the moving average approach is an adequate one; otherwise, it's use ought to be discontinued.

Related to this first shortcoming is the unresponsiveness or sluggishness of the technique. For large values of n, current sales data make up only a small proportion of the total before averaging. Thus, if there is a radical and permanent shift in the direction of the sales pattern, the moving average won't reflect this until the preshift data are eliminated from the total. On the other hand, a small n value will result in a highly responsive, even volatile, system that overstates one-time fluctuations. The forecaster must be familiar with the product in order to choose wisely the value for n.

The size of the data base required to operate a moving average model is also a function of the number of periods. Extensive records must be maintained for each product. If n is increased, this data file increases accordingly.

Finally, because the moving average technique is a way to measure central tendency of data, the computed value is inappropriately called a forecast. Instead, any average is representative of the interval over which it was calculated. If the value must be located at some point within this interval, the midpoint is a much more logical point than an endpoint (as is the case with using the av

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average value as a forecast). Theoretically, any moving average value represents some past time interval and shouldn't be interpreted as a forecast.

Exponential Smoothing.--Certain of the shortcomings of the moving average method have been eliminated by exponential smoothing, which is really nothing more than a weighted type of moving average.[17] (The derivation which follows is based on work by Brown.[18,19]) Exponential smoothing bases the new estimate of sales on the previous estimate incremented by some fraction of the amount by which the old estimate differed from actual sales. Expressed in equation form, the relationship is

$$E(t) = E(t-1) + \alpha(D(t-1) - E(t-1))$$

where $E(t)$ is the estimate for period t, $D(t-1)$ is the actual demand for period t-1, and $\alpha \leq 1$. If like terms are combined, the equation becomes

$$E(t) = \alpha D(t-1) + (1-\alpha)E(t-1).$$

Brown has shown that by substituting consecutive values for $E(t-1)$, $E(t-2)$, etc., a form of weighted average is derived where

$$E(t) = \alpha D(t-1) + \alpha(1-\alpha)D(t-2) + \alpha(1-\alpha)^2 D(t-3) + \ldots + \alpha(1-\alpha)^k D(t-k-1).$$

The current estimate is a sum of past sales multiplied by different weights, which sum to one. The resulting equation i

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$$\text{New Average} = \alpha\,(\text{New Demand}) + (1-\alpha)\,(\text{Old Average}).$$

This formula doesn't correct for trend. It is possible to alter this equation so that corrections for trend are automatic. An estimate of the present trend could be

$$\text{Trend} = \text{New Average} - \text{Old Average}.$$

Reasoning analogous to that underlying the derivation of the New Average yields

$$\text{New Trend} = \alpha\,(\text{Current Trend}) + (1-\alpha)\,(\text{Old Trend}).$$

So the estimate for sales is the combination of trend and average values. The expected sales total is

$$\text{Expected Sales} = \text{New Average} + \frac{(1-\alpha)}{\alpha}\,(\text{New Trend}).$$

The analysis can be carried further if needed. Second and third order formulae which include the trend and the acceleration of change, respectively, can be derived.[20] The second order approach involves calculating the New Average as just shown, but calling the result the New First Average. That is,

$$\text{New First Average} = \alpha\,(\text{New Demand}) + (1-\alpha)\,(\text{Old First Average}).$$

Another average, based on the previous computation is

$$\text{New Second Average} = \alpha\,(\text{New First Average}) + (1-\alpha)\,(\text{Old Second Average}).$$

The latest forecast is

New Forecast = 2(New First Average) - New Second Average.

The trend value is

New Trend = New First Average - New Second Average.

Last, the final forecast is

New Final Forecast = New Forecast + New Trend.

Third order analysis requires that a new Third Average be computed so that the acceleration factor can be derived. The final forecast includes, then, the New Forecast, the New Trend (rate of change in forecast), and the New Acceleration (rate of change of rate of change in forecast). Both second and third order models are very sensitive to shifting sales.[21] Further corrections are possible to adjust for seasonality patterns in the data.[22]

A final variation of exponential smoothing is adaptive smoothing. Here, the value of the smoothing constant (α) is reviewed regularly, perhaps each time a new forecast is made. The value for the smoothing constant used to make the next projection is that value which would have given the most precise estimate for the last forecast period. In other words, alternative α values are used to project last period's sales. These several projections are compared with last period's actual sales. The smoothing constant value yielding the projection closest to actual sales is used to generate the next forecast.

Exponential smoothing is, because of its origin, more complicated than the moving average technique. This complexity can hinder the adoption of exponential smoothing as a method of forecasting. Lack of understanding may cause firms to select another, less sophisticated approach. Sophistication isn't inherently good, but to rule out a technique because of its complexity is unfortunate.

A serious disadvantage is the distortion over time in amplitude of the smoothed sales flow. The distortion depends on the nature of the input, the order of the smoothing model, and the proportion of disturbance or "noise" in the input information.[23,24] A random input, such as sales being twice the volume in a certain period as compared with any other period, would cause the forecasting model to overestimate for the next period. Then, the anticipation of a continued decline because of a return to previous sales levels would cause the subsequent period's sales estimate to be decreased. This distorted value would gradually be "washed out" of the system. The predictive pattern would be that of a dampened oscillation over time.

Several positive attributes can, however, be mentioned. After the model has cycled one time, the only data which must be saved are the most recent prior values of

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of the trend and the average (or the previous average and the most recent demand if the non-trend-adjusted version is used). Data storage requirements are practically nonexistent. Further, the computation is simple. Last of all, exponential smoothing is very appropriate for short-interval forecasting because in such cases causality or association can't be handled in a practical way.

Time Series Analysis.--A time series is a group or set of statistical observations arranged in chronological order.[25] There may or may not be a relationship between or among the values of the series. If such a relationship doesn't exist, successive values are said to be independent. Obviously, this study is not concerned with independent time series because they cannot be forecasted. Dependency is exhibited if successive values can be estimated based on previous values.

The standard time series model is composed of four components. These are:

1. Secular trend
2. Cyclical movements
3. Seasonal patterns
4. Irregular fluctuations.

Secular trend is described as the underlying general tendency of the time series. It is a long-term concept, encompassing ten or more years for adequate description. By definition secular trend is a stable phenomenon, manifesting itself in the form of a smooth line if plotted graphically.

Representation of the secular trend can be achieved by a variety of approaches. The simplest is merely to plot the data on a graph and visually fit a line to estimate trend. This is a very quick method, but it is dependent upon the bias of the drawer. Any two people are likely to develop different lines; hence, there are no criteria for fitting the line.

Another possibility is to divide the data into two equal time intervals. Then the average value for each of the two intervals is computed. These averages are plotted at the midpoints of the two intervals and are connected with a straight line. By finding the arithmetic difference between the two mean values and dividing this by the number of time periods, the slope of the line can be determined. The origin of the line can be arbitrarily set anyplace on the time scale by moving away from either of the means. This technique isn't biased like the free-hand method, but it is still very crude. Only straight lines can be generated, a very real weakness.

Last, a line can be fitted to a set of data on the basis of one of several statistical criteria. Perhaps the sum of the absolute differences between actual and computed (using the trend line) values could be minimized. A rather common approach is to minimize the standard error of the estimate. This leads directly to the "least-squares" method of line-fitting. Here, the sum of the squares of the differences between corresponding actual and computed (using the trend line) values is minimized. This means that

$$\varepsilon(Y-Y_t)^2 \text{ is a minimum}$$

where Y represents the actual values and Y_t refers to the corresponding computed trend values. An additional property of the least-squares method is that the sum of the differences between actual and computed values is zero. In other words,

$$\varepsilon(Y-Y_t) = 0.$$

Calculus can be applied to assure that these two restrictions are enforced. If a rectilinear relationship is assumed, the trend equation is of the form $Y_t = a + bX$, where Y_t is the forecasted (dependent) variable and X is the time (independent) variable. Values for a and b must be chosen such that the aforementioned conditions hold. Thus, the deviations which are to be minimized are functions of a and b. So

$$f(a,b) = \varepsilon(Y-Y_t)^2.$$

Since $Y_t = a + bX$, this relationship can be substituted into the above equation. Thus,

$$f(a,b) = \varepsilon(Y - a - bX)^2.$$

To minimize f(a,b), compute partial derivatives with respect to a and b and set them equal to zero. Hence,

$$\frac{\partial f(a,b)}{\partial a} = (-2)\varepsilon(Y - a - bX) = 0 \text{ and}$$

$$\frac{\partial f(a,b)}{\partial b} = (-2X)\varepsilon(Y - a - bX) = 0.$$

These two equations can be solved to get the so-called "normal equations"

$$\varepsilon Y = na + b\varepsilon X$$

$$\varepsilon XY = a\varepsilon X + b\varepsilon X^2.$$

Because of arbitrary coding of the time (X) variable, the εX term drops from each equation because it equals zero. The remaining relationships are easily solvable for a and b

$$\varepsilon Y = na \qquad\qquad a = \varepsilon Y/n$$

$$\varepsilon XY = b\varepsilon X^2 \qquad\qquad b = \varepsilon XY/\varepsilon X^2.$$

Curvilinear trend lines can be derived simply by assuming any of several possible curved relationships between X and Y and repeating the preceding minimization steps.

The least-squares and similar approaches seem to be the most useful of the trend-fitting techniques. Least-squares satisfies a specific set of criteria; it is unbiased and consistent. Further, it can be used to develop both straight- and curved-line relationships.

Cyclical movements refer to activities of the business cycle which occur over two to ten or more years. These recurring cycles are generally measured by estimating the interval between consecutive like turning points (e.g., from peak to peak). Length and amplitude of the cycle vary from product to product. The absence of a constant period and amplitude for a given product makes prediction even more difficult.

The combination of interproduct variation and intraproduct inconsistency results, as would be expected, in no highly accurate method for forecasting this particular part of the time series model. The standard approach is to describe the trend and seasonal factors and to combine the cyclical and irregular factors as a residual.[26] In particular cases the development of basic trigonometric functions to mirror the cyclic element might be feasible if consecutive periods are nearly the same and the amplitude variation is minimal. Fourier series analysis might also be attempted under such circumstances.[27]

Seasonal patterns reflect the variations which occur regularly and complete a cycle each year. Such factors as weather, customs, and religion are usually considered to be the major causes of seasonality. Higher sales during the days before Christmas exemplifies the impact of the seasonal element.

Numerous approaches for depicting seasonal patterns have been developed. Among these methods are (1) general average, (2) link-relative, and (3) ratio-to-trend.[28] The general average technique involves fewer computations and is probably the easiest to understand. Historic data for several periods are tabled. Then average sales values for each quarter (or month) are computed, and average quarterly (monthly) sales for the entire time (the "general average") is calculated. Indexes are derived by dividing the four (twelve) quarterly (monthly) averages by the general average. These indexes must sum to 400 (1200) to be adjusted for trend.

The link-relative method formulates the indexes into a chained or linked sequence by basing each index on the previous one. Again the data are arranged in table format by year. Indexes are computed by dividing quarterly (monthly) sales by sales for the immediately preceding period. In this way the indexes are linked together. The average index for each period is determined. Since the original data contain a trend factor, this can be removed by assuming a rectilinear relationship and adjusting the average indexes. As always, quarterly (monthly) indexes should be adjusted so that they sum to 400 (1200).

The last main approach to developing seasonal indexes, ratio-to-trend, is the most complex. The initial step is to devise a trend line to represent the historic data. A least-squares approach would be acceptable, as would a four-quarter (twelve-month) or longer moving average because a long-term average eliminates seasonal fluctuations. Ratios of actual sales to trend values are calculated and tabled by year. Then average quarterly or monthly indexes can be computed and adjusted to sum properly.

Certainly these means of isolating the seasonal element differ in usefulness. The ratio-to-trend approach involves more computation, yet it will permit curvilinear trend assumptions. All the other approaches assume a rectilinear trend. The link-relative method is the easiest to use because once an initial trend value is known, all other seasonal-adjusted estimates for a given year can be obtained by a simple multiplication. The general average technique is a simple and "common sense" method for obtaining rough indicators of the seasonal factor.

The fourth and final time series component is irregular fluctuations. These movements are erratic and unpredictable. They result from such causes as disasters and windfalls. Because of their very nature, irregular fluctuations are not able to be forecasted; instead, they are included as residual variations.

These four time series components are typically related to each other in either a multiplicative or additive model. The general form of the multiplicative model is

$$Y = T \times C \times S \times I$$

where

Y = actual sales data

T = secular trend

C = cyclical movements

S = seasonal patterns

I = irregular fluctuations.

Y and T are in terms of sales dollars or units. S, C, and I are ratios (or percentages) which adjust the trend to equal actual sales. An additive model can be used which has the form

$$Y = T + C + S + I.$$

In this case all components are in terms of dollars or units.

Time series analysis offers several advantages to its users.[29] It forces forecasters to probe into the component factors which affect sales. By isolating the various influences, management hopefully can develop a better understanding of products and their sales patterns. Related to this first advantage is the systemitized approach to forecasting offered by time series analysis. It is an organized, step-by-step method which should result in consistent findings when applied by any trained forecaster.

A third reason for adopting time series analysis is that considerable detail is possible. Naturally much work would be necessary to derive initially the equation parameters for many products and regions, but then a computer could perform the forecasting and revisions with ease by simply iterating through a matrix of equation parameters.

Unfortunately, short-term forecasting using time series analysis is a bit risky, especially if the data base used to build the model is formulated in terms of longer time periods. For example, if quarterly historic data were used to construct the relationships, monthly or weekly forecasts are theoretically possible, but practically unsound.

Regardless of the data, trend and cyclical components are multiyear in nature. This violates the earlier one-year-or-less definition of a short-term period.

The need for considerable historic data has been alluded to already. In addition, technical know-how for developing the projection model from this broad spectrum of data is vital. In the hands of a novice, time series analysis as a forecasting tool could be a dangerous weapon.

A series shortcoming is the lack of a causal relationship. Time series analysis assumes a continuation of prior sales movements. There is no intrinsic relationship between time and sales volume. Of course, if adequate research and study suggest a continuation of past patterns, then time series analysis is quite useful.

Finally, there is a chance that random or irregular factors present in past data may overshadow relatively the effects of the predictable time series components. Care must be taken to isolate the regular factors without being misled by the unusual fluctuations.

Regression and Correlation Analysis.--Regression analysis and correlation analysis are sometimes mistakenly defined alike. Actually regression analysis refers to methods for estimating values of a variable based on information about one or more other variables. Correlation analysis encompasses measurement of the degree or strength of the association among the several variables.[30]

Regression analysis can be categorized as either simple or multiple. Simple regression involves estimating values for one variable (dependent) based on corresponding values for one other variable (independent). Multiple regression, then, forecasts dependent variable values on the basis of values for two or more independent variables.

No directional causality is implied for dependent and independent variables. A cause-effect relationship could, in fact, exist in either direction; however, determination of causality is not a necessary condition.

A graph or scatter diagram is an advisable first step in the use of simple regression analysis. The diagram depicts the general nature of the relationship and aids in the selection of the mathematical archetype.

As was the case with time series analysis, regression analysis utilizes a goodness-of-fit criterion in developing an equation to represent historic data. The most widely used rule is, again, to minimize the sum of the squares of the deviations of actual and computed sales values (vertical deviations with sales plotted on the ordinate). The analysis is similar to that described for time series, except that the X value is no longer restricted to a time dimension. The units of X may be in terms of any dimension measurable on an interval scale. Obviously for multiple regression a scatter diagram is difficult to draw for two independent variables and impossible for three or more.

Several assumptions underlie the use of regression analysis for forecasting. They are as follows:[31]

1. The regression error must be randomly distributed with zero expected value.

2. The variance of the regression error must be the same for all values of X (homoscedasticity).

3. Individual forecast errors must be statistically independent of each other (no autocorrelation[32]).

4. Individual forecast errors must be uncorrelated with the independent variable in the forecast equation.

5. The underlying relationship between Y and X must be strictly linear if the regression slope parameters and forecasts based upon it are to be independent of the distribution of the X's in the sample.

A sixth restriction, applicable in the case of multiple regression, is that multicollinearity should be minimized and, ideally, equal to zero. It is beyond the scope of this paper to explain rigorously the impact of imposing these six restrictions. Each condition can be commented on in terms of its practical importance.

The first assumption has intuitive appeal even for the nonstatistician. The error in using the regression formula ($Y-Y_c$) to estimate sales should be randomly distributed and should sum to zero for a large number of observations. Otherwise, the so-called error would be predictable and could be incorporated into the formula. Only when the expected value is zero is the equation reliable.

Homoscedasticity simply means that the variance of the regression error is independent of the location within the relevant range of the predictive equation. For example, if Y is an increasing function of X, then larger Y values are associated with larger values of X. Homoscedasticity implies that the variance of the prediction error is the same for both large and small values of X. The confidence interval about the regression line is of constant width for all X values and is not extreme-value sensitive.

Autocorrelation of forecast errors generally causes the forecast variance and the variance of the regression slope parameter to be biased downward. This implies more information about the regression slope, b, than is actually available.[33] Autocorrelation should be minimized.

The fourth assumption relates somewhat to the concept of homoscedasticity. Here the regression error is not permitted to be an increasing or decreasing function of the independent variable. If there is a relationship between X and error, the forecast can reflect this association. This restriction is more important for structural analysis, for obtaining unbiased b estimates, than for forecasting.[34]

Model linearity refers to the regression equation's coefficients. Adding a cX^2 term to the right side of the standard $Y = a + bX$ equation does not result in a nonlinear function. The variables are still included in linear combinations. However, adding an X^c term generates a nonlinear form. Logarithms provide a means of eliminating nonlinearity in this second example. If the underlying relationship between Y and X is curvilinear, the distribution of the independent variable must be controlled to ensure proper interpretation of the regression parameters.[35] Perhaps successive rectilinear equations over restricted ranges of X could be used to approximate the curved relationship.

The existence of multicollinearity implies dependence among or between the independent variables. Multicollinearity reduces the efficiency of the estimates for the regression parameters; however, for efficiency in forecasting sales (Y) the interrelationships among dependent variables pose no real problems. Of importance is the amount of information about Y available through the use of the independent variables taken in concert, not separately. If two independent variables correlate perfectly, one can be dropped because it doesn't add any insight not already present by including the other one.

A number of measures have been popularized for examining the strength of the relationship between the dependent and independent variables. These are the coefficients of correlation (r), determination (r^2), nondetermination (k^2), alienation (k), and association (A). These variables can be represented symbolically. For any X value, three Y values are of interest. These are Y, the actual or observed Y value; Y_c, the value computed by using the regression line; and $\overline{Y}$, the mean of the historic Y values. The total variance, σ_y^2, or the variance of Y values about their mean, $\overline{Y}$, is $\varepsilon(Y-\overline{Y})^2/n$. The unexplained variance, σ_{yc}^2, or the variance of Y values about the regression line, is $\varepsilon(Y-Y_c)^2/n$. The explained variance, σ_{yx}^2, or the variance of Y_c values around the mean, $\overline{Y}$, is $\varepsilon(Y_c-\overline{Y})^2/n$. It can be shown that

$$\frac{\varepsilon(Y-\overline{Y})^2}{n} = \frac{\varepsilon(Y-Y_c)^2}{n} + \frac{\varepsilon(Y_c-\overline{Y})^2}{n}$$

or

$$\sigma_y^2 = \sigma_{yc}^2 + \sigma_{yx}^2$$

thus

$$1 = \sigma_{yc}^2/\sigma_y^2 + \sigma_{yx}^2/\sigma_y^2.$$

$\sigma_{yx}^2/\sigma_y^2 = r^2$ = coefficient of determination
= the relative reduction in squared error (variance) due to estimating values of Y from values of X.

$\sigma_{yc}^2/\sigma_y^2 = k^2$ = coefficient of nondetermination
= the relative amount of squared error (variance) remaining due to estimating values of Y from values of X.

$r = \sqrt{r^2}$ = coefficient of correlation.

$k = \sqrt{k^2}$ = coefficient of alienation = the remaining relative amount of absolute error due to estimating values of Y from values of X.

$A = 1-k$ = coefficient of association = the relative amount of reduction in absolute error due to estimating values of Y from values of X.

It is difficult to say which of these measures provides the greatest insight into the strength of the association between X and Y. The interpretation of r^2 as a relative type of measure is, perhaps, more logical than that of r, which is dimensionally meaningless. However, r is easily analyzed by using statistical testing. Because of their interrelated nature, all coefficients can and should be calculated once r^2 or k^2 is known.

A primary reason for utilizing correlation and regression analysis is objectivity. The technique practically guarantees a cold, hard look at a situation without the danger of human bias. Of course, a forecaster could eliminate some possible independent variables from the study by allowing his intuition to guide him. Generally, regression and correlation analysis leads to an objective and measurable result.

The preliminary investigation required to develop a set of potential independent variables leads to a more thorough understanding of the factors influencing sales.

The subtleties of the relationship between sales and other factors become clearer. There may be a temptation to interpret a strong association as causality, but this may not be true. It is possible, however, to discover a causal relationship. Such a finding would obviously be invaluable to all those who rely on the forecast for information.

Because the effects of different independent variables on sales may vary throughout the country or by product, many variables may have to be selected; nevertheless, regression and correlation analysis is still very useful. Different sets of equations on a regional basis may enhance forecasting accuracy. Certainly in the limit every product in every location could be studied individually to determine the most suitable variables and equations.

A final reason for the possible adoption of this technique is the availability of a measure of the strength of the predictive equation. By looking at the five coefficients derivable from the historic data, management can evaluate the reliability of the projections. A critical assumption here is that past relationships will continue to hold, at least on a relative basis.

This previous point introduces a negative consideration: the impact of residual or excluded independent variables. Surely no analyst is capable of achieving a perfect relationship ($r^2 = 1.0$) among sales and all needed independent variables on every attempt. Even the slightest imperfection sets the stage for later forecasting error. For example, within the current range of values an excluded independent variable may have a negligible impact on sales. Suppose the strength of the association increases considerably beyond the current range. Unless someone notices this, the forecast goes awry without a reasonable explanation.

The availability of data related to the independent variables could be regarded as another limiting feature of this technique. If indexes are used as predictors, especially aggregates of economic activity, oftentimes only annual data are available. Unless the independent variables are leading series, they may have to be predicted in order to be used as input to the regression equations.

A considerable volume of data is required to operationalize this type of model. Detailed historical analysis is necessary to derive the regression equations. Continuous updating is advisable so that the parameters will reflect the most recent tendencies. Lack of data timeliness, availability, or accuracy could each have a detrimental effect on forecasted output.

Last, it is apparent that considerable technical expertise is a must in order to understand and to develop the relationships. This point can be re-emphasized merely by studying any intermediate or advanced text dealing with regression and correlation analysis. Likewise, those using the forecast may be mystified by the inner workings of the model.

Comparison of Sales Forecasting Techniques

To attempt to generalize about the relative merits of the aforementioned forecasting techniques is to be somewhat arbitrary at best. Surely, the rankings depend upon the experiences of the user, as well as his reading knowledge of the alternatives. Regardless, a relative ranking is presented in Table 3.1. Cross-rankings between quantitative and nonquantitative classes are not attempted because of noncomparability. For instance, it is not patently obvious, except for a specific case, whether or not polling a sales force costs more than running a computerized regression model.

The ranking scheme is from one to four. A "1" is the best in the sense of least-cost, most detailed, fastest, etc. Equal rankings are indicated by an average of the specific rankings involved. For example, two 2.5's

TABLE 3.1.--Comparison of Sales Forecasting Techniques

Techniques	Ranking Criteria									
	Cost	Level of Detail	Accuracy	Turning Points	Market Factors	Inputs	Planning Horizon	Timing	Rigor	Clarity
(FL) Factor Listing	1	3.5			2	1	2.5	1	4	
(JE) Jury of Executive Opinion	2	3.5			3.5	2	2.5	2.5	3	
(SF) Sales Force Composite	3	1			3.5	3	2.5	2.5	2	
(UE) Users' Expectations	4	2			1	4	2.5	4	1	
(MA) Moving Average	1	4			3	1	2	3.5	4	
(ES) Exponential Smoothing	2	1			3	2	1	3.5	2.5	
(TS) Time Series Analysis	3	2.5			3	3	4	1.5	2.5	
(RC) Regression and Correlation Analysis	4	2.5			1	4	3	1.5	1	

indicate a tie between the second and third methods. Also, no rankings were developed for the selection criteria of accuracy, turning points, and clarity. These are best measured, as noted before, in terms of absolute standards germane to a specific company and situation.

The rankings deserve some comment to clarify or, as the case may be, to justify the tabled results. Cost would seem to increase going from Factor Listing (FL), to Jury of Executive Opinion (JE), to Sales Force Composite (SF), and finally to Users' Expectations (UE). Increased manpower requirements characterize this sequence. In addition, UE entails devising a sampling instrument and the attendant costs of testing and tabulating.

SF yields a more detailed forecast because it is a buildup approach. UE may come close to this level of detail, but at the cost of an extremely thorough sampling. FL and JE, because of their general nature, practically preclude any detail.

UE can reveal the important market factors if the test instrument is well-rounded and properly constructed. The FL approach suggests management's list of possible factors, but JE and SF only indirectly incorporate these market factors.

It is logical that required inputs would parallel cost movements. FL requires only a set of factors with intuitive weightings. JE calls for top executives to pool their knowledge and to expend a certain amount of effort and time. To implement an SF approach, considerable manpower must be used, including both field sales personnel and sales managers. An adequate UE forecast calls for marketing research people, a test instrument, research validation, tabulation, and interviewer or postal service costs.

Analyzing relative strength in terms of the planning horizon is a difficult task. It seems that the FL and JE methods might be more useful for long-term forecasting, while SF and UE lend themselves to a shorter time period. The first two approaches tend to be more general and planning oriented. On the other hand, salesmen and customers may have more precise estimates for the near future. Overall, none seems to be good for both long- and short-term forecasting.

The timing criterion has been applied assuming that the forecast being sought is not a first-time one. In other words, the projection mechanism is already is existence. An FL approach should be the fastest to operate because of its basic simplicity. An SF or JE estimate should be next fastest if the process has already been formalized.

The proper signals need only to be sent to those involved to trigger the return of the individual forecasts. Last, UE requires prodding many customers to respond, not always an easy task, even if good customer-firm relations exist.

The degree of rigor is inversely related to cost. A valid customer survey would be most appealing to the theoretician because of its representativeness. A detailed sales staff survey might approach a customer survey in rigor, but the information gathered would still be second-hand. Even more removed from the market place are the results obtained from the FL and JE approaches. They are the least exacting.

The quantitative techniques are also listed in order of increasing cost--Moving Average (MA), Exponential Smoothing (ES), Time Series Analysis (TS), and Regression and Correlation Analysis (RC). Again, this sequence corresponds to increasing input requirements. MA requires only the most recent n values for sales and a calculator (or a computer for many computations). ES may be even simpler in terms of raw data requirements, but greater technical know-how is needed. TS calls for much data, technical capability, and computing equipment. Finally, RC is even more demanding than TS with respect to data and technical ability because of possible multivariate, nonlinear applications.

Perhaps ES is the most flexible in level of detail. It can be implemented at nearly any level, and it is especially useful for generating product-by-product projections. TS and RC are just as effective theoretically as ES, but there are certain practical limitations. Sales of low volume items can't be estimated with confidence, and relationships between independent variables and a specific product may be weaker than for product classes or areas of the country. MA is practically limited because it is an averaging method. Low volume or high volume, volatile products make averaging historic data a useless exercise.

Only RC actually considers market factors in the form of the independent variables incorporated into the model. The other three quantitative approaches emphasize data patterns, not relationships or causalities.

The four techniques appear, at first glance, to be about equally appropriate for different length planning horizons. Actually only ES offers true flexibility, but it generally is used at the shorter end of the time scale. TS, by virtue of its component structure, can be utilized only over a longer-range interval. Projections should not be computed for periods shorter than those of the historic data used to derive the equations. The same warning is relevant for MA. Last, RC's usefulness is largely a function of the periodic availability of values for the independent variables. Often such data are obtainable only on a yearly basis.

TS and RC can both generate forecasts throughout their relevant ranges. As long as the assumed relationships hold, the equations can be used. MA and ES are data-bound in that they both require the latest value for actual sales before a new forecast can be produced. TS and RC are capable of forecasting at a more advanced date than either MA or ES.

The most rigorous of the quantitative techniques is RC. Nonlinear and multivariate alternatives are possible, as well as simple linear models. Several restrictions on data and model structure must be met. Finally, five coefficients for evaluating the strength of the relationship can be derived. TS is based on a best-fit criterion, and it decomposes historic data into four component flows. ES can be weighted to be very responsive to current input, or just the opposite. The MA approach is obviously the least sophisticated; it is a simple average over several periods.

Selection of Forecasting Technique

The remaining task at the present time is to choose the sales forecasting technique to be used in conjunction

with the LREPS model. The foregoing presentation, analysis, and comparison of techniques provide the framework for this selection. The discussion which follows is organized on a priority basis.

First, since the LREPS model is a quantitative, computerized simulation, the forecasting mechanism must lend itself to either logical or symbolic expression. All eight techniques satisfy this test, although the quantitative methods are somewhat easier to program.

Next, all data input must be available at the start of a simulation and be capable of being updated through feedback linkages in the model. The nonquantitative techniques start to fall short at this point. For example, to anticipate and to program all the thought processes in which an executive or a salesman might engage while updating his initial forecast is an impossible task. Likewise, to conduct an opinion poll of simulated product users is to know in advance the way in which they think, making the poll results trivial. The nonquantitative approaches to sales forecasting can be eliminated from consideration.

Third, the need is for a short-term mechanism capable of forecasting in detail by product and by geographic region. Fourth, the operating cost is inconsequential because any technique will not contribute substantial additional cost when compared with existing model operating costs. Based on level of detail required and the desired planning horizon, exponential smoothing is the most appropriate choice. In addition, this approach is less demanding in terms of inputs than the more rigorous techniques.

Timing becomes less important because of the relatively short time interval being studied. Also because of the one year time span, the importance of market factors is diminished. This forecasting mechanism is for control purposes, not for long-range planning.

As a result, the importance of detail, inputs, and the planning horizon seem to indicate an exponential smoothing model. This, then, is the adopted forecasting technique. The format of the model is

$$\text{New Forecast} = \alpha(\text{New Demand}) + (1-\alpha)(\text{Old Forecast}).$$

Summary

The objective of this chapter was to describe the alternative forecasting techniques so that a wise selection of the technique to be used in conjunction with the LREPS model could be made. As was shown, there are two main categories of techniques, nonmathematical and mathematical. Included in the nonmathematical group are factor listing, jury of executive opinion, sales force composite, and users' expectations. The mathematical approaches are moving average, exponential smoothing, time series analysis, and regression and correlation analysis.

Each technique has its strengths and weaknesses. To choose correctly the most appropriate technique, management needs to compare a set of selection criteria with the relative rankings of these techniques. The situation facing the firm dictates which technique is suitable.

For purposes of short-term computer experimentation, exponential smoothing appears to be the most useful of the various techniques. Forecasts for short time periods are possible, as are regional and product forecasts.

CHAPTER III--FOOTNOTES

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CHAPTER IV

FORECASTING ACCURACY

Introduction

The critical nature of sales forecasting as the core of the planning process has been mentioned, as have been approaches for estimating future sales volumes. In order to ensure sound forecasts, however, the firm needs bases for evaluating the reliability or accuracy of these projections. Further, the assessment of the forecasting mechanism should be a continuous process; a model which is appropriate now may not be valid in future time periods. To validate a model with the historic data used to develop it is surely an incestuous approach.

The question of how to measure forecasting accuracy is not a simple one. Certain mathematical forecasting techniques have built-in measures to guide the user in their application. These specific measures are not universally applicable. In this study only general techniques for determining the accuracy of any approach to forecasting are presented.

Hirsch and Lovell suggest several criteria which can be used to appraise alternative measures of forecasting accuracy:[1]

1. It is obviously advantageous to work with a measure that may be regarded as an index of the cost to the firm of erroneous forecasts.

2. It is useful to have a measure of forecast accuracy that is independent of units of measurement so that the relative accuracy of forecasts by large and small firms will be comparable.

3. It is helpful, at least for certain purposes, if the yardstick of precision rates the forecaster relative to the difficulty inherent in the type of series he is trying to forecast.

4. It is useful to judge the forecasts both with and without systemstic bias.

The first rule implies that the magnitudes of the error levels are important if the impact of a given error is to be determined. The second guideline suggests the need for a dimensionless, relative measure of error. Third, the sales pattern of the firm must be analyzed. Finally, bias should be removable. The overall need is, then, for an absolute, relative, difficulty-weighted, and unbiased error measure. Apparently no one gauge will be able to satisfy these all-inclusive, even contradictory, criteria.

The remainder of this chapter looks at accuracy measurement in terms of several perspectives. First, common statistical techniques are presented. Next, a generalized turning-point approach is covered. Last, evaluation based on firm objectives is suggested in addition to the previous approaches.

Statistical Accuracy Evaluation

As might be suspected, there are several ways to measure forecasting accuracy with mathematical derivations. A listing of such methods would include the following:[2,3]

1. Standard deviation
2. Mean-square error
3. Mean absolute deviation
4. Correlation coefficient
5. Theil's inequality coefficient
6. Adaptations of previous measures.

Each measure is now discussed in detail, highlighting the reasons for the possible use of each.

Standard Deviation

The standard deviation is an obvious choice as a yardstick for appraising forecasting accuracy. The general formula for computing the standard deviation of a sample is

$$s = \sqrt{\frac{\Sigma(Y-\bar{Y})^2}{n}}$$

where s is the sample standard deviation, Y is an individual observation, $\overline{Y}$ is the average of all such sample observations, and n is the number of observations. For use in the context of a forecasting evaluant, each Y can be interpreted as the difference between a forecasted and an actual sales value, $Y_f - Y_a$. So $\overline{Y}$ is the mean of all such values in the sample and is equal to $\overline{Y_f - Y_a}$.

As is the case with other measures which follow, the standard deviation does not satisfy all of the criteria noted at the outset of this chapter. It is an absolute measure, so interfirm comparisons are not possible. The first point, suggesting an error index related to cost, is tested in Chapter VI for a combination of error measurement methods. No reading on the inherent complexity of the forecasted time series is supplied by the standard deviation. In general, this criterion is beyond the scope of this research and is left to econometricians. Unfortunately, the standard deviation can hide consistent over- or underestimation, so it does not remove systematic bias.

Statistical testing is possible by utilizing the variance, the square of the standard deviation. The F test permits comparison between forecasting approaches by comparing the resulting variances in ratio form.

Mean-Square Error

An alternative to the standard deviation is the mean-square error (MSE), which can be shown to be related to the standard deviation. An expansion and rearrangement of terms yields

$$\frac{\varepsilon(Y-\bar{Y})^2}{n} = \frac{\varepsilon Y^2}{n} - \frac{(\varepsilon Y)^2}{n} .$$

The first term on the right of the equality is the mean-square error. Since it is a component of the standard deviation, it is simpler to compute. The size of the numbers involved when using the mean-square error is one draw-back of the technique; hence, comparisons between firms is not meaningful.[5]

Work has been done which indicates that the mean-square error may be proportional to certain production and inventory costs.[6] A more comprehensive model, such as LREPS, could be used to verify these claims. Because it squares an absolute difference, the mean-square error would flag any steady positive or negative forecasting mistakes.

Mean Absolute Deviation

The general form for the mean absolute difference is

$$\frac{\varepsilon|Y|}{n}$$

where, according to convention, Y is the difference between actual and forecasted sales. This approach ignores the sign of the difference and gives the average value of the unsigned forecasting error. This technique is the simplest so far, and it is the easiest and fastest one to calculate. However, comparisons between large and small firms are impossible because the measure is absolute, not relative. Consistently bad estimates are pinpointed because of the absolute value.

Correlation Coefficient

There may be an association between predicted and actual changes in sales volumes. A correlation coefficient which measures the strength of this association can be computed. The formula

$$r^2 = 1 - s_e^2/s_a^2$$

where r^2 is the coefficient of determination, s_e^2 is the variance of the forecast error, and s_a^2 is the variance of the sales data.[7] The interpretation of r^2 is the same as for the coefficient of determination discussed in the previous chapter in the section dealing with regression and correlation analysis. The range of values possible for r^2 is from zero to one.

This gauge is a relative one, so it encourages matching among companies. If a firm consistently under-estimates sales, it could receive a perfect score of unity. Thus, the correlation coefficient does not eliminate bias.

Theil's Inequality Coefficient

Theil developed a test statistic which is bounded at the lower extreme by zero.[8] The measure is

$$U = \sqrt{\frac{MSE}{(Y_a)^{2/n}}} .$$

A perfect forecast yields a U of zero, while forecasting error results in U values greater than zero. If U=1, the same result could have been achieved by forecasting a value of no change from the previous actual value. If U is greater than one, the forecast of no change was better than the forecast used.

The relative value is desirable for making comparisons. It imposes a penalty for systematic linear bias because of the incorporation of the mean-square in the relationship.[9]

Adaptations of Previous Measures

Hirsch and Lovell have suggested several transformations and combinations of the aforementioned measures.[10] The first such coefficient is

$$r_1^{\,2} = 1 - \frac{MSE}{\varepsilon(Y_a)^{2/n}} = 1 - U^2 \quad .$$

The value of this adaptation is in the very meaningful interpretation which can be given to values of r_1^2. An r_1^2 of one indicates perfect forecasting. A value of zero suggests the same results could have been realized by making the naive forecast of no change. Finally, negative values imply the forecaster is doing worse than could have been done with the naive estimate.

Another possibility is

$$r_2^2 = 1 - MSE/s_a^2.$$

This coefficient compares the accomplishments of the forecaster with the root-mean-square-error obtained by a naive forecaster who consistently predicts the most recent average sales value as the estimate. Unless the actual data exhibit a trend, this coefficient is useless. It does show that the forecaster working with a series displaying a consistent trend is working with a simpler problem.

Additional manipulations can be performed which reflect seasonal or cyclic fluctuations. If certain characteristics of the actual sales pattern are known or suspected, error measurement can be refined considerably.

A general improvement can be made to correct all of these measures to relative form. This is to define the actual and forecasted values in relative terms. That is, let a_t be the actual relative change in sales and f_t be the forecasted relative change, both for period t. Then,

$$a_t = \frac{Y_{a,t} - Y_{a,t-1}}{Y_{a,t-1}} \qquad f_t = \frac{Y_{f,t} - Y_{a,t-1}}{Y_{a,t-1}}$$

where $Y_{a,t}$ is actual sales in period t and $Y_{f,t}$ is forecasted sales for period t.

This conversion is especially important for using the F test to compare variances for different forecasting periods. For example, comparing variances for the difference between actual and forecasted sales in absolute terms for two different intervals, one being one day and another being three months, would probably be a waste of time. If average daily sales is 100 units and the range is $\pm$10%, then to forecast the average would be to err by no more than 10 units. With quarterly sales equal to 6,300 units (because one quarter equals 63 days within the LREPS model) and the range being $\pm$10%, forecasting the average could result in an error of 630 units. The standard deviation of the forecast for the larger prediction interval would be much larger than for the one day interval. However, using the relative definition of the standard deviation would eliminate this noncomparability.

If a and f are substituted for Y_a and Y_f, respectively, in the foregoing presentation, the adjustment for relativity is included. Thus, in the previous formulae Y now becomes a - f instead of $Y_a - Y_f$.

Nonmathematical Accuracy Evaluation

The ways just presented to determine forecasting accuracy are ones which all firms and managers may not understand. They probably would feel comfortable in terms of peer group evaluation if they used such methods. In other words, if the benefits of using such evaluatory techniques are ignored, there may be pressure to use these methods "just because we should."

This hypothetical situation, if it exists, is a sad one indeed. For persons who may be trapped by such circumstances, a possible solution can be cited. A less sophisticated technique, at least in terms of the mathematics, is the analysis of turning points. One can argue that the critical element of sales forecasting is to determine the direction of change of sales volume.[11] Given the direction, either a continuation of the present or a change in trend (a turning point), any of the previous forecasting techniques could be used with an acceptable degree of precision. Accordingly, the "hit" proportion on predicting turning points is a simple measure of forecasting prowess. An arbitrary "batting average" can be set as a minimum acceptable proportion of correct directional estimates. If a company is not anticipating turning points a high enough proportion of the time, then the application and choice of technique should be re-evaluated.

The value of correctly foreseeing turning points often is not appreciated by forecasters. A simple example dramatizes the crucial nature of such anticipations. Suppose a firm's sales volume is increasing by about 10% per time period with the range of the increase being between 8% and 12%. The length of the time period, the number of products involved, and the geographic region in question are not important for purposes of this illustration. Now suppose for next period the firm projects another 10% incremental increase in sales when, in fact, a 10% decrease is realized. The net effect is an overestimate of 20%. This error is considerably larger than the historical ±2% per period. If the firm had based its operating plans on the tolerance level of 2%, then the 20% could prove to be disastrous.

Another illustration highlights individual product studies. A firm might be able to forecast within an acceptable range for a product group. For simplicity imagine a grouping of 10 products. Suppose five products have been increasing in volume over time, and five others have been declining in sales. If the sales of each set of five were comparable, a reversal by each would leave total sales generally unchanged. The internal changes would make a shambles of physical distribution performance. There would be stockouts, excess inventories, poor service, premium replenishment costs, and backorders.

Thus far, only the proportion of turning points correctly prognosticated has been mentioned. At least two statistical tests can be used to evaluate the firm's record of anticipating these directional switches. A logical first choice would be an application of the binomial test. A brief example shows the usefulness of this test. If the process by which a turning point is forecast involves someone merely flipping a coin, then the probability of correctly forecasting a turn when it occurs is 0.5. A comparison of an actual z (or t) value with a critical z (or t) value based on the desired confidence level could be made. The actual value is computed from

$$z \text{ (or } t) = (p - 0.5)/\sqrt{(.5)(.5)/n}$$

where p is the proportion of turning points correctly estimated and n is the number of turning points or sample size. If n is sufficiently large, say, greater than 30, then the z statistic is appropriate; otherwise, t is used. The hypotheses and the corresponding acceptance and rejection regions depend upon the objectives of the researcher.

The runs test, used in conjunction with the binomial test, may be more enlightening. It is possible that the firm is forecasting only one-half of the turning points. Thus, the results of the binomial test would not be significant. If the proportion of mistakes (or correct estimates) follows a nonrandom pattern, then the runs test would reveal this. The runs test identifies the extreme cases of many or few runs (sequences of like events) in a sample. As an extreme case, with C indicating a correct turning point forecast and I denoting an incorrect one, imagine the following sample of 20 forecasts:

CCCCCIIIIICCCCCIIIII

The proportion of correct projections is exactly 0.5, and the number of runs is four. The probability of observing four or fewer runs with two subsamples of 10 elements each is 0.001. Thus, it is very unlikely that the above pattern is a chance occurrence.

It should be pointed out that analysis of turning points is more appropriately applied to planning or long-term forecasting. When the forecasting interval is large, a directional error has a greater impact. Operating forecasts made weekly can be updated to compensate for directional errors. Annual forecasts for a planning horizon of several years had better be directionally correct;

otherwise, they are worthless.

Accuracy Evaluation by Objectives

During the course of selecting and evaluating a forecasting model, a company can easily become involved with the details of the process and lose sight of broader objectives. Certainly the assumptions underlying the various techniques must be considered, and the planning horizon should be studied carefully. The forecast is not, however, an end in itself. The value of the forecast is measured by how much it contributes to the planning process. Should not forecasting accuracy be measured in a like manner? How is effective planning manifested? One gauge is the constrained level of cost or profit. The constraints may complicate the problem considerably, but cost and profit are measureable accounting concepts.

The LREPS model presents an opportunity to examine the relationship between forecasting accuracy and physical distribution system costs. For each forecasting model used measures of forecasting error are collected. At the same time, physical distribution costs are monitored. Thus, cost and error are tracked simultaneously. If accuracy is truly reflected in the system objective, minimized constrained physical distribution cost, then error and cost profiles should be quite similar. The ideal forecasting mechanism is the one which yields minimum total costs.

This concept can be generalized to any system utilizing a forecast as an input. To be safe, patterns of cost and error should be reviewed for similarities. Possibly one system component of relatively larger size might not rely on the accuracy of the forecast; hence, little benefit would accrue to the firm which emphasizes increased precision in its estimates. Usually an insightful way to compare forecasting alternatives would be to compare respective system costs.

Summary

A forecasting model cannot be ignored once it is in operation. It should be monitored regularly to assess its performance. Several approaches for carrying out this evaluation have been presented. Statistical analysis is quite popular, and many variations of standardized statistics have been developed. As an alternative, turning point analysis offers the less quantitative forecaster a means of evaluating performance.

Regardless of the forecasting technique and error analysis employed, the objective of the forecast should not be overlooked. Forecasts provide, in the limit, valuable input to the planning process. To a lesser extent, different segments of the firm need projections. A sophisticated planning model, such as LREPS, can utilize a complex and accurate forecasting mechanism. On the other hand, for other uses a less complex forecasting model could probably sacrifice some accuracy, yet still be a valuable tool.

CHAPTER IV--FOOTNOTES

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[8]H. Theil, *Applied Economic Forecasting* (Amsterdam: The North-Holland Publishing Co., 1966), pp. 26-32.

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[10]*Ibid*., pp. 39-42.

[11]Erickson and Lewis, ch. 7.

CHAPTER V

RESEARCH METHODOLOGY

Introduction

The general form of the short-term build-up forecasting model has been conceptualized and programmed. The research to this point has been aimed at fulfilling the first part of the overall research objective, that of developing a forecasting archetype. This chapter begins the presentation of a continuing illustration of how the general model can be applied in a particular situation, the remaining part of the overall objective. It should be noted that the data used in this example are disguised because of the competitive nature of the industry in which the sample firm operates.

First, the forecasting model is described in its entirety. Next, the researchable hypotheses which guided the experimentation are outlined. Finally, the research sequence used in carrying out the computer experimentation is presented.

The General Model

The forecasting mechanism discussed is flexible in terms of three dimensions. In Chapter I it was suggested that the forecasting technique, the level of detail, and the prediction interval should be variables which can be assigned different values. The model was designed with this in mind. Each of these three dimensions can be varied as the situation dictates.

In Chapter III exponential smoothing was chosen as the appropriate technique for short-term forecasting. The ZIP regional system and the broad range of possible tracked products found in LREPS allow the use of many techniques at the same time. However, only exponential smoothing was deemed suitable for this search. To maintain maximum flexibility, the smoothing constant was allowed to vary by product and by region. At one extreme, the same smoothing constant can be used for all products and regions. At the other extreme, each product area can be assigned a different smoothing constant.

The second dimension, level of forecasting detail, is operable at four levels. These are the firm, the product, the DU (ZIP Sectional Center), and the product-DU. More levels are theoretically possible, but were not modeled.

One of the unique features of this model is that it

facilitates the development of aggregate forecasts by accumulating lower-level estimates. For example, product forecasts can be generated by summing all product-DU forecasts for that product. Alternatively, the forecast can be made at the product level, but product-DU projections would then be only arbitrary fractions of this product total. Even though the aggregate forecasts might be equal under the two approaches, the detailed forecasts under the build-up method should prove to be more accurate and, thus, more useful.

Variations in the prediction interval are quite easy to achieve. The forecasting module within the LREPS model is simply called at different times during the simulation run. Frequent callings generate frequent forecasts, but for shorter periods, and vice versa. Again, different product-DU's can be assigned unequal forecasting intervals.

The computer experimentation described in Chapter VI deals with these three dimensions as they relate to a specific company. The dimensions are interrelated to formulate a specific forecasting model.

Researchable Questions and Hypotheses

Several questions were devised which served to focus the research on specific topics. These questions are:

1. What are the "best" values for the smoothing

constants of the predictive equations for the sample data? These values can be determined through experimentation--evaluated on the basis of forecasting accuracy and physical distribution costs--or by examining previous research aimed at this problem.

2. What prediction interval (day, week, month, etc.) is most appropriate? What is the functional relationship between physical distribution costs and the size of the prediction interval?
3. What is the nature of the build-up function which provides the national forecast from the local forecasts? In other words, how much detail is required for a satisfactory forecast?
4. What is the relationship between physical distribution costs and system service levels? Cost has been traditionally considered to be an increasing function (at an increasing rate) of service level.

A set of testable research hypotheses can be derived from each question. From Question 1 a relationship between equation parameters (smoothing constant values) and cost can be hypothesized:

H_0: There is no association between smoothing constant values and physical distribution costs.

H_1: There is an association.

Since both data sets are at least interval in nature, regression and correlation analysis is applicable. The smoothing constant can be treated as the independent variable and cost as the dependent variable. The significance of the sample correlation coefficient (r) can be learned by using the t statistic

$$t = r/\sqrt{(1-r^2)/(n-2)}.$$

A two-tailed test is in order with H_0 being rejected if the absolute value of the computed t is greater than the critical t value.

The following relationship between physical distribution costs and the size of the prediction interval is based on Question 2:

H_0: There is no association between the size of the prediction interval and physical distribution costs.

H_1: There is an association.

As for the previous question, the sample correlation coefficient can be examined by the use of the t statistic.

The emphasis of Question 3 is on the derivation and comparison of alternative build-up functions. This can be done by comparing sample variances for the same forecasting level for any two alternatives. The variances are in relative terms. The hypotheses are:

H_0: The variances for any ZIP area (DU) and product are equal for the two build-up functions.

H_1: The variances are unequal.

Additional hypotheses about other equivalent forecasting levels are formatted similarly.

The ratio of the two variances being compared exhibits an F distribution. The test statistic is

$$F = s_1^2/s_2^2$$

where the s^2's are the sample variances with s_1^2 arbitrarily chosen as the larger value for convenience in comparing actual F values with tabled critical F values. H_o is rejected if the actual F value exceeds the critical value.

Another set of comparisons relating to the selection of an adequate level of detail is based on Question 3. Given the accuracy and associated physical distribution cost at one level, does the next level of forecasting detail offer a significant improvement? The supposed relationships of the sample variances are:

H_0: The variances are equal for the two levels of forecasting detail.

H_1: The variances are unequal.

Once more, the F test can be used as described for the previous hypotheses.

The relationship between physical distribution costs and forecasting accuracy can be hypothesized as a result of the preceding analyses:

H_0: There is no association between forecasting error and physical distribution costs.

H_1: Higher levels of forecasting error are associated with higher levels of physical distribution costs.

This set of hypotheses can be tested by computing the value of Spearman's rank correlation coefficient (r_s). The nonparametric test is in order because several measures of error are reasonable, as can be seen from the discussion in Chapter IV. Thus, a weighted composite index of error measures can be displayed only in rank order. The computed r_s is based on

$$r_s = \frac{n\sum_{i=1}^{n} x_i y_i - (\sum_{i=1}^{n} x_i)(\sum_{i=1}^{n} y_i)}{\sqrt{\left[n\sum_{i=1}^{n} x_i^2 - (\sum_{i=1}^{n} x_i)^2\right]\left[n\sum_{i=1}^{n} y_i^2 - (\sum_{i=1}^{n} y_i)^2\right]}} .$$

In this instance x_i refers to forecast error and y_i refers to physical distribution costs--both ranked ordinally. The computed r_s is compared with the critical value of r_s, based on sample size and significance level. Since the hypothesized relationship is a direct one, the critical

r_s has a positive sign. If the computed r_s is greater than the critical r_s, H_0 is rejected.

The subject of Question 4 is the relationship between physical distribution costs and service. The specific hypotheses are:

> H_0: There is no association between physical distribution cost and service.
>
> H_1: Higher physical distribution costs are associated with higher service levels.

With service as the independent variable and cost as the dependent variable, regression and correlation analysis is applicable. Again, the t statistic in one-tailed form is suitable for the testing of these hypotheses.

Research Sequence

The questions are ordered to provide a sequence for the experimentation. The analyses of Questions 1, 2, and 3 were carried out concurrently. That is, smoothing constant values, prediction intervals, and build-up functions were derived simultaneously. Initial values were selected on the basis of research by Packer[1] and others. Changes were made to yield different combinations of these three factors. The result was a convergence on an optimum combination for the selected alternatives. This phase of the research is presented in Chapter VI.

The second set of experiments was designed to isolate the effect of physical distribution service on costs. Since the structure of the components of total cost could also have changed, these costs components were traced too. The results of these experiments are covered in Chapter VII.

CHAPTER V--FOOTNOTES

[1]A. H. Packer, "Simulation and Adaptive Forecasting as Applied to Inventory Control," Operations Research (July, 1967).

CHAPTER VI

DEVELOPMENT OF THE DETAILED FORECASTING MODEL

Introduction

The general short-run forecasting mechanism with exponential smoothing as the selected technique serves as the framework for the detailed sales forecasting model. Specific levels for the three dimensions of prediction interval, level of detail, and smoothing constant are chosen for consideration. Various combinations are tested to determine a heuristically optimum set. Since an infinite number of combinations are possible, only a limited number are examined.

The following relationships are studied in this chapter:

1. The relationship between the exponential smoothing constant and physical distribution costs.

2. The relationship between the prediction interval and physical distribution costs.

3. The relationship between levels of forecasting detail.

4. The relationship between forecasting accuracy and physical distribution costs.

For all experimentation the same pattern of actual simulated sales is used. The daily sales total is considered to be increasing by a constant amount (rectilinear trend). Variation in sales is achieved by assuming sales values to be normally distributed about this trend line. These random fluctuations represent chance variations in daily sales. Even if a firm experiences rigidly increasing sales (a strict linear trend), day-to-day variations are likely to occur. Each day the trend value for sales is adjusted by the product of a normal random deviate times the standard deviation of daily sales.

To simplify experimentation the LREPS structure has been condensed. Instead of examining many products and 390 Demand Units (DU's), 10 sample products and 31 DU's are utilized. This represents a partial product line and a region of the country. This greatly reduces computational cost and time, while still facilitating the testing of the build-up concept.

Smoothing Constant and Prediction Interval Experimentation

Smoothing constant and prediction interval values are handled concurrently because, as stated in Chapter II, they interrelate as variables in the planning process. The choice of values for one of these variables affects the range of choices for the remaining one.

Several writers have researched the range of appropriate smoothing constant values.[1,2] Brown notes that a value of 0.01 results in a sluggish and nonresponsive model, while 0.5 is a volatile and overly sensitive choice. He suggests further that 0.10 is a satisfactory alternative to these extremes.[3] For this research the following five values were selected:

0.01 0.05 0.10 0.30 0.50

The choice of a prediction interval is more difficult. Since the overall period of analysis is one year, this is the maximum value. Such a choice would not facilitate the initialization needed to allow the exponential smoothing model to function properly. For this reason the lengthiest interval examined is three months. Even this selection results in only four forecasted periods, a relatively small number of observations.

The LREPS model has been designed to process no events shorter than one day, so this is the lower bound on the prediction interval. Because of this design constraint, one week is the shortest selected interval. The prediction intervals used are as follows:

1 wk. 2 wks. 1 mo. 2 mos. 3 mos.

There are 25 combinations of smoothing constant and prediction interval values, as shown in Table 6.1. For each combination variable physical distribution cost was collected. These data are presented in Tables 6.2 and 6.3 with fixed prediction interval and smoothing constant values, respectively.

Variable physical distribution cost was selected for analysis because of the short-term nature of these experiments. Of the cost components within LREPS, including inbound transportation (Manufacturing Control Center to Demand Unit), outbound transportation (Distribution Center to Demand Unit), throughput, ordering, facility, and inventory, only inbound transportation and inventory costs vary with service requirements in the short run. Higher service levels (delivery to more customers with less variation) are achieved with the larger inventories and frequent replenishments (inbound shipments); therefore, cost is increased. The other components remain fixed for periods of one year or less.

Smoothing Constant Analysis

The first set of research hypotheses tested related the smoothing constant to physical distribution costs:

TABLE 6.1.--Combinations of Smoothing Constant and Prediction Interval Values

Experiment	Smoothing Constant	Prediction Interval
11	0.01	1 wk.
12	0.01	2 wks.
13	0.01	1 mo.
14	0.01	2 mos.
15	0.01	3 mos.
21	0.05	1 wk.
22	0.05	2 wks.
23	0.05	1 mo.
24	0.05	2 mos.
25	0.05	3 mos.
31	0.10	1 wk.
32	0.10	2 wks.
33	0.10	1 mo.
34	0.10	2 mos.
35	0.10	3 mos.
41	0.30	1 wk.
42	0.30	2 wks.
43	0.30	1 mo.
44	0.30	2 mos.
45	0.30	3 mos.
51	0.50	1 wk.
52	0.50	2 wks.
53	0.50	1 mo.
54	0.50	2 mos.
55	0.50	3 mos.

TABLE 6.2--Physical Distribution Cost as a Function of Smoothing Constant

Prediction Interval	Smoothing Constant	Variable Physical Distribution Cost/lb.
1 wk.	0.01	$0.010553
	0.05	0.011552
	0.10	0.012318
	0.30	0.011991
	0.50	0.012170
2 wks.	0.01	0.010363
	0.05	0.010854
	0.10	0.010833
	0.30	0.011105
	0.50	0.011418
1 mo.	0.01	0.010187
	0.05	0.010320
	0.10	0.010333
	0.30	0.010466
	0.50	0.010743
2 mos.	0.01	0.010197
	0.05	0.010178
	0.10	0.010359
	0.30	0.010345
	0.50	0.010430
3 mos.	0.01	0.009877
	0.05	0.009962
	0.10	0.009860
	0.30	0.010088
	0.50	0.010165

TABLE 6.3.--Physical Distribution Cost as a Function of Prediction Interval

Smoothing Constant	Prediction Interval	Variable Physical Distribution Cost/lb.
0.01	1 wk.	$0.010553
	2 wks.	0.010363
	1 mo.	0.010187
	2 mos.	0.010197
	3 mos.	0.009877
0.05	1 wk.	0.011552
	2 wks.	0.010854
	1 mo.	0.010320
	2 mos.	0.010178
	3 mos.	0.009962
0.10	1 wk.	0.012318
	2 wks.	0.010833
	1 mo.	0.010333
	2 mos.	0.010359
	3 mos.	0.009860
0.30	1 wk.	0.011991
	2 wks.	0.011105
	1 mo.	0.010466
	2 mos.	0.010345
	3 mos.	0.010088
0.50	1 wk.	0.012170
	2 wks.	0.011418
	1 mo.	0.010743
	2 mos.	0.010430
	3 mos.	0.010165

H_0: There is no association between smoothing constant values and physical distribution costs.

H_1: There is an association.

For each set of research hypotheses there are corresponding statistical hypotheses, based on the population parameters in question. For the above hypotheses, the sample correlation coefficient, r, expresses the strength of the relationship between the two variables. The smoothing constant is treated as the independent variable in the analysis. The statistical hypotheses about the population correlation coefficient, ρ, are these:

H_0: $\rho = 0$.

H_1: $\rho \neq 0$.

This test was conducted at a .10 level of significance. The t statistic is appropriate with the actual t value computed from

$$t = r/\sqrt{(1-r^2)/(n-2)}$$

where n is the sample size. In this analysis physical distribution costs were regressed on smoothing constant values with the prediction interval held constant. Five samples, each containing five data pairs, result from such an approach.

The structure of the hypotheses implies a two-tailed test. The critical t value for three (n-2) degrees of freedom at the .10 level is 2.353. The resulting decision rule is:

If $|t| > 2.353$, reject H_0 and accept H_1;
otherwise, accept H_0.

The results of this group of tests appear in Table 6.4. The data were fit to the following four general line forms using the least-squares criterion:

1. $Y = a + bX$
2. $Y = a + b(\log X)$
3. $Y = a(b)^X$
4. $Y = a(X)^b$.

There is substantial evidence to suggest a direct relationship between smoothing constant values and variable physical distribution costs. With sales following an increasing trend pattern, variations are due mainly to chance fluctuations. Larger smoothing constant values tend to exaggerate the effect of a random fluctuation and would trigger a system over-reaction, such as a large replenishment order to cover a sudden increase in sales. Smaller smoothing constant values overlook this "noise" and smoothly increase the forecast to match the sales growth.

Other than it is a direct one, the exact relationship is difficult to describe. Equation four seems to be the best overall choice for all five data groupings; however, the simple linear trend line, equation one, reflects

TABLE 6.4.--Regression of Physical Distribution Costs (Y) on Smoothing Constant Values (X) with Prediction Interval Fixed

Fixed Prediction Interval	General Equation Form	Sample Correlation Coefficient	Computed t	Critical t	Decision
1 week	1	.598237	1.293	2.353	accept H_0
	2	.869414	3.048	2.353	reject H_0
	3	.592032	1.272	2.353	accept H_0
	4	.860181	2.921	2.353	reject H_0
2 wks	1	.916063	3.956[b]	2.353	reject H_0
	2	.969889	6.898[a]	2.353	reject H_0
	3	.914428	3.913[b]	2.353	reject H_0
	4	.970579	6.982[a]	2.353	reject H_0
1 month	1	.977428	8.013[a]	2.353	reject H_0
	2	.899816	3.572[b]	2.353	reject H_0
	3	.977835	8.089[a]	2.353	reject H_0
	4	.902033	3.619[b]	2.353	reject H_0
2 months	1	.841555	2.698	2.353	reject H_0
	2	.858466	2.899	2.353	reject H_0
	3	.841024	2.693	2.353	reject H_0
	4	.859169	2.908	2.353	reject H_0
3 months	1	.925962	4.247[b]	2.353	reject H_0
	2	.813759	2.425	2.353	reject H_0
	3	.925893	4.245[b]	2.353	reject H_0
	4	.815474	2.440	2.353	reject H_0

[a]significant beyond the .01 level
[b]significant beyond the .05 level

a strong association for four of the five samples.

It should be emphasized that this is an aggregate relationship because the same smoothing constant was applied to all products in a given experiment. Since all products were assigned a similar sales pattern, the overall pattern proved to be an accurate reflection of the individual product patterns. Relative sales amounts did, however, vary considerably among products. This did not pose a problem because there was no apparent relationship between volume and smoothing constant. The only problem was an artificial one, created by the use of the simulation process. Only a fraction of any product's sales can be simulated during an experiment. Extrapolation is used to attain total sales. A product with a relatively small sales volume is difficult to simulate accurately. The simulated volume for slow-moving items could possibly be too light to forecast within this model. This parallels the real-world problem of inactive products; therefore, these products were maintained within LREPS in spite of this forecasting-volume problem.

Based on this analysis the firm with this product configuration and sales pattern should choose smoothing constant values in the 0.01 to 0.10 range. Higher values overexcite the physical distribution system, and these extreme reactions can only lead to higher cost.

Prediction Interval Analysis

The next set of hypotheses refer to the possible relationship between the prediction interval and physical distribution costs:

H_0: There is no association between the size of the prediction interval and physical distribution costs.

H_1: There is an association.

Again the sample correlation coefficient, r, can be tested to determine the strength of the relationship. The statistical hypotheses are as follows:

H_0: $\rho = 0$.

H_1: $\rho \neq 0$.

As in the earlier experiments the t test is employed at the .10 level of significance. Five samples of five pairs of values for the prediction interval and variable physical distribution costs were analyzed for fixed values of the smoothing constant. The decision rule is identical to that presented in the previous section.

The experimental findings are shown in Table 6.5. The same four general equations were fit to the data. These results show an even stronger relationship than the previous ones. Several t values are significant beyond

TABLE 6.5.--Regression of Physical Distribution Costs (Y) on Prediction Interval Values (X) with Smoothing Constant Fixed

Fixed Smoothing Constant	General Equation Form	Sample Correlation Coefficient	Computed t	Critical t	Decision
0.01	1	-.928320	-4.325[c]	-2.353	reject H_0
	2	-.940970	-4.815[b]	-2.353	reject H_0
	3	-.928665	-4.337[c]	-2.353	reject H_0
	4	-.940524	-4.795[b]	-2.353	reject H_0
0.05	1	-.856581	-2.875	-2.353	reject H_0
	2	-.969793	-6.886[a]	-2.353	reject H_0
	3	-.862749	-2.995	-2.353	reject H_0
	4	-.973986	-7.445[a]	-2.353	reject H_0
0.10	1	-.780945	-2.166	-2.353	accept H_0
	2	-.911353	-3.835[c]	-2.353	reject H_0
	3	-.787968	-2.217	-2.353	accept H_0
	4	-.919466	-4.051[c]	-2.353	reject H_0
0.30	1	-.839247	-2.674	-2.353	reject H_0
	2	-.960530	-5.981[a]	-2.353	reject H_0
	3	-.846424	-2.753	-2.353	reject H_0
	4	-.966007	-6.472[a]	-2.353	reject H_0
0.50	1	-.893245	-3.441[c]	-2.353	reject H_0
	2	-.987063	-10.663[a]	-2.353	reject H_0
	3	-.900543	-3.589[c]	-2.353	reject H_0
	4	-.990446	-12.441[a]	-2.353	reject H_0

[a]significant beyond the .01 level
[b]significant beyond the .02 level
[c]significant beyond the .05 level

the .01 level. There is almost conclusive evidence indicating an indirect relationship between the prediction interval size and physical distribution costs. The explanation is a straight forward one. For any prediction interval, each forecasted value for a given product is the same for each day of that interval. Since there is an increasing trend in the data, a longer prediction interval causes the average forecasted value to be used to estimate sales for more days. If the average value reflects a random fluctuation, it is too high or too low. An overestimate results in soaring inventory costs. An underestimate leads to increased inbound transportation cost to handle backorders. The longer prediction interval means that a bad forecast can't be corrected as fast as is possible with a very short interval.

This company should utilize short forecasting intervals for its products. The smooth sales pattern is traced best with a small prediction interval (5 to 10 days) which allows random movements to be eliminated quickly.

Once again, this is an aggregate relationship, examined only for the case where all products use the same interval. It is possible that different products could use different intervals to reduce further the overall system cost. This possibility is covered later in this chapter.

Multivariate Analysis

With statistically significant relationships existing between variable physical distribution costs and the smoothing constant and between variable physical distribution costs and the prediction interval, a natural extension is a multiple regression with two independent variables. A multiple linear regression line was derived as follows:

$$Y = 0.011165 + 0.0011728lX_1 + 0.0000239346X_2$$

where Y is variable physical distribution cost, X_1 is the smoothing constant, and X_2 is the prediction interval. The proportion of the total variance in Y associated with this line is .61751, yielding a coefficient of multiple correlation of .785818. The standard error of the coefficient of multiple correlation is given by

$$s_{r_{1\cdot 2,3}} = (1-r^2)/\sqrt{(n-3)}.$$

The value for the standard error from this data is .0816. The ratio of r to $s_{r_{1\cdot 2,3}}$ is 9.63, meaning that r differs from zero by 9.63 standard deviations. This value is significant well beyond the .01 level.

A comparison of this coefficient of multiple correlation with the simple correlation coefficients observed for the simple linear regressions performed earlier reveals that the multiple coefficient is smaller than all but two of the ten simple coefficients. This seems, at first, to be inconsistent; however, an explanation can be given. First, the simple regressions were based on samples of only five observations each, while the multiple regression was performed on 25 sets of data. It is easier to fit a line to a smaller number of observations. As the sample size increases, the likelihood of observing extreme values increases.

Second, the highly correlated linear relationships varied from sample to sample. For example, the linear relationships between variable physical distribution cost and the smoothing constant for fixed prediction intervals of two weeks and three months, respectively, are

$$Y = 0.0105813 + 0.00173588X \text{ and}$$

$$Y = 0.00987518 + 0.000600107X.$$

Both correlation coefficients are about .92. The "a" values in the two equations are comparable, but the "b" values differ by a factor larger than three. Trying to fit one line to this data to approximate ten unrelated lines weakens the overall relationship. The multiple relationship still permits fairly good estimates of cost, based on a standard error of the estimate of 0.00043782. Using the multiple regression line, a forecaster can estimate costs to within \$.001/lb. about 98% of the time.

Level of Detail Experimentation

Two of the three dimensions of the forecasting model have been analyzed. The appropriate level of forecasting detail must now be determined. This analysis is viewed from two perspectives. First, the same level of detail is compared for alternative build-up functions. Second, for the same level of detail a build-up model is compared with a breakdown application.

The initial experiments included 25 sets of values for the smoothing constant and the prediction interval. It seems reasonable, however, that different products might be traced more accurately with different smoothing constants or prediction intervals. An additional simulation run was devised to allow for this possibility. Each of the ten tracked products was assigned the smoothing constant and prediction interval values which minimized the product's relative variance between forecasted and actual sales. This is the so-called "best" build-up function, shown in Table 6.6. Comparisons of relative variances can then be made for the same level of forecasting detail to see if the added flexibility is statistically significant.

Further, different approaches in using the "best" model can be studied. One approach is to forecast at the product-DU level. A second method is to forecast at the

TABLE 6.6.--The "Best" Build-Up Function

Product Number	Smoothing Constant	Prediction Interval
1	0.30	3 mos.
2	0.10	3 mos.
3	0.05	3 mos.
4	0.01	2 mos.
5	0.10	2 mos.
6	0.10	1 wk.
7	0.10	1 wk.
8	0.05	1 wk.
9	0.05	1 wk.
10	0.50	1 wk.

product level and allocate product sales to the DU's on some arbitrary basis.

The measure of variance used is a relative one. The general formula for the sample variance is

$$s^2 = \varepsilon(Y-\overline{Y})^2/n$$

where Y is an observation, $\overline{Y}$ is the mean of all observations, and n is the number of observations. To use s^2 as a relative measure, the Y values must be redefined. Y is now defined as the difference between relative actual sales, a, and relative forecasted sales, f. The formulae for a and f are

$$a_t = \frac{Y_{a,t} - Y_{a,t-1}}{Y_{a,t-1}} \qquad f_t = \frac{Y_{f,t} - Y_{a,t-1}}{Y_{a,t-1}}$$

where $Y_{a,t}$ is actual sales for period t and $Y_{f,t}$ is forecasted sales in period t. This conversion facilitates comparisons between products with different volumes or prediction intervals. These relative values have no meaning whenever $Y_{a,t-1}$ is zero because division by zero yields unpredictable results. When $Y_{a,t-1}$ was observed to be zero, the relative values were not included in the calculation of the relative variance.

Intralevel Detail Analysis

The following research hypotheses guide the comparison of identical levels of detail between the "best" function and any other function:

H_0: The variances for any ZIP area (DU) and product are equal for the two build-up functions.

H_1: The variances are unequal.

If $s_{ij1}{}^2$ represents the relative forecast variance of product i in DU j for alternative one and $s_{ij2}{}^2$ is the variance for alternative two, then the F test statistic is either

$$F = s_{ij1}{}^2/s_{ij2}{}^2 \qquad \text{or} \qquad F = s_{ij2}{}^2/s_{ij1}{}^2$$

depending upon which variance is larger. The larger value is arbitrarily assigned to be the numerator for comparison with tabled critical F values.

The statistical hypotheses, with σ's representing the population relative variances, are these:

H_0: $\sigma_{ij1}{}^2 = \sigma_{ij2}{}^2$.

H_1: $\sigma_{ij1}{}^2 \neq \sigma_{ij2}{}^2$.

Since critical F values depend on the degrees of freedom (sample size) for both variances, no one critical value can be stated. The general form of the decision rule is

If computed F > critical F, reject H_0;
otherwise, accept H_0.

A .10 level of significance was used for all comparisons.

The "best" function (experiment 26) was compared with the simulation run utilizing a smoothing constant of 0.10 and a prediction interval of three months (experiment 35). This run is one of the lowest in terms of variable cost per unit, and its backorder percentage is comparable to that of the "best" function. In terms of service for a given unit cost, however, the "best" function offers the more desirable result.

The relative variances of the forecast error were compared for each product-DU in the two simulations. The

TABLE 6.7--Summary of Product-DU F Tests

		Larger Variance Significant		
		Yes	No	Total
Experiment with Larger Variance	26	51	113	164
	35	53	93	146
Total		104	206	310

results are shown in Table 6.7.

With 10 products and 31 DU's a total of 310 F ratios were computed. For 104 product-DU's the difference in relative variances is significant at the .10 level; however, each run has almost the same number of significant ratios. In addition, twice as many of the F values are not significant at the tested level. The conclusion based on the product-DU evidence is that the two simulations seem to be equally effective in forecasting capability.

A test for the significance of the proportion of F tests favoring one or the other of the experiments offers corroborative evidence in favor of the above conclusion. If p is the proportion of larger F ratios for experiment 26, then the probability of observing 164 or more F ratios is the probability that z (a standard normal deviate) is greater than $(164-150)/\sqrt{310(.25)}$. This is equivalent to

P(z > .902) = .1788, a value much larger than conventional significance levels of .05 or .10.

This data can be examined at the DU level of the product level, but the same conclusion is reached. For the DU level the results are summarized in Table 6.8.

TABLE 6.8.--Summary of DU F Tests

		Larger Variance Significant		
		Yes	No	Total
Experiment with Larger Variance	26	10	3	13
	35	14	4	18
Total		24	7	31

The proportion of significant F ratios is considerably higher for the DU level as compared to the product-DU leve, but the total is fairly equally divided between the two experiments. The probability of observing 18 in one of two classes in a sample of 31 is considerably greater than .10 (about .18).

At the product level the data tend to favor experiment 26 as the better choice, but the results are not statistically significant. Experiment 35 has the larger variance for seven of the 10 products; however, the probability of this happening is .17, above the .10 level.

The only conclusive evidence is the difference in overall variance for the two experiments. The F value is 1.853 with the variance for experiment 35 being the larger of the two. This F value is significant well beyond the .02 level. This may appear to be in conflict with earlier findings, but there is a very good reason for such a result. A re-examination of the product-DU variances reveals that, while the two experiments have approximately the same proportion of large variances, experiment 35 generated many extremely large variances. For the 51 product-DU's that exhibited significantly larger variances from experiment 26, most were significant at the .10 level only. On the other hand, the 53 significant variances from experiment 35 were often significant well beyond .02 or even .01 levels.

The variances must be compared at all four levels, the distribution center, the DU, the product, and the product-DU, to establish which experimental results are superior. Even this guarantees only an indication of statistical significance. Managerial significance must also be considered.

Although experiment 35 is less effective than 26 in forecasting seven of the 10 tracked products and has a larger overall variance, these seven are ranked fourth to tenth in sales volume. Experiment 35 does predict the top

three products in sales volume more accurately. The net effect is that each approach forecasts about one half of the total sales volume more effectively than the alternative. Again neither experiment can be picked as the better one.

Interlevel Detail Analysis

The research hypotheses for this stage of the study are:

H_0: The variances are equal for the two levels of forecasting detail.

H_1: The variances are unequal.

The variances are computed for the same level of detail, the product level; however, forecasts are generated at the product level for one alternative and at the product-DU level for the other. The F test can be used to compare the relative variances. The test statistic is

$$F = s_{i1}^2/s_{i2}^2 \qquad \text{or} \qquad F = s_{i2}^2/s_{i1}^2$$

depending upon which yields the larger F value. Here s_{i1}^2 is the variance for product i accumulated from all product-DU forecasts, and s_{i2}^2 is the variance based on product level forecasts.

The statistical hypotheses are these:

H_0: $\sigma_{i1}^2 = \sigma_{i2}^2$.

H_1: $\sigma_{i1}^2 \neq \sigma_{i2}^2$.

If the computed F value exceeds the critical F value (based on sample sizes and .10 significance level), then H_0 is rejected; otherwise, it is accepted.

Experiment 26 is based on the smoothing constant and prediction interval values shown in Table 6.6. The forecasts are developed at the product-DU level. Experiment 27 is the same as 26 with one important exception: The forecasts are computed at the product level and allocated to the DU's on the basis of the weighted index for each DU. Experiment 26 is a build-up approach. The results are presented in Table 6.9.

TABLE 6.9.--Summary of Build-Up Breakdown Comparison

Product	Experiment with Larger Variance	Significant Difference
1	27	no
2	26	no
3	26	no
4	27	no
5	26	no
6	27	no
7	26	no
8	27	no
9	26	no
10	27	no

Since the products are ranked high to low by sales volume, clearly neither 26 nor 27 has an advantage. This position is further enhanced by the F value of 1.049 for the ratio of the two overall variances, easily an F value due to chance alone. It appears that for this data the product forecasts could be allocated to the DU's with little to no loss in forecasting accuracy as compared with a more detailed forecasting approach.

This conclusion is due primarily to the allocation of simulated actual sales to DU's on the same basis as forecasted sales, the DU weighted indexes. With different allocative bases experiment 26 would most likely be a considerably more accurate approach.

Cost-Accuracy Considerations

Determination of the specifications of the build-up function facilitates the analysis of the effect on physical distribution costs of forecasting accuracy. The related research hypotheses are:

> H_0: There is no association between forecasting error and physical distribution costs.
>
> H_1: Higher levels of forecasting error are associated with higher levels of physical distribution costs.

Spearman's rank correlation coefficient is used to test these hypotheses because the measure of error developed is an index or composite value. A gauge such as the variance is a useful estimate of error, but it overlooks systematic bias. A consistent 10% overestimate, for example, is not identified by the relative variance of the forecasting error. To overcome this deficiency, the variance can be used in conjunction with a measure sensitive to systematic bias, such as Theil's inequality coefficient.

Values for the relative variance and for Theil's coefficient were collected for each of the first 25 experiments detailed in Table 6.1. The 25 variances were ranked in order, from low to high, from one to 25. The same ranking was applied to values for Theil's coefficient. An index for each experiment was obtained by multiplying the ranking of each of the two measures by 0.5 and summing the two products. The equal weights were arbitrary, based on the assumption that the two error measures are equally important. The values for the two error measures, their respective rankings, and the weighted indexes appear in Table 6.10. Variable physical distribution costs and rankings are also included in this table.

Spearman's rank correlation coefficient is computed from

$$r = \frac{n \sum_{i=1}^{n} x_i y_i - \left(\sum_{i=1}^{n} x_i\right)\left(\sum_{i=1}^{n} y_i\right)}{\sqrt{\left[n \sum_{i=1}^{n} x_i^2 - \left(\sum_{i=1}^{n} x_i\right)^2\right]\left[n \sum_{i=1}^{n} y_i^2 - \left(\sum_{i=1}^{n} y_i\right)^2\right]}}$$

TABLE 6.10.--Indexes of Forecasting Accuracy

Experiment	Total Relative Variance	Rank	Theil's Coeff.	Rank	Composite Weighted Index	Rank	Variable PD Cost	Rank
1	1.2535	22	.9586	22	22	23	.019553	16
2	1.4257	25	.9883	24	24.5	25	.019363	13
3	1.3591	24	.9077	16	20	22	.010187	7
4	1.1737	20	.9907	25	22.5	24	.010197	8
5	.9658	9	.9817	23	16	17	.009877	2
6	.8809	3	.8090	4	3.5	3	.011552	22
7	1.0279	13	.8253	9	11	9	.010854	19
8	1.2641	23	.8625	14	18.5	20.5	.010320	9
9	1.0288	14	.9516	21	17.5	18	.010178	6
10	1.0445	17	.9370	20	18.5	20.5	.009962	3
11	.8760	2	.8123	5	3.5	3	.012318	25
12	.9960	11	.8001	1	6	5	.010833	18
13	1.0306	15	.8131	6	10.5	7.5	.010333	10
14	.9286	8	.9173	18	13	14	.010359	12
15	1.2176	21	.9068	15	18	19	.009860	1
16	.9851	10	.8322	11	10.5	7.5	.011991	23
17	1.0780	19	.8245	8	13.5	15	.011105	20
18	.7530	1	.8065	3	2	1	.010466	17
19	.8941	5	.8038	2	3.5	3	.010345	11
20	.8953	6	.9318	19	12.5	12.5	.010088	4
21	1.0356	16	.8604	13	14.5	16	.012170	24
22	1.0239	12	.8458	12	12	10.5	.011418	21
23	1.0738	18	.8156	7	12.5	12.5	.010743	17
24	.8937	4	.8280	10	7	6	.010430	14
25	.9058	7	.9150	17	12	10.5	.010165	5

where the x_i's are weighted index rankings and the y_i's are physical distribution cost rankings.

The statistical hypotheses are as follows:

H_0: $\rho = 0$.

H_1: $\rho > 0$.

The critical r_s for a one-tailed test at a .05 significance level for a sample of 25 is 0.400. The related decision rule is

If computed $r_s > 0.400$, reject H_0;
otherwise, accept H_0.

The computed value of r_s based on this data is 0.470, which is significant at the .05 level. H_0 is rejected, and it is concluded that there is a direct relationship between variable physical distribution cost and forecasting error. While the relationship isn't strong, it is statistically significant, implying that the hypothesized relationship (H_1) does exist. Inaccurate forecasts overstate inventory and result in higher inbound transportation costs to deliver the needed backorders.

This is further proof of the importance of accurate forecasts. There are no automatic physical distribution system responses to compensate for the consequences of erroneous forecasts.

Summary

This chapter presented the application of the general forecasting model to a specific situation. Different smoothing constant values, prediction intervals, and levels of detail were examined for usefulness. The firm selling the 10 sample products in the specified area of the country should heed the following recommendations:

1. Select smoothing constant values from the 0.01 to 0.10 range.

2. Select prediction intervals from the one to two week range.

3. Forecast at the product level rather than the product-area level.

Finally, physical distribution costs were found to be increasing with forecasting error increases. This emphasizes the importance of forecasting precision.

CHAPTER VI--FOOTNOTES

[1]Brown, pp. 53-54.

[2]Hirsch and Lovell, pp. 141-169.

[3]Brown, p. 54.

CHAPTER VII

PHYSICAL DISTRIBUTION COST-SERVICE TRADEOFF

Introduction

The detailed forecasting model can be used in conjunction with other models or by itself to verify or to disprove theories in business. As noted earlier, however, the forecast serves as a vital input to many processes of the firm. Further experimentation with the model alone beyond validation would seem to be pointless. The other possibility, the merger of the forecasting model with a model of firm activity, is much more promising.

The LREPS model, as a representation of the distribution system, provides the backdrop for studying propositions heretofore tested with simple, incomplete models. Since the application of the systems concept to physical distribution, the relationship between system cost and the attendant customer service level has been under close scrutiny.[1,2] This relationship is a natural one to be studied with such a comprehensive model as LREPS and is considered in detail in this chapter.

Traditional Propositions

Before presenting the current thinking on the relationship between cost and service, these two terms should be defined. Cost refers to total physical distribution cost, the sum of the component costs for facilities, inventories, transportation, communication, and unitization.[3] Tradeoffs are allowed between and among these five components to achieve service levels at minimum cost. Since this is a short-term analysis, only those costs which vary during this time span are examined. This includes inventory and inbound transportation costs.

In this analysis service refers to transport capabilities, rather than the broader marketing definition. Such aspects as condition of goods are assumed to be unchanged as service level is altered.

Service is a two-fold concept, covering both speed and consistency of service. Speed and consistency are analogous to the mean and standard deviation of a probability distribution, respectively. Speed refers to the average time needed to move an item between two points, normally a warehouse and a buyer. Consistency describes the variation in speed over a number of observed transfers.

To specify fully a service level, both speed and consistency must be defined. For example, a service objective may be to provide five-day delivery to at least 80% of the customers and seven-day delivery to all others. Taken alone, the five-day average time doesn't explain service.

The last definitional problem is the functional relationship between cost and service. A given service level can be attained through many system configurations at differing costs. The reference here is to the least-cost system for each level of service. The cost-service line, if plotted graphically, is the lower bound of the cost-service space, which represents all combinations of cost and service.

Cost has been considered an increasing function of the service level at an increasing rate. Costs spiral upward as perfect service, delivery to 100% of the customers in the minimum possible time using the swiftest mode of transportation available from every inventory location, is neared. Magee has suggested that the effect of distribution on sales is a function of location, inventories, and system responsiveness. He contends that to fill 95% rather than 80% of orders from stock, a 15% change, is to increase inventory costs by about 80%.[4] An interesting hypothetical example was formulated by Hill showing that something less than perfect service should be the goal. The inordinately high cost of increased service levels would not be offset by the added product demand.[5]

Heskett, Ivie, and Glaskowsky relate alternative system configurations to after-logistics-costs profit to show that the best system in terms of service isn't necessarily the most profitable.[6] This example is especially expressive of the viewpoint hopefully adopted by marketers: Service provided should also be a function of service expected by the customer, not only be a function of attainable service.

Bowersox, Smykay, and LaLonde noted that the typical firm usually balances "reasonable" performance levels against "realistic" costs.[7] The prohibitive nature of extremely high service forces the firm to back away from it.

Experimental Results

Service can be analyzed from another perspective, that of the customer order cycle. The buyer views the order cycle as consisting of five elements:[8]

1. Order initiation and dispatch time
2. Order transmission time
3. Order processing time

4. Order shipment time

5. Order receipt time.

The supplier controls the order processing stage and exerts influence on the alternatives used in the order transmission and order shipment stages. These three stages are elements of the normal customer order cycle of LREPS. A fourth element, the stockout delay, is an additional LREPS feature which can be added to the normal cycle to find the total order cycle of the supplier. For the LREPS model variations in each of these four components determine what proportion of customers are served within a specified time, as well as the statistical variance of the total order cycle.

Order processing is based on Monte Carlo random variate functions. The following discrete probability distribution is used:

Probability	Order Processing Time
10%	0 days
60%	1 day
30%	2 days

Any function describing reality can be used. If a distribution center is operating above a specified volume, an additional one-day order processing delay is added to a percentage of the orders equal to the percentage of operations above the defined level.[9]

Order transmittal and outbound (from Distribution Center) transportation times were developed in a similar fashion. Sets of three concentric circles were placed around each Distribution Center to indicate one, two, and three day service. If a Demand Unit fell within the innermost circle, it would receive one-day service on average. If it was within circle two and outside circle one, it could expect two-day service. Communications rings can be interpreted identically. With many ring sets available each Distribution Center can be assigned different communications and delivery rings. Variances about these average order transmittal and delivery times are formulated on the basis of several Monte Carlo functions, like the order processing functions. Each Distribution Center can achieve different consistency of service.

Finally, the stockout delay is computed during the simulation cycle, not prior to execution, as are the previous elements of the order cycle. The stockout delay is the sum of out-of-stock days divided by the sum of out-of-stock units.

LREPS provides summaries of Distribution Center performances after each experiment. More specifically, the following service measures are computed:[10]

1. Customer service penalty time (stockouts)

2. Mean and standard deviation of normal customer order cycle time

3. Mean and standard deviation of customer delivery time

4. Total customer order cycle time

5. Percent of case units backordered

6. Mean and standard deviation of product stockout days

7. Normal order cycle time proportions

8. Domestic average service time

9. Average lead time for each DC-MCC link.

An accurate measure of system service performance can be obtained by allowing inventories to be negative, if needed (in other words, no stockouts). Every time a potential stockout occurs, the order is filled and backordered. The measure of performance is the percent of case units backordered. A high backorder percentage implies poor service. Improved service is realized at an increased cost; therefore, percent case units backordered should be an inverse measure of service achievement.

For the cost-service experiments the normal order cycle time distribution was specified as follows:

Proportion of Orders	Normal Order Cycle Time
.13	4 days
.70	5 days
.17	6 days

The standard deviation of the normal order cycle was set at 0.8 days.

The research hypotheses describing the cost-service interaction are as follows:

H_0: There is no association between physical distribution cost and service.

H_1: Higher physical distribution costs are associated with higher service levels.

Regression and correlation analysis is appropriate because both sets of data are ratio in nature. Percent case units backordered is the independent variable, and cost is the dependent variable. Since high service levels imply low percentages of backorders, the statistical hypotheses about ρ, the population correlation coefficient describing the relationship between cost and backorders, are formulated as follows:

H_0: $\rho = 0$.

H_1: $\rho < 0$.

The structure of the hypotheses implies a one-tailed t test with

$$t = r/\sqrt{(1-r^2)/(n-2)}$$

where r is the sample correlation coefficient and n is the sample size. The sample data are 25 pairs of variable physical distribution cost-percent case units backordered values (Table 7.1). The critical t value for a one-tailed

TABLE 7.1.--Physical Distribution Cost-Service Values

Experiment	% Cases Backordered	Variable Physical Distribution Cost/lb.
41	0.325	$0.011991
51	0.350	0.012170
31	0.425	0.012318
21	0.500	0.011552
42	0.525	0.011105
52	0.600	0.011418
32	1.100	0.010833
22	1.275	0.010854
43	1.275	0.010466
53	1.500	0.010743
11	1.525	0.010533
12	2.000	0.010333
44	2.050	0.010345
54	2.150	0.010430
12	2.175	0.010363
13	2.350	0.010187
23	2.375	0.010320
45	2.800	0.010088
55	2.825	0.010165
35	2.850	0.009860
34	3.125	0.010359
25	3.125	0.009962
15	3.575	0.009877
14	3.975	0.010197
24	4.200	0.010178

test at the .05 level of significance for 23 degrees of freedom is 1.714. The decision rule is

If $t < -1.714$, reject H_0;
otherwise, accept H_0.

The four general equation forms described in Chapter VI were fit to this data. The results of this analysis are shown in Table 7.2. All four t values are

TABLE 7.2.--Cost-Service Regression

Equation	Sample Correlation Coefficient	Computed t	Critical t	Decision
1	-.845808	-7.603	-1.714	reject H_0
2	-.947242	-14.173	-1.714	reject H_0
3	-.856195	-7.948	-1.714	reject H_0
4	-.950914	-14.737	-1.714	reject H_0

significant well beyond the .05 level, suggesting a very strong inverse relationship between percent backorders and variable physical distribution costs. In addition, since the fourth equation provides the best fit (least unexplained variance), the relationship of cost to service is likely one which increases at an increasing rate.

These 25 cost values can be considered short-run minima for given service levels. Facilities are fixed during this time span, and transportation and communications networks are the most economical of the available alternatives.

This cost-service relationship must be used in conjunction with the firm's overall profit function. The cost of transport service is only one of several components of the total profit picture. A systems perspective is

required to reach the optimum profit position. For example, transport service has an impact on sales revenue. To provide high service to the extent that the marginal cost of service exceeds the marginal revenue generated is not an economically sound policy.

Summary

A specific application of the forecasting-LREPS model has been presented in this chapter. The direct relationship between physical distribution cost and service has been substantiated statistically using the sample data. Based on the different functional forms fit to the data, the cost-service relationship appears to be increasing at an increasing rate.

CHAPTER VII--FOOTNOTES

[1]D. J. Bowersox, "Physical Distribution Development, Current Status and Potential," Journal of Marketing (January, 1969), pp. 63-70.

[2]Bowersox, Smykay, and LaLonde, ch. 1.

3. Ibid., ch. 5.

[4]J. F. Magee, "The Logistics of Distribution Systems," Harvard Business Review (July-August, 1960), pp. 89-101.

[5]"The Case for 90% Satisfaction," Business Week (January 14, 1961), pp. 82-85.

[6]J. L. Heskett, R. M. Ivie, and N. A. Glaskowsky, Business Logistics (New York: The Ronald Press Co., 1964) pp. 173-174.

[7]Bowersox, Smykay, and LaLonde, p. 116.

[8]D. McConaughy and C. J. Clawson (eds.), Business Logistics--Policies and Decisions (Los Angeles: Research Institute for Business and Economics, University of Southern California, 1968), pp. 120-125.

[9]Helferich, pp. 179-180.

[10]Ibid., pp. 268-270.

CHAPTER VIII

SIMULATED SALES FORECASTING: FINDINGS AND IMPLICATIONS

Introduction

The overall purpose of this research has been to devise a way to deal with the measurement problem of evaluating a sales forecasting mechanism. Until now management has been forced to wait until forecasted time periods became history before assessing forecasting capability. The combination of a forecasting archetype with the LREPS model provides the firm with an approach for evaluating the forecasting model before it is used. Only after-the-fact investigation yields positive proof regarding forecasting accuracy, but the approach suggested in this dissertation reduces substantially the uncertainty involved in developing a forecasting system.

This chapter first summarizes the results of applying this new forecasting approach to sample data. As a result of this application, a generalized approach to short-term sales forecasting can be suggested. Next, the extension of the short-term to long-run applications is developed. Finally, the research areas worth further investigation are discussed.

Summary of Experimental Results

The forecasting model was constructed with flexibility along the three dimensions of forecasting technique, prediction interval, and level of detail. Exponential smoothing was chosen as the specific forecasting technique. Experimentation was conducted with the sample data to determine the appropriate levels for these three dimensions. The basis for evaluation was minimized physical distribution costs, measured by LREPS. Since the period of interest was one year, only those costs which varied in the short-run were isolated. These include inventory and inbound transportation costs. The assumed sales pattern was that of an increasing linear trend with random fluctuations allowed to occur about the trend line.

The linear assumption is actually more rigorous than a nonlinear assumption. With small sample sizes, as was the case with the data used in this research, curved lines often provide a better fit. If a straight line can be applied, stronger statements can be made regarding the functional relationship.

Smoothing Constant Analysis

Smoothing constant values (the parameter of the simple exponential smoothing formula) were regressed against variable physical distribution costs. The relationship was found to be a direct one with higher smoothing constant values associated with higher variable cost values. Sample correlation coefficients were found to be statistically significant, based on the t statistic, at the .10 level. Some coefficients were significant beyond the .01 level. The tested values for the smoothing constant were 0.01, 0.05, 0.10, 0.30, and 0.50. Based on this analysis the firm supplying the sample data should consider small smoothing constant values in the 0.01 to 0.10 range.

Prediction Interval Analysis

Similar regressions were performed on pairs of values for the prediction interval and physical distribution cost. The values for the prediction interval which were examined were one week, two weeks, one month, two months, and three months. Exceptionally strong inverse relationships were discovered between the two variables. Most sample correlation coefficients were significant beyond the .05 level. It was recommended that the firm in question should utilize a very short prediction interval, one or two weeks.

A multiple correlation was carried out treating variable physical distribution cost as the dependent variable and the prediction interval and the smoothing constant as independent variables. A significant ($r = .78$) relationship was observed, although it was not as strong as those of the simple regressions. A larger sample encompassing many strong individual relationships which were not as strongly interrelated accounts for this.

Level of Detail Analysis

The forecasting archetype permits forecasting at four levels of detail: the Distribution Center, the product, the Demand Unit (DU), and the product-DU. Two types of experiments determined the most appropriate forecasting model for a given level of detail and also the needed level of detail.

For the first analysis two simulation runs were compared: (1) a model using the same smoothing constant and prediction interval for all tracked products and (2) a model using the smoothing constant and prediction interval for each product which minimized that product's relative variance between forecasted and actual sales. Forecasts were generated at the product-DU level, and comparisons of the relative variances at all four forecasting levels for the two simulations were made using the F statistic. Only at the Distribution Center level was there a statistically significant difference (.10 level) favoring the second forecasting model. However, because the second model was less precise in forecasting the high volume products, no definite preference could be reached based on statistical evidence. The decision was left to management to determine which products and market segments are vital to the firm's future. The model which served these forecasting cells best is the probable choice.

The second analysis compared two versions of the model which utilized the best smoothing constant and prediction interval values for each product. The first version forecasted at the product-DU level, while the second version generated product forecasts which were allocated to the DU's. The F test was used to compare product variances for the two methods to see if the added detail of the product-DU approach was needed. No significant difference was observed; therefore, the simpler model was just as effective as the more complex one for the sample data.

Effect of Forecasting Accuracy

To determine the importance of forecasting accuracy to the operation of the physical distribution system, an index of forecasting error was regressed against variable physical distribution cost. The index was composed of equal-weighted rankings of the relative forecasting variance and Theil's inequality coefficient. The variance measured the consistency of the forecast error and Theil's coefficient pinpointed any steady over- or underestimated forecasts. Twenty-five pairs of values for the two variables were gathered through simulation runs.

Spearman's rank correlation coefficient was computed to be 0.470, significant at the .05 level. This tends to suggest a direct relationship between forecasting error and variable physical distribution costs for the sample data. A further contention is that this is likely to be a general relationship found within nearly all firms.

Physical Distribution Cost-Service Relationship

Experts have suggested for several years that physical distribution cost is an increasing function of service (and probably at an increasing rate). Since the LREPS model provides several measures of service as well as cost, this hypothesized relationship could be tested.

By allowing all orders to be filled regardless of the existing inventory levels (possible only in a simulated environment), an accurate measure of service was obtained. Each time an order would have caused a stockout, the order was filled and a backorder was placed. The measure of service developed was percent of case units backordered, an inverse measure of service achievement.

The regression of percent backorders against variable physical distribution cost yielded a statistically significant (beyond the .01 level) negative correlation coefficient. Cost is an inverse function of percent backorders, implying a direct relationship between cost and service. Of the four mathematical relationships derived, the strongest was an exponential form. This means that the direct relationship is probably at an increasing rate. This analysis lends strong support in favor of the traditional propositions about the cost-service tradeoff.

A General Approach to Short-Run Forecasting

From the experimental results developed for this particular company, some general guidelines for organizing and implementing the short-term forecasting process can be stated. It should be pointed out again that forecasting is part, a central component, of the more comprehensive management task of planning. Since the type is defined by the interval over which the plans are developed, short-term planning is necessarily a subset of long-range planning. As a result, short-term forecasting must be synchronized with long-term forecasting. The combination of several short-term forecasts should coincide with the overall long-term forecast for the total time span.

Because this research is based on the build-up concept, this agreement is critical. Long-range projections are defined as the summation of shorter-term forecasts. If management has thoroughly organized the planning process, long-range objectives should imply short-term goals. This channel should flow in both directions; hence, short-range forecasts, as responses to short-term objectives, should aggregate over time to yield a suitable long-term forecast, in line with the long-range planning objectives.

To operationalize the short-term forecasting process, the following steps should be taken:

1. Determine the precise use of the forecast.

2. Segment the market into homogeneous areas.

3. Develop similar product groups.

4. Collect required data.

5. Specify the three dimensions of the general short-term forecasting model.

6. Review model results regularly.

7. Check results with alternative method.

Each step is discussed in terms of its content and its function in the entire short-term forecasting process.

Forecast Objective

The initial step is to define exactly the purpose of the forecast. The position of the forecast in the overall planning scheme must be specified in order to complete the remaining steps. Many uses for sales forecasts were listed in Chapter II. In this research the forecast served to control inventory levels and replenishment orders. The marketing department may want to evaluate the impact of alternative short-term tactics, such as coupon campaigns or sales. Perhaps personnel is developing manpower plans to cover peak-season production activity. Each department within the company can utilize these short-range estimates for its own purposes.

Because departmental needs vary, the forecast needs depend somewhat upon the requesting department. The marketing example cited above suggests detailed product-market segment projections. The personnel example implies gross sales data along with standard production per man information, although a varied product line might have to be forecasted in detail.

A very explicit statement of forecast objectives often makes the remaining steps in the forecasting process self-evident. Data needs become obvious, as does the level of forecast detail. Considerable savings in man hours could result from extra effort at this initial stage.

Market Segments

The identification of market areas with similar characteristics helps to simplify the forecasting problem. The common features should, however, be transformable into action. This is important primarily to marketers. Characteristics which suggest marketing tactics are much more valuable than those which offer nothing beyond neat categories. This latter case is better than no classifying scheme whatsoever. These control units can be treated in a similar fashion for forecasting purposes. Perhaps the same forecasting techniques and equation parameters will be applicable.

Another reason for segmenting is to isolate areas that are very difficult to forecast because of low sales volumes, unpredictable competitive action, or other reasons. These "bad" segments can be approached more intuitively, while the other areas can be analyzed with more conventional

techniques.

It is conceivable that different departments might prefer unique market segments or control units for forecasting. A uniform classifying system is desirable, but not at the cost of generating useless forecasts. This problem is one which must be solved at the time it appears because no universal set of categories currently exists.

Product Groups

Product groupings accomplish the same goal as market segments: simplified forecasting because of similar patterns of sales. Groupings should be made with this in mind, not on the basis of like product characteristics. Extremely unrelated products may exhibit like sales behavior. Again departmental differences may dictate several grouping configurations. For example, forecasts for inventory control purposes may not interest the financial manager who is evaluating product line performance.

Data Collection

The main emphasis of this step is on the shape of anticipated sales patterns and the availability of historic sales and associative data. This step interrelates considerably with the subsequent one, the general forecasting model dimensions; however, it is important enough to merit separate attention.

The sales pattern greatly affects the dimensions of the model. The specific technique utilized will depend upon the regularity of fluctuations (perhaps the seasonal and cyclic components of the time series model). If random movements are prevalent, then maybe a very short prediction interval will be needed to enable quick adjustments to be made in the forecast.

Historic data, as input to a data bank, also determine which techniques are feasible. For example, time series analysis and regression and correlation analysis utilize considerable historic, and for the latter, associative, data.

With product and market groupings outlined management has a framework for data collection. These classifications can serve as common denominators or control units for the formatting and storing of data. The importance of a central data bank should be noted. Even though different departmental objectives probably cause separate short-run forecasts to be generated, these projections should ideally be drawn from a common source of information. By designing flexibility along the three dimensions discussed in the next section, management can derive different forecasts from the same data bank by specifying the control unit set and the levels of these three dimensions. The only remaining problem is that of suitable report formatting, a relatively simple problem in comparison with those just mentioned.

General Forecasting Model Dimensions

This is the stage in the forecasting process upon which this research is primarily focused. Three specific dimensions have been delineated: the forecasting technique, the prediction interval, and the level of detail. These dimensions are operable within an overall framework of product-market area grids (forecasting cells). Management can prescribe the right dimensions levels by defining an objective function to be optimized with these three dimensions as the independent variables.

Simple regression analysis can be used to determine the nature of the relationship between the forecasting technique parameters and the dependent variable of the objective function. A similar approach can be applied to the prediction interval. If possible, a multivariate relationship should be derived. If significant relationships are found, then the appropriate ranges for the technique parameters and prediction interval can be specified.

Level of detail analysis encompasses a re-examination of the first two dimensions, as well as a third area for making model specifications. The former refers to the assignment of prediction interval values to the forecasting cells. The preceding discussion implies an aggregate level (same interval for all cells) study. Possibly more reliable forecasts would result from using several prediction intervals for different products. This can be determined by comparing forecasting error (e.g., variance between forecasted and actual sales, Theil's inequality coefficient, other statistics, or composite indexes of several measures) for different levels of the first two dimensions. The comparisons are made at the same level of forecasting detail.

Once the prediction interval and forecasting technique parameters have been finalized, the overall level of detail can be determined (product-market segment, product, product group, market segment, etc.). The purpose of such comparisons is to eliminate spurious detail. If forecasts for individual products yield satisfactory results when compared with forecasts derived at the product-market segment level, the additional forecasting level is of little to no marginal value.

This dissertation has emphasized statistical analyses as the bases for choosing values for these three dimensions. While this is the recommended approach, less sophisticated methods may be just as valid. Managerial judgment is vital to forecasting and should be given consideration. The proper balance between judgmental and experimental findings is hard to attain, yet each of the two is necessary.

Forecast Review

Because the business environment is so dynamic, conditions can suddenly change, making the forecasting model obsolete. This is a rather extreme and unlikely possibility. More probably, competitive action will cause a forecast to be incorrect. Periodic reviews enable management to "retrack" the forecasting mechanism so that forecasts are again within the tolerance limits.

As the forecast is revised, perhaps different marketing plans should be constructed to anticipate the change. The purpose of the forecast is to provide useful input to the total planning process. To be useful, forecasts must be timely and must reflect current conditions.

Result Verification

This step does not imply the development of an alternative forecasting mechanism as elaborate as the first. Instead, this may be the time to apply managerial judgment and intuition. The forecast review helps to realign the existing forecasting model, based on experience with that particular system. Verification offers a fresh viewpoint.

Extensions to Long-Range Forecasting

The transition from short- to long-range forecasting can be most easily described after contrasting short- (tactical) and long-range (strategic) planning. Steiner lists 15 points as bases for distinction.[1] A comparison of strategic and tactical planning appears in Table 8.1.

This comparison has a direct impact on the conversion of the short-term forecasting process, described in the preceding section, to cover long-range estimating. First, the specific use of the forecast is more difficult to state; nevertheless, this is still a crucial first step. Long-range goals, objectives, policies, and strategies form the foundation for the forecast. The very nature of the planning process entails the formation of objectives and purposes; hence, this first step is less likely to be overlooked for long-range forecasting than for short-term forecasting.

The market-product classification is likely to be less difficult for long-range forecasting. The corporate and broad nature of strategic planning will usually be

TABLE 8.1.--Comparison of Strategic and Tactical Planning

Comparative Basis	Tactical Planning	Strategic Planning
1. Level of conduct	lower management	upper management
2. Regularity	fixed schedule	continuous, but irregular
3. Subjective values	lower weighted	higher weighted
4. Range of alternatives	smaller	greater, by definition
5. Uncertainty	less	more
6. Nature of problems	structured, repetitive	unstructured, unique
7. Information needs	narrower, internal	broader, external
8. Time horizons	shorter	longer
9. Completeness	narrower focus	broader focus
10. Reference	based on strategic plan	original
11. Detail	more	less
12. Type of personnel involved	lower management	upper management
13. Ease of evaluation	easier (short time)	harder (several years)
14. Development of objectives, policies, and strategies	historically based	new, flexible
15. Point of view	functional view	corporate view

concerned with large geographic regions and product groups or the entire line.

Because of the general emphasis of long-range forecasting, the data required are to generate aggregate estimates. Perhaps annual or quarterly data are all that are needed. The time period for which the data are collected may be much larger. Long-range forecasting extends far into the future, making use of a strong historic foundation for extrapolation purposes. If the future is thought to be relatively independent of the past, then the extensive historic base is less important; however, the newer relationships must be based on valid and current information.

The difference in long- and short-term forecasting can be handled by the flexible forecasting archetype upon which this dissertation is based. The model can accommodate several ranges of alternatives by inputting many simulated actual sales patterns. Each pattern reflects a different set of assumptions; therefore, the model can be designed to anticipate the sales pattern thought to be the most likely to occur.

The model can be operated whenever a forecast is needed. Possible forecasts could be generated on a regular basis in addition to the "as needed" projections. The forecast interval can be defined for practically any feasible length. For long-range forecasting a one-year interval might be useful. Ten to fifteen, or even more, one-year periods could be forecasted consecutively to build the long-run forecast. An alternative approach is to continue short-term forecasting and accumulate them in the same fashion. Both approaches could be used to develop forecasts for the same long-term period for comparative purposes (step 7--check results--in the forecasting process).

Further flexibility is provided by selecting different forecasting techniques. For this research exponential smoothing was the appropriate technique. Methods more suited for long-range forecasting, such as time series analysis and regression and correlation analysis, might be chosen. No matter which technique is selected, it can be applied at any level desired.

As an example, a complex multiple regression relationship might be derived utilizing the same equation parameters (with adjustments made for relative volume differences) for all products and market segments. At the other extreme, different regression equations could be formulated for each market and product. The aggregate nature of long-range forecasting lends itself more to the general approach, but either one is a viable alternative.

The remaining two steps in short-term forecasting are equally valid for long-term forecasting. The model should be reviewed periodically, and results should be checked using other methods.

In summary, this build-up forecasting model used along with LREPS has been designed to traverse the timing-detail separation between long- and short-term forecasting. The prediction interval, forecasting technique, and level of detail can be combined to forecast for tactical or strategic purposes. Combining these dimensions with alternative hypothetical sales patterns effects maximum forecasting flexibility. The other short-run forecasting steps are relevant for long-run forecasting as well. The real difference is in the depth and breadth of managerial perspective and approach.

Implications for Future Research

Expansion of this research into other directions appears promising. Additional research areas can be classified according to the following scheme:

1. Extensions of current research problem
2. Tests of additional business-related hypotheses
3. Sophistications of the general forecasting mechanism
4. Alternative approaches to forecasting.

Examples from each of these three major areas are discussed below.

Extension of Current Research Problem

Several studies can be conducted with the sample data used for this dissertation. First, the assumed actual sales pattern could be altered to reflect changing environmental and marketing conditions. The only pattern tested was an increasing linear trend, subjected to random fluctuations. A seasonal pattern would be an obvious choice because many firms experience regular variations in sales throughout the course of a year. Another possibility is a decaying sales function. All such patterns wouldn't be relevant at the same time, but such experimentation would prepare a company for the different stages in the product life cycle.

A second inventory location would introduce interactions not presently observed with the single warehouse model. LREPS assigns Demand Units (DU's) to Distribution Centers on a priority basis. The second placement would allow orders resulting in stockouts at one location to be filled from the other site. This complicates the forecasting problem; however, it is an added dimension of reality.

More combinations of forecasting levels might also be attempted. This research presented a comparison of only two levels and no variation in the level of detail within a given experiment. The experimental evidence indicated certain of the products could be forecast in the aggregate, while others might be handled more accurately with forecasts at each DU. Experiments using different combinations of these two levels could be compared, approaching gradually the precide model which minimizes forecasting error for this data. Overly zealous pursuit of this so-called accuracy should be avoided. Since the simulated actual sales input is hypothetical, pinpoint forecasts would represent spurious accuracy.

By increasing the simulated sales volume per unit of time, certain of the approximations inherent in the simulation process would be overcome. For example, certain products with high absolute sales volumes, but low relative to other tracked products, might not appear to be active in several DU's. By increasing the volume per time period, the probability of the product appearing on the generated simulated invoices increases. It should be emphasized that this is a valid experimental approach. Increased simulated sales decreases the proportion of extrapolated to simulated sales. This increases the reliability of the experimental results. As long as the total of actual simulated sales and extrapolated sales is realistic, the results are valid.

As a final improvement in experimental technique, sample sizes could be increased. Only five pairs of smoothing constant-cost and prediction interval-cost values were collected for each sample. The very significant relationships discovered tended to minimize the problem of sample size; nevertheless, larger samples generally are more reliable.

All of the steps suggested as being desirable were not taken because of a cost-time constraint. Additional funding and several more months would have been required to probe thoroughly into all of these areas.

Tests of Additional Business-Related Hypotheses

To enumerate all of the possible areas of business which could be examined using the LREPS-forecasting mechanism as a starting point is an impossible task. The first step might be to consider additional forecasting-distribution system interactions. For example, in the short-run only inbound transportation and inventory costs were found to vary with the quality of the forecast. Longer term analysis should result in more component variations within the physical distribution system. LREPS can be directed to add Distribution Centers to the national network according to predetermined decision rules. If the forecast is too high to the extent that an additional Distribution Center is "built" three to six months too soon, the cost of such an error could be measured directly. The best forecast in the long-run might be the one that postpones Distribution Center additions as long as possible from a cost-service viewpoint.

This example leads to another area of examination: the interrelationship among forecasting (planning), physical distribution, and other business areas. A natural area would be finance, since it monitors all other activities within the firm.[2] Research has been done to establish relationships between financial variables and changes in the structure of the distribution system.[3] By adding the forecast as a causal factor in this changing logistics structure, forecasting and finance can be related. The impact of forecasting accuracy on the sources of funds is an example of a specific research project.

The forecast mechanism could be detached from the LREPS model and combined with another simulation of firm activities. A production system model, including the materials procurement network, would interrelate with the forecasting model. Eventually, if all such models could be connected, the firm itself could be analyzed. This last possibility is still several man-years of work away from occurring.

Sophistications of the General Forecasting Mechanism

The existing model can be improved in a number of areas. The first such improvement could be to make the three dimensions more dynamic. With feedback linkages built into the model, regular monitoring of results could be achieved. For example, in this research the exponential smoothing approach could have been replaced by a form of dynamic smoothing. That is, the last period's forecast could be generated using several smoothing constants. The smoothing constant resulting in the most accurate forecast would be used to generate the next forecast. Variations on this basic theme could also be implemented. Some products could be forecasted using dynamic smoothing and several smoothing constants, while other products with stable sales patterns might use the existing approach.

A two-step dynamic smoothing model could also be used. Four or five initial smoothing constant values could be used to narrow down the range of possible values. Given the best initial values, additional values within a smaller range might be tested. Gradually the most suitable value would be found.

Another method is to develop a warning system by checking forecasting accuracy regularly. When the forecasting error exceeds some predetermined level, the dynamic smoothing module could be activated. The current value for the smoothing constant is used until the error becomes unacceptable. This approach reduces computing time by executing the dynamic smoothing programs only when they are needed, not every time a forecast is generated.

The prediction interval can be analyzed dynamically. The forecasting error can be checked to guard against poor interval choices. Periodic regressions of the most recent data (dependent variable) against prediction interval values could be made to determine the general line form. If the relationship isn't strong, adaptations in the interval can be initiated.

The appropriate level of detail can also be determined dynamically by checking the forecasting error. If the forecasts are not satisfactory, the next level of detail can be the new forecasting base.

A second sophistication that is warranted is the elimination of the homogeneity assumption about the DU's. Simulated actual sales are allocated to the DU's on the basis of the DU's relative population. Some variation is achieved by allowing DU populations to grow at different rates. By adding different allocation bases, a possibility already provided for within LREPS, DU's with unique features could be simulated. For the sample data analyzed in this research, population was a satisfactory DU descriptor; however, for other firms this may not be the case.

Additional flexibility could be attained by inputting simulated actual sales in another fashion, actual sales dollars by product and DU, instead of allocating sales to these cells. This would eliminate some of the random simulation approximations referred to in earlier sections. Actual sales would be recorded precisely. The Order File Generator within LREPS could still be used to simulate the invoice detail required to meet sales specifications.

More and varied statistical analyses could be attempted to aid in the development of the forecasting model detail. Some of the measures of forecasting error discussed in Chapter IV, beyond the variance and Theil's inequality coefficient, could be examined through experimentation. Perhaps certain measures of error are useful only as a function of the actual sales pattern. Other variables within the model could be tracked and related to the prediction interval, equation parameters, and level of detail dimensions. For example, average inventory levels could be related to these model dimensions.

Alternative Approaches to Forecasting

This dissertation has focused on the joint usage of a forecasting framework and the LREPS model, including the Order File Generator. The forecasts were generated within the forecasting model, and simulated actual sales were disseminated throughout the geographic market area by the Order File Generator. Serving as the objective function to be optimized, the LREPS model reflected the reactions of the physical distribution system to different levels of forecasting accuracy. These accuracy levels resulted from different settings for the three dimensions of the forecasting module.

The LREPS model, taken alone is an equally viable forecasting tool. Annual sales data can be inputted exogenously through the Supporting Data Subsystem. The mechanism which distributes sales dollars across products and territories can be used to forecast the future. Relationships between product category sales or product sales and selected independent variables can be derived for every Demand Unit (DU) from historic data. Detailed (by product and by DU) forecasts are easily obtained once the historic relationships are determined. The physical distribution system, as simulated by LREPS, can again be used as the objective function.

Seasonal and cyclic influences can be incorporated into this approach. The exogenous sales input can be adjusted by cyclic indexes to reflect general economic conditions. The seasonal variations can be anticipated by associating indexes with each day simulated by LREPS. Quarterly seasonal factors can be included by assigning the same index to each day in the quarter. More precision can be obtained by gradually changing the indexes on a day-to-day basis.

Using LREPS as the forecasting mechanism eliminates having to design the three dimensions of the forecasting model developed in this dissertation. LREPS can be used directly to generate forecasts. The forecasting module developed through this research is easily "uncoupled" from LREPS to stand alone. The LREPS forecasting mechanism would be somewhat more difficult to use independently, although it is possible with some minor modifications of the model structure.

This alternative forecasting approach involves using LREPS as the primary forecasting instrument instead of as a controlled experimental environment. The conclusions reached in this dissertation could be validated by this other method. If the two approaches to forecasting resulted in similar forecasted values, more confidence could be placed in the estimates. Conversely, unlike forecasts would cause management to investigate the causes for divergence. An attractive area for additional study would be a statistical comparison of the results of these two forecasting methodologies.

CHAPTER VIII--FOOTNOTES

[1]Steiner, pp. 37-39.

[2]The idea for this potential research can be attributed primarily to Dr. Michael L. Lawrence, Assistant Professor of Finance, University of Missouri, Columbia.

[3]M. L. Lawrence, Development of a Dynamic Simulation Model for Planning Physical Distribution Systems: The Financial Implications of Warehousing Decisions (unpublished doctoral dissertation, Michigan State University, 1972).

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