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Sales forecasting accuracy over time: An empirical investigation

Zbib, Imad J., Ph.D.

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U·M·I
300 N. Zeeb Rd.
Ann Arbor, MI 48106

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This study investigated forecasting accuracy over time. Several quantitative and qualitative forecasting models were tested and a number of combinational methods was investigated.

Six time series methods, one causal model, and one subjective technique were compared in this study. Six combinational forecasts were generated and compared to individual forecasts. A combining technique was developed.

Thirty data sets, obtained from a market leader in the cosmetics industry, were used to forecast sales. All series represent monthly sales from January 1985 to December 1989. Gross sales forecasts from January 1988 to June 1989 were generated by the company using econometric models. All data sets exhibited seasonality and trend.

Three accuracy measures were employed in the investigation. These are: 1) Mean percentage Error (MPE), 2) Mean Absolute percentage Error (MAPE), and 3) Root Mean Squared Error (RMSE).

Nonparametric statistical tests (Friedman nonparametric analysis of variance and the Wilcoxon matched-pairs signed-

ranks test) were employed to test whether the difference in performance among the methods was due to chance. Given the relatively small sample, these tests are preferred to the parametric t-tests.

Results indicated that combining several quantitative techniques is better than individual methods; that a weighted average combining is better than a simple average combining; that quantitative methods are more accurate than subjective methods; that combining quantitative and qualitative methods provide better forecasts than the individual methods; that the level of accuracy depends on the time horizon of the forecast; and that causal models are superior to time series methods.

Future research should focus on the reasons for the differences in accuracy achieved by the different forecasting techniques. More quantitative and subjective methods should be investigated at both macro and micro levels. In addition, future research should focus on different demographic data to confirm the results of this study. Finally, the study suggests that better methods of averaging forecasts be investigated.

SALES FORECASTING ACCURACY OVER TIME:

AN EMPIRICAL INVESTIGATION

IMAD J. ZBIB, B.S., B.B.A., M.S.

APPROVED:

Major Professor

Minor Professor

Committee Member

Committee Member

Committee Member

Chair of the Department of Management

Dean of the College of Business Administration

Dean of the Robert B. Toulouse School of Graduate Studies

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Imad J. Zbib, B.S., B.B.A., M.S.

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CHAPTER I

INTRODUCTION

Background

In today's complex and competitive economy, planning is one of the most important managerial functions that determines the success or failure of a business organization. Planning not only reduces uncertainty by anticipating changes in the environment, it also explains the effect of the actions managers might take in response to change (Robbins 1988). Planning is essential if organizations are to achieve effective levels of performance. It is also a viable way of pursuing a competitive advantage.

Planning focuses on the future. Many of the decisions made in business involve anticipation of future events. Examples include decisions regarding location of facilities, production planning, product and service design, personnel, advertising, financing, and plant expansion. Because all of these decisions involve future actions, the importance of forecasting as a managerial tool is implicit for effective planning (Makridakis et al. 1983).

Forecasting is one strategy that managers may use in order to respond effectively to changes in the environment. It enables managers to anticipate the future and reduce some of the uncertainties that cloud the planning process (Stevenson 1990).

Makridakis et al. (1983), defined forecasting as " the prediction of values of a variable based on known past values of that variable or other related variables." Adam and Ebert (1989) identified forecasting as a process of estimating a future occurrence by casting forward past data.

The practice and the importance of forecasting in planning has increased considerably over the past few decades (Hogarth and Makridakis 1981). Studies such as Makridakis et al. (1983) and Wall et al. (1989) suggested that forecasting is an integral part of the decision-making process. American companies spend millions of dollars on prediction, making forecasting an important business (Granger 1980). Mentzer and Cox (1984) noted that "Sales forecasting is rapidly becoming one of the most crucial aspects of planning for companies." Gerstenfeld (1971) found a positive relationship between industries' growth rates and their use of technology forecasting techniques. He also indicated that organizations using formal forecasting techniques experience greater sales growth and profitability than those that do not.

Forecasting is an issue that has been of increasing concern to many scholars and practitioners (Makridakis and

Wheeleright 1987). The existence of several forecasting methods, from the simple intuitive approach to sophisticated computerized mathematical models, raise a controversial question. Increasingly, managers are asking which forecasting technique is most accurate for their particular application.

Many research efforts, both on the theoretical and empirical level, have focused on the importance of forecasting accuracy. Makridakis (1983) indicated that accuracy is a very important factor in forecasting. He stated that "in many situations even small improvements in forecasting accuracy can provide considerable savings." In investigating appropriate levels of accuracy, Wheelwright and Makridakis (1980) found that for some planners forecasts anywhere between plus or minus 10 percent of actual sales satisfied their purposes. In other situations, Wheelwright and Makridakis (1980) pointed out that a variation of as little as 5 percent could pose major problems for certain companies. As a consequence, accurate sales forecasting has become a requirement for success in business (Mahmoud 1984).

Although research has identified the importance of accuracy in forecasting, most studies have not fully explained which forecasting techniques provide more accurate forecasts. For example, results have been mixed when quantitative and qualitative forecasting techniques were compared. A comprehensive study of this subject was performed by Makridakis and Hibon (1979). The results of this study indicated that quantitative methods such as simple naive, moving average, and exponential smoothing were superior to management judgment. In addition, Mahmoud (1984) found that "on the whole, past research suggests that quantitative methods outperform qualitative methods."

On the other hand, several studies recognize the potential benefits of subjective forecasts (e.g., Mabert 1976, Staelin and Turner 1973, Dalrymple 1987). For example, Dalrymple (1987) reported that the sales force composite and the jury of executive opinion were the methods used most often in sales forecasting. Further, Staelin and Turner (1973) emphasized that managers can be good sources of forecast data due to their access to the richly detailed market information they gather.

Other scholars found that combining two or more methods can result in reduced forecasting error (e.g., Bates and Granger 1969, Cooper and Nelson 1975, Doyle and Fenwick 1976, Makridakis et al. 1982, Dalrymple and Parsons 1983, Winkler and Makridakis 1983, Mahmoud and Makridakis 1989, Bunn 1989). For instance, Doyle and Fenwick (1976) noted that forecasters can obtain more useful information through combining than through the use of a single technique. Cooper and Nelson (1975) indicated that robustness could be improved by combining different forecasting techniques. According to Makridakis and Winkler (1983), rather than choosing a single model to do the forecast, an average of several models would be better.

Certain streams of forecasting research have investigated the effectiveness of combining qualitative and quantitative forecasting methods. Winkler and Makridakis (1983) and Dalrymple and Parsons (1983) suggested that combining management judgment and systematic methods is desirable because, through this combination, managers can utilize the information contained in both approaches. Granger and Newbold (1977) concluded that the accuracy of the forecast can be improved when judgmental forecast and causal models are combined. Mahmoud (1982) and Makridakis et al. (1983) found an improvement in the forecasting accuracy and a reduction in the cost of forecasting when combining quantitative and qualitative methods. This conclusion is supported by other empirical studies conducted by Fildes and Fitzgerald (1983), Moriarty and Adams (1984), and Lawrence et al. (1986). A consistent conclusion throughout these studies is that combining qualitative and quantitative forecasting methods can improve the accuracy of forecast because more relevant information is retained.

Problem

Many studies have compared the accuracy of quantitative against qualitative forecasting techniques (e.g., Makridakis 1982, Mahmoud 1984, Makridakis and Hibon 1979, Moriarty and Adams 1984). Research results have been contradictory, however. For example, some studies (e.g., Mahmoud 1984) found that quantitative forecasts provide superior accuracy over subjective forecasts. Others (e.g., Moriarty and Adams 1984, Dalrymple 1987) concluded that qualitative forecasts are more accurate.

In still other studies, researchers (e.g., Mabert 1976, Staelin and Turner 1973, Dalrymple and Parsons 1983, Mahmoud 1984, Winkler and Makridakis 1983, Mahmoud and Makridakis 1989, Bunn 1989) have recommended the combination of qualitative and quantitative techniques.

More recent studies have not resolved these inconsistencies. In many cases, the investigators claimed that combining methods provides more accurate forecasts than using one approach alone. Nevertheless, few studies have empirically tested the effectiveness of combining quantitative methods with management judgment (e.g., Lawrence et al. 1986, Moriarty and Adams 1984, Moriarty 1985, Zbib and Savoie 1989). The inconsistencies noted above, along with the lack of convincing empirical research, specially on a micro level, suggest that further research into the accuracy of combining forecasts is warranted. In fact, Mahmoud (1984) suggested that more theoretical and empirical research is needed to determine whether combining is better, and which techniques should be combined. In another study, Mahmoud and Makridakis (1989) stated that "the field of forecasting needs further insights into combining." Lawrence et al. (1985) specifically suggested that a combination model incorporating judgmental forecasting models should be investigated. In still other studies, more empirical research dealing with micro time series were recommended (e.g. Sanders and Ritzman 1989). These studies suggest that more comparisons of forecasting methods should be made using micro data, such as data on individual products.

Objectives

The proposed study investigates the accuracy of both quantitative and qualitative forecasting techniques implemented by a large corporation. Of particular interest is whether combining these two techniques can improve estimating accuracy over alternative methods.

Another objective of this study is to examine the consistancy of accuracy over time. In addition, this study investigates the difference among selected combining methods.

Research Questions

The purpose of the study can be stated in the form of the following research questions:

1. Combinations of forecasts from several quantitative methods provide better results than individual forecasts.

2. Errors of combined forecasts differ with various combining techniques.

3. Quantitative forecasting methods provide more accurate forecasts than do subjective methods.

4. Forecasts of combining quantitative and subjective

methods lead to improvements in accuracy. Specifically, combining extrapolation and management judgment methods is expected to produce better forecasts than the single best model.

5. The accuracy of the forecasts improves with shorter time horizons.

6. Causal methods are more accurate than extrapolation methods.

Importance of the Study

Planning is an integral part of a manager's job (Stevenson 1990, Hogarth and Makridakis 1981). A typical objective in planning is to improve sales volume. Within this context, forecasting sales is the first step in the process of planning. Forecasts provide the information needed by decision makers to plan more appropriately and thus to maintain or increase their sales.

Forecasters must choose among different forecasting techniques, as the number of techniques outstrips the time available to forecast. Since the accuracy among techniques may vary, the technique selected may have an impact on the performance of the organization.

Consequently, accuracy plays an important role in choosing the best forecasting method (Mahmoud, 1984). Sales traditionally are forecast using quantitative methods, qualitative methods, or a combination of both. Studies concerning which of these techniques is more accurate have been inconsistent. This study proposes to explore these inconsistencies and shed new light on the effectiveness of combining quantitative techniques with management judgment. The intent of this study is to provide information of practical interest to managers, forecasters and consultants to firms engaged in forecasting.

Preview

This study is divided into five chapters. The first chapter has provided a broad introduction to the study. The second chapter of this study reviews the literature relevant to the research in question. The third chapter describes the methodology used for gathering and analyzing the data. Chapter four reports the results of the study. Finally, chapter five presents conclusions and suggestions for future directions for research.

CHAPTER II

REVIEW OF LITERATURE

This chapter reviews the literature that is directly related to the present study. First, a historical perspective of the forecasting literature is presented. Secondly, research linking forecasting and planning is reviewed. Finally, a comprehensive discussion of the different forecasting techniques and their accuracy is presented along with the different combining procedures.

Historical Perspective

Human beings have been seeking to foretell the future since the beginning of civilization. The idea of forecasting was first expressed verbally in the Indo-European Languages (Godet 1979). Prescientific means were used as means to forecast coming events. Examples include observing the stars, reading holy books, examining natural disasters, using dice and cards, and palm reading (Beckwith 1986).

Before the industrial revolution, forecasting in the conventional business sense was unknown. In the early 1700s, the word "forecasting" was not mentioned in any of the major encyclopedias or indexes. Richelet's dictionary of 1739 defined prediction as "theological term; used of God and means knowledge of what will come (Jouvenel 1964). Under this definition, predicting the future was conceived as something that could be done only by God.

Scientific techniques to forecasting were not introduced until the late 1700s. In 1795, Marquis de Condorcet, a French mathematician, was the first person to predict major political and social trends scientifically (Beckwith 1986). Although his work represented an important step forward, Condorcet's efforts are rarely cited in modern books and articles on forecasting.

In the early 1800s, Saint-Simon and Auguste Comte restated and endorsed some of Condorecet ideas. They also introduced some of their own (Taylor 1975). Saint-Simon stated that, "A scientist ... is a man who predicts." He also emphasized that in order to predict the future, it was necessary to understand the past (Taylor 1975). Saint-Simon believed that reasoning based on religious and metaphysical methods had been losing ground to the increasing use of the scientific methods. Comte (cited in Franklin 1986), who was the first to use science to predict the future social evolution, suggested that people need a true picture of humanity, agreeing with Simon. He also stated that knowledge was necessary for predictions, and that prediction was necessary for control. Comte believed that in order to predict the future, past social trends should be analyzed. He called this a "historical" method (Franklin 1968).

In the second half of the 1800s, Karl Marx and

Friedrich Engels created a new scientific method to predict social trends and workers' productivity. Their method of economically interpreting the history is considered a great contribution to the science of futurism. Marx and Engels also used statistical trends to project the future (Beckwith 1986).

In the early 1900s, Herbert Wells stated that society should think more seriously about the future. He wrote several articles on forecasting social trends during the 20th century. In 1901, he wrote his first book, Anticipations of the Reaction of Mechanical and Scientific Progress upon Human Life and Thought, which was an important contribution to the field of forecasting (Beckwith 1986). In this book Wells proposed creating a school to teach methods to predict the future.

In 1932, Clifford Cook Furnas wrote his famous book America's Tomorrow. Furnas forecasted technological change based on scientific evidence and statistical trends (Furnas 1932).

In 1940, Schumpeter came up with a different approach to predict the future. He claimed that one could not predict the future through scientific techniques that only extrapolate past trends. Rather, predictions must be based on what he called trend projection (Schumpeter 1942). Ferdinand Lundberg, on the other hand, stated that in many cases predicting the future should be based on the projection of the past. He proposed a subjective approach using the opinions of experts (Lundberg 1963).

In more recent decades, public interest in forecasting has grown rapidly. The progress in this field has attracted the attention of scholars and practitioners. A number of books and articles have been written about the value of forecasting and the quality of different techniques. Some articles have concentrated on philosophical issues such as whether it is more important to improve the accuracy of the available forecasting techniques or to improve the ability to live with poor forecasts (Flores and Whybark 1986). Table 1 provides a historical summary of advances forecasting.

Table 1.-- Historical Summary of Forecasting

Time Period	Concept/Approach	Contributor (Source)
Before 1700s	Prescientific: stars, holy books.	Indo-European (Godet 1979)
Early 1700s	Theological term: prediction is done by God.	Richelet's Dictionary (Jouvenel 1964)
Late 1700	Scientific approach: predicted political and social trends.	Marquis de Condorcet (Beckwith 1986)
Early 1800s	Scientific approach: predicted future social evolution based on past trends.	Saint-Simon and Auguste Comte (Taylor 1975)
Late 1800s	New scientific method: used statistical trends to project workers' productivity.	Karl Marx and Friedrich Engels (Beckwith 1986)

Table 1-- Continued.

Time Period	Concept/Approach	Contributor (Source)
1901	Wrote several articles on forecasting social trends during the 20th century. He proposed creating a school to teach methods to predict the future.	Herbert Wells (Beckwith 1986)
1932	Wrote America's Tomorrow Used scientific evidence & statistical trends to forecast technological changes.	Clifford Cook Furnas (Furnas 1932)
1940	Trend projection method: used subjective methods to predict the future.	Schumpeter (Schumpeter 1942)
1940	Qualitative approach: opinions of experts.	Ferdinand Lundberg (Lundberg 1963)
1960s	Exponential Smoothing techniques	Brown, Holt, Winters, & Pegels (Makridakis et al. 1983)
	Combination of forecasts	Chester Barnard

Importance of Forecasting

The growing interest in forecasting can be attributed to the increase in the rate of technological change and in man's activities. "Change is accelerating and its effects are so pervasive...but those who first become aware of future trends are best placed to benefit from them." (Godet 1979).

Strategic planning has been growing in businesses as a guide to building profitable portfolios. Hughes and Singler

(1983) state that strategic corporate planning operates in an uncertain environment. When managers plan, they define in the present what their organizations will do in the future. Therefore, the first step in planning is predicting the future demand for products and services and the resources needed to produce these outputs (Gaither 1990). Corporate goals and continued survival often revolve around sales volume. Effective sales forecasting has become essential for the success of companies, increasing the need for accurate predictions of both unit and dollar values (Mahmoud 1987, Mahmoud and Pegels 1990).

Through sales forecasting, managers can reduce some of this uncertainty by predicting what will be sold and when. Firms can grow only if they are adaptable to changes in the environment. A good plan, linked to environmental forecasting would enable companies to respond to changes, thus avoiding surprises and uncovering new opportunities (Michman 1989). Remus and Simkin (1987) state "A good forecast allows an organization to take advantage of opportunities and avoid pitfalls in the environment through timely decision making."

Many authors have discussed the importance of forecasting to organizations. For example, Makridakis and Wheelwright (1987) stated, ".. in the turbulent environment of the 1970s and early 1980s, the need for forecasting became widely recognized." Firms need forecasts of events in all phases of their organization. Virtually all departments have some need for the annual sales forecast. Production, finance, personnel, accounting, and all of the marketing functions use the sales forecast in their planning activities" (Hughes 1987). Makridakis at al. (1983) supported this viewpoint, noting that forecasting is an integral part of the decision making process. Armstrong (1978) goes so far as to maintain that forecasting is necessary every time a decision is made.

Production planners need forecasts to schedule production activities, hire and train workers, and purchase raw materials (Coccari 1989). Purchasing managers try to finalize buying commitments weeks before they actually need the products. In so doing, they also use forecasts to maintain proper stock positions. In the process, forecasting becomes an essential element of any inventory control system (Abbot 1979).

Moreover, financial planners need forecasts to plan their cash and borrowing positions in advance. Personnel uses forecasts as well as a guideline to determine both work force availability and composition (Eby and O'Neill 1977). Accountants need accurate forecasts of revenues and expenditures to prepare their budgets (Donnelly et al. 1987). Finally, marketing depends on sales forecast to calculate the number of salesmen needed to properly service selling areas and to determine the advertising expenditures likely to be needed during the forecast period (Eby and O'Neill 1977). Wright et al. (1986) agree adding that sales forecasting is an integral part of the marketing decision support system (DSS).

The importance of accurate prediction is not limited to the business sector, however. According to Bretschneider and Corr (1979), politicians have been placing increased importance on forecasting in state and local governments due to increasing financial constraints. Gambill (1978) found that 45 percent of the states responding to his survey used econometric methods to forecast their revenues.

Forecasting Techniques

In each management area where sales forecasting is needed, matching appropriate techniques to specific problems is important. The present question facing decision makers is not simply whether to forecast or not. Instead, managers must be more concerned about what technique to use.

Forecasters have a wide range of techniques from which they can choose. Techniques vary from the naive, simple approach to complicated mathematical and statistical computerized models. These models vary in their cost, their underlying assumptions, their complexity, and their accuracy (Mahmoud 1984).

Different types of quantitative methods, as well as qualitative techniques, do exist. Quantitative methods involve either an extrapolation of historical data (time series) or development of associative models (causal). Qualitative techniques, on the other hand, are based on judgments and consist mainly of subjective input which allows inclusion of soft information. These methods may involve several levels of complexities from intuitive hunches about the future to scientifically conducted market surveys (Gaither 1990).

A classical article appeared in the Harvard Business Review in 1971 evaluating eighteen forecasting techniques that, according to the authors, every planner should know (Georgoff and Murdick 1986).

The authors divided these methods into (1) qualitative methods, (2) time series analysis and projection, and (3) causal methods. Another article appeared in the same journal in 1986 summarizing the current state of forecasting (Georgoff and Murdick 1986). It is interesting to note that, inspite of the phenomenal advances made in science and technology during that fifteen years, the techniques discussed in 1971 and 1986 are very similar. These methods are summarized in table 2.

Table 2.-- Summary of Forecasting Techniques *

Technique	Description
Qualitative Methods	
Delphi method	Questions panel of experts for opinions.
Panel Consensus	A panel of experts in a field meets to formally develop consensus on a particular forecast.
Sales-force Composite	Questions salespeople for estimates of expected sales in their territories.
Market Research	Systematic, formal procedure that attempts to measure customer intentions by collecting a sample of opinions.
Visionary Forecast	Now known as "Scenario Development Methods." Individuals believed to be visionary prepare several scenarios to predict future events.
Historical Analogy	Given information about similar events, forecasters attempt to predict future events in the life cycle of an organization.
Time Series Analysis and Projection	
Moving Average	Uses historical data to calculate an average of past demand. This average is then used as a forecast.
Exponential Smoothing	Similar to the moving average, but more weight is given to the most recent periods. The pattern of weights is exponential in form.

Table 2-- Continued.

Technique	Description
Adaptive Filtering	A weighted combination of actual and expected outcomes is systematically adjusted to reflect any changes in data pattern.
Time Series Extrapolation	This technique derives a prediction of outcomes from the future extension of a least squares function fitted to a data series.
Box-Jenkins	A computer based procedure that produces an autoregressive, integrated moving average model. Forecasters propose and analyze models in computer simulation. Then, data are tested and models are revised until the results are close to the actual historical data.
X-11 (Time Series Decomposition)	This technique decomposes a time series into seasonal, trend cycles, and irregular elements.
Trend Projections	Depending on the nature of the data, a linear or nonlinear function is developed and used to project into the future.
Regression Model	From past data a functional relationship is established between some set of independent variables X1, X2,...Xn and an independent variable Y. This relationship is then used to predict future events.
Econometric Models	These models are generally series of linear equations involving several interdependent variables.

Table 2-- Continued.

Technique	Description
Leading Indicators	Generates forecasts from one or more preceding variable that is related to the variable to be predicted.
Correlation Methods	The forecast is based on the patterns of covariation among variables.
Input-Output Models	They are used to provide long-term trends for the econometric models. They also explain how a change in one industry affects other industries.

* Generated from Georgoff and Murdick (1986)

In selecting a specific forecasting method, decision makers must consider many factors such as the purpose of the forecast, the availability and structure of the data, ease-of-use, the time horizon of the forecast, the costs involved, and the accuracy of the forecasting technique (Mahmoud 1982, Makridakis and Wheelwright 1979).

According to Sartorius and Mohn (1976), the accuracy of the forecasting technique must be considered once the purpose of the forecast has been defined. Anandalingan and Chen (1989) stated that accuracy is the most important factor in forecasting. This view is also supported by Makridakis et al. (1982). They noted that "in many situations even small improvements in forecasting accuracy can provide considerable savings" (Makridakis et al. 1982).

An assessment of current knowledge about forecasting is provided by Makridakis (1986). He stated that studies of forecasting techniques have produced contradictory results and that no study has proven superiority of one method over another. Other studies by Moriarty (1985), Wright et al. (1986), Dalrymple (1987), Tyebjee (1987), and Miller (1985) confirm that no unique model exists that can predict most effectively in all situations.

Quantitative Methods

Quantitative techniques have been investigated extensively in the forecasting literature (Armstrong and Grohman 1972, Adam and Ebert 1976, Makridakis and Wheelwright 1979, Moriarty and Adams 1979, Makridakis et al. 1982, Mahmoud 1982, 1984, Moriarty 1985, Carbone and Gorr 1985, Dalrymple 1987). For example, Adam and Ebert (1976) reported that Winters' method provided more accurate results than human forecasts. Mabert (1975) concluded that forecasts based on opinions of corporate executives and sales people are less accurate and more expensive than those based on other quantitative methods. In a more recent study, Carbone and Gorr (1985) found that objective methods gave more accurate results than eyeball extrapolation.

The supporters of quantitative methods believe that a number of inherent difficulties in conducting qualitative research diminish its utility. Accordingly, qualitative researchers have been particularly concerned with the validity and accuracy of their studies. Kirk and Miller (1987) report that reliability is often questioned in qualitative studies for several reasons. The most critical reason is the incompetence, bias, or dishonesty of the researcher. McDonald (1985) reported that, even though qualitative research reduces some of the threats to validity, questions concerning the researcher's bias, experience, preconceptions, and expectations still arise. He also adds that the researcher suspends personal beliefs, perspectives, and predispositions when engaged in qualitative studies. Miles (1979) believes that qualitative research has serious weaknesses. The most serious of these weaknesses is the fact that the methods for analyzing qualitative data are not standardized. He points out that the researcher is faced with a bank of qualitative data and has very few guidelines to follow.

Other studies focused only on comparing the performance of different quantitative methods. Within this stream of research conflicting findings have raised serious questions about which method to use. The quantitative models have typically been grouped according to two types, time series and causal.

The first type assumes that the past data are indicative of the future. According to this technique, forecasts are based on past values, past errors, or both. These models are often called extrapolative models. The second type, on the other hand, assumes that the variable being forecasted is a function of some other variable or variables. Classical models of this type are regression and econometric models. The objective of these two causal models is to investigate the relationship between the variables of interest and use this relationship to forecast future values of the dependent variable based on values of the independent variables (Gaither 1990).

According to Makridakis et al. (1983), time series models are easier to use than causal models. In an earlier study conducted in 1976, Makridakis reported that explanatory models require several independent variables whose magnitude must be evaluated before any predictions can be made. Newbold and Granger (1974) offer support for this point, also noting that "relevant extraneous information may be unavailable or only obtainable at a prohibitively high cost."

In the last few years, a considerable number of empirical studies have compared the performance of time series and econometric forecasting models. A comprehensive survey of research into this issue was performed by Fildes (1985). The references noted by Fildes found contradictory results. Of the 20 studies included in his work, 15 showed econometric methods to be more accurate, three showed equivalence, and two showed econometric techniques to be less accurate than other methods.

Studies such as Christ (1975) and Armstrong (1985) concluded that econometric models are superior to time series models. Armstrong (1985), for example, reported seven empirical comparisons of long-range forecasting techniques. In each comparison, Armstrong found that econometric methods were more accurate than extrapolation. On the other hand, studies by Cooper (1972), Nelson (1973), Reid (1971; 1975), and Schmidt (1979) indicated that Box-Jenkins models are stronger than econometric methods. A study by Kinney (1978), however, concluded that the performance of both techniques is equivalent. Other studies (Leser 1968, McNeese 1979, 1982, Armstrong 1978) reported that complex and sophisticated methods are not necessarily more accurate than simple techniques. Groff (1973), Makridakis and Hibon (1979), and Makridakis et al. (1982) investigated the performance of sophisticated and simple time series techniques. They also concluded that sophisticated methods are not better than simple approaches. Carbone et al. (1983) adding, "simpler methods were found to provide significantly more accurate forecasts than the Box-Jenkins method when applied by persons with limited training.

In comparing the performance of smoothing models, Gross and Ray (1965) reported that exponential smoothing performed better for short-term forecasting. In a subsequent study, Kirby (1966) concluded that Ray's results are valid only for the very short term forecast (month-to-month). For a time period of one to six months, both moving average and exponential smoothing techniques outperformed regression analysis. Enns et al. (1982) found a multiple exponential smoothing model to have a number of structural and performance advantages over simple exponential smoothing model.

Dalrymple (1987) designed a survey to investigate how companies prepare sales forecasting, what methods they use, and the performance of their forecast. He found that the naive method was the most popular with 30.6 percent of the respondents indicating its use. The moving average was the second most popular (20.9 percent), while only 11.22 percent reported using the exponential smoothing. An interesting finding was that only 1 percent of the companies surveyed said they used the naive method for long term forecasts.

Carbone and Makridakis (1986) reported that deseasonalized single exponential smoothing performed fairly well when a pattern change took place at the end of the data. They attribute this to the fact that exponential smoothing tracked the changing mean of the product. McLeavy et al. (1981) stated that exponential double smoothing was most accurate for studies with low noise levels. Wight (1974), on the other hand, stated that exponential double smoothing is difficult to understand. Wright (1986) extended the single exponential smoothing and the Holt's methods to the case of irregular time intervals. After applying their extended model to six published series, they found it more computationally efficient, and easy to use.

In other studies, Whybark (1971) created hypothetical demand patterns to compare four adaptive exponential smoothing models. He concluded that adaptive models are useful when the demand functions are complex. He also added that some adaptive models are better than others, depending on the stability of demand. Moreover, Adam et al. (1979) compared seven individual item forecasting models. They found that simple methods are superior to other models. These findings are supported in a recent study conducted by Koehler (1985). The results of this work also showed that simple time series models to be better than the Box-Jenkins.

Geurts and Kelly (1986) investigated whether the forecasting techniques used by manufacturers to forecast sales can be used to predict retail sales accurately. They used monthly sales data over a 13-year period and found that for forecasting retail sales, time series methods outperform judgment and econometric models. They also concluded that exponential smoothing techniques are better than Box-Jenkins in forecasting department store sales.

In investigating the predictive ability of several extrapolative methods, one particular study by Makridakis et al. (1982) provides some interesting insights into the performance of exponential smoothing models. They employed different methods of time series for 1001 products, concluding that single exponential smoothing techniques are very accurate for monthly data. For yearly and quarterly data, however, the Lewandowski's method was superior while no difference in performance was found between Holt and Holt-Winters' methods. In the same study, the researchers found that simple methods outperformed sophisticated methods when micro data were used. However, on the macro level, the authors found the reverse to be true.

Qualitative Methods

Even though quantitative methods have held a historically prominent role in business, many managers believe that the need for incorporating their judgment into the forecast is inescapable. Winkler (1987) suggested that the judgment of experts is necessary to evaluate relevant data indirectly and to obtain the results needed in a standard setting. He also noted that "judgmental forecasts are useful in many public policy decisions." A study by Basu and Schroeder (1977) showed that the forecasting errors were reduced significantly, from 20 percent to less than 4 percent when the Delphi technique was used. Dalrymple (1987) reported that the sales force composite and the executive opinion, both subjective, were widely used by American firms. He also concluded that forecasting errors can be reduced by making seasonal adjustment. These findings support an earlier survey conducted by Dalrymple in 1975.

Many researchers find that qualitative research has several advantages. Wallace (1984), for example, emphasized that qualitative research provides flexibility to uncover new issues and insights. Qualitative data are "rich, full, earthy, real, and holistic" (Miles 1979). Several other advantages have been identified by Wells (1986). He reported that qualitative data are more likely to be available when needed and are less expensive to collect. Evered and Louis (1981) and Beyer and Trice (1982) stated that interpretive research may generate situationally applicable guidelines more directly relevant to the problems faced by managers.

The acceptance of subjective forecasting is also supported by studies by Mentzer and Cox (1984) and Lawrence, Edmundson and O'Connor (1985). After analyzing a sample of 111 time series, Lawrence et al. (1985) found that judgmental forecasts were as accurate as statistical techniques. In comparing objective methods with management judgment, Carbone and Gorr (1985) conducted an empirical study using MBA students and a sample of 10 time series. They concluded that judgmental adjustment improved the accuracy of the objective forecasts.

Mahmoud et al. (1988) noted that quantitative techniques are not commonly used for certain types of sales forecasting such as industrial marketing. Moreover, Powell (1979) emphasized that, until more dependable quantitative methods are available, decision makers should rely on their judgment.

Lewandowski (1987) describe three methodological reasons that cause forecasters to switch from quantitative to qualitative methods. He stated that quantitative techniques are very difficult understand for the average person, that they involve a number of unrealistic assumptions, and that they do not integrate extrapolative and explicative variables into one model. To solve these problems, Lewandowski created a system that enables the users to include explanatory variables which might improve the forecast. Jenks (1983) concurs, stating, "Quantitative advanced techniques such as regression modeling, Box-Jenkins, exponential smoothing and many more typically require staff specialists to develop them, they require time, research and experimentation to find satisfactory relationships." He adds that quantitative methods are not capable of anticipating one-time events such as a surprise competitive development, nor they are accurate for long term planning without management adjustment.

In comparing different judgmental forecasting techniques, Armstrong (1975) conducted a comprehensive review for the social sciences. His study found that causal judgmental methods were more accurate than naive judgmental techniques. He also reported that subjective judgmental methods were less accurate than objective judgmental methods.

In analyzing the performance of analysts in forecasting, Jonston and Schmitt (1974), Critchfield et al. (1978), and Brandon and Jarrett (1979) noted that, if given accurate information, analysts can predict better than quantitative methods. However, Armstrong (1984) reports that management judgmental forecasting is more accurate than analysts' judgmental forecasts. Schnaars and Topol (1987) investigated whether multiple scenarios improve the accuracy of judgmental sales forecasts. Their study showed no evidence of any improvement.

Combining Forecasts

Because of the inconsistencies mentioned above, and difficulties in choosing an accurate forecasting technique that will work in different situations, much research has been devoted to combining forecasts. According to Pokemper and Baily (1970), combining has become a common practice among business forecasters. Combining forecasts helps decision makers to improve the accuracy of their predictions (Georgoff and Murdick 1986).

The concept of combining to improve the predictive ability of the available forecasting models has been investigated in many contexts during the past few years. Bunn (1989) stated that the idea of combining forecasts goes all the way back to the early 1960's. At this time, Bernard, according to Bunn, "took the first initiative to focus upon the forecasting context, and took as a motivating premise the apparently sensible desire to use all available evidence in making forecasts."

In the same article, Bunn (1989) discussed the power of this technique when he obtained an 80 percent reduction in mean squared error through combining in a study of two reported models for forecasting monthly tourists visiting a popular resort island. He reported that "purely objective combinations of forecasts are currently enjoying renewed interests." With reference to Zellner (1971), Bunn (1989) emphasized the utility of the Delphi technique by describing the increased acceptability of incorporating the Bayesian approach, using multiple experts and different sources of evidence. Bunn's argument reinforced the use of multiple models for forecasting.

Makridakis et al. (1982) and Makridakis (1983) conducted empirical experiments to test the performance of numerous methods of forecasting based on several accuracy measures. They concluded that a simple average and a weighted average of six forecasting methods were more accurate than any of the individual methods included in the study. In an other study by Makridakis and Winkler in 1983 the authors concluded that combining forecasts from two or more methods to obtain a single forecast can yield fewer forecasting errors. More specifically, the error reduction when combining as few as two models was 7.2 percent. When five models were included in the combination, the error reduction increased to 16.3 percent. In a subsequent study, Armstrong (1986) investigated the literature of combining forecasts. He found that the forecast accuracy increase varied from zero to 23 percent.

In an earlier study, Bates and Granger (1969) concluded that a linear combination of forecasts can result in lower mean square error than either of the individual forecasts. Mahmoud (1984) stated that through combining we can obtain more accuracy because more information about the potential market is retained. He also reported that "In today's increasingly volatile markets, the combining of forecasting methods is particularly important." In a subsequent survey, Mahmoud and Makridakis (1989) stated that "theoretical work and empirical studies have demonstrated beyond reasonable doubt that there are considerable benefits to be gained from combining forecasts." They added "the effect of combining is that the forecasting errors of the various models/methods and or people included are 'averaged out' making the composite error smaller on the average." This view is supported by Flores and White (1989). They pointed that any combination of forecasts provides more accurate results than the individual forecasts regardless of the combining technique used.

Combining Qualitative Methods: In combining different judgmental methods, Ashton and Ashton (1985) obtained more accuracy when a number of subjective forecasts made by advertising sales executives were combined. Lawrence et al. (1986) also concluded that the accuracy level was always improved when a set of judgmental methods was aggregated. This is also supported by a more recent study conducted by Flores and White (1989). The researchers compared the performance of subjective and objective combination of several judgmental forecasts. Their conclusion was that combining methods always improve the accuracy of individual forecasts.

Combining Quantitative Methods: Other studies investigated the performance of combining quantitative techniques only (Bates and Granger 1969, Newbold and Granger 1974, Pindyck and Rubinfeld 1976, Falconer and Sivesind 1977, Dalrymple 1978, Adams 1978, Mabert 1978, Gregg 1980, Mahmoud 1982, Makridakis et al. 1982, 1984, Winkler and Makridakis 1983, Makridakis and Winkler 1983, Longbottom and Holly 1985, Bopp 1985, Mills and Stephenson 1985, Russell and Adam 1987). All of these studies found that the combined approach provided better accuracy.

For example, Makridakis and Winkler (1983) used 111 time series to combine fourteen quantitative methods. Using the simple average in the combination, the researchers concluded that the accuracy of combined forecasts was influenced by the number of methods used and the type of methods being averaged. In an other study, Winkler and Makridakis (1983), applied 10 forecasting techniques to the 1001 time series used in Makridakis et al. (1982). Again, the results showed an improvement in the accuracy when the methods were combined.

Combining Quantitative and Qualitative Methods: Combining quantitative and judgmental methods has also been examined extensively in the forecasting literature (e.g., Gold 1979, Mahmoud 1982, Fildes and Fitzgerald 1983, Moriarty and Adams 1984, Zarnowitz 1984, Moriarty 1985, Lawrence et al. 1986, Newbold et al. 1987, Mahmoud and Makridakis 1987, Zbib and Savoie 1989, Pereira et al. 1989). For example, Lawrence et al. (1986) reported an improvement in accuracy when statistical and judgmental forecasts are combined. Pereira et al. (1989) combined time series forecasting with subjective predictions from open-market operators. Their results showed that more accuracy can be obtained when these techniques are combined. Brandt and Bessler (1983) combined several forecasting methods (Quantitative and qualitative) to forecast livestock prices. They found that the combining method reduced large forecasting errors.

Moriarty and Adams (1984) suggested a combinational model that includes both systematic and judgmental forecasts. In a subsequent study, however, Moriarty (1985) combined management judgment and time series and found no significant improvement in accuracy. He, therefore, recommended that both methods should be retained. Moreover, Mahmoud and Makridakis (1989) stated that "it is advisable that managers prepare a judgmental forecast separately and then formally combine it with a quantitative forecast."

Combining Techniques

Forecasting methods can be aggregated using different combining techniques that vary from simple averages to more complex weighted methods. Many combining methods have been proposed, including unrestricted regressions (Granger and Ramanathan 1984), historical weighing (Doyle and Fenwick 1976), subjective weights (Doyle and Fenwick 1976), Odds-Matrix method (Gupta and Wilton 1987), weighted average based on the sample covariance matrix (Newbold and Granger 1974, Makridakis and Winkler 1983), linear combination (Holden and Peel 1986), constrained versus unconstrained weights (Nelson 1972, Makridakis et al. 1982, Granger and Ramanathan 1984), focus forecasting (Smith and Wright 1978), composite predictors (Moriarty and Adams 1984, Phillips 1987), weighing based upon actual forecast error (Russell and Adam 1987), and multiple objective linear program model (Reeves and Lawrence 1982, Gulledge et al. 1986). Mahmoud and Makridakis (1989) provide a thorough review.

In their often cited study (known as the M-Competition), Makridakis et al. (1982) used both the simple and a weighted average, based on the covariance matrix of fitting errors. The results of this study supported the simple approach. Also favoring the simple approach to combining are studies by Einhorn (1972), Gupta and Wilton (1978), Mahmoud (1982), Ashton (1982), Carbone et al. (1983), Winkler and Makridakis (1983), Figlewski and Urich (1984), Lawrence et al. (1986), Clemen and Winkler (1986), Kang (1986), and Holden and Peel (1986). For example, Lawrence at al. (1986) stated that the simple average was less time consuming and more accurate than judgmental combination. Kang (1986) agrees, noting that the simple average is superior to the weighted average because the weights in the later are unstable.

While the simple average has gained the interests of many researchers and has proven accurate and robust, its theoretical justification remains absent (Gupta and Wilton 1987). Studies such as Bates and Granger (1969), Newbold and Granger (1974), Makridakis et al. (1982), Makridakis and Winkler (1983), Granger and Ramanathan (1984), Engle et al. (1985), and Diebold and Pauly (1987) concluded that the weighted average techniques are superior to the simple average. Gupta and Wilton (1987) introduced a new weighted combining method, called the Odds-Matrix (OM) method. They claimed that the OM method is highly robust and superior to simple averaging, especially if the forecasts errors are nonstationary. Others (Nelson 1972, and Holmen 1987) concluded that a linear combination provides more accuracy than other methods, especially the simple average.

Flores and White (1989) conducted an experiment to compare the accuracy of subjective and objective combining methods. Their results favored the subjective approach. Moreover, Sessions and Chatterjee (1989) investigated the performance of ten combination methods (six optimal and four ad hoc) and concluded that the combining methods that allow local bias adjustment are superior to the simple average method.

Gunter and Aksu (1989) introduced a new method to combining that involves combining the combined forecasts resulted from several combination methods employed at the preceding step (Known as N-Step combinations). Their results showed that more accuracy can be obtained when this concept is used.

Since the body of literature dealing with the accuracy of forecasting techniques is extensive, summarizing and classifying such studies would be useful,so that their relevance can become clear. In Appendix A, a summary of selected studies in the area of forecasting accuracy is presented.

Accuracy Measures

Since accuracy plays a vital role in assessing forecasting techniques, many studies have attempted to find the best way to measure how accurate the forecasting model is. Unfortunately, none of these studies has resulted in a single universally accepted instrument (Makridakis et al. 1983). A summary of accuracy measures, based on several sources, is provided by Makridakis and Wheelwright (1978) and Mahmoud (1984, 1989).

In evaluating the results of any forecasting method, many comparative techniques are available. Some of these techniques are more popular than others. "Clearly the forecaster or the practitioner is faced with a trade-off between the cost of applying a forecasting technique or an opportunity loss from basing decisions upon an inaccurate forecast and the value of increased accuracy in the selection of a technique." (Mahmoud 1984).

The most widely used method is the mean squared error (MSE). However, this technique has two problems. According to Makridakis et al. (1983), an MSE that is developed during the fitted phase may give misleading information about the accuracy of the model at the forecasting phase. Another problem with this method, according to the authors, is that different forecasting techniques use different procedures in the fitting phase. Other studies also criticize the use of this measure for comparisons containing more than one set of data (Winkler and Makridakis 1983, Gardner 1983, Guerts 1983). Their argument is that this criterion is highly influenced by the magnitude of the data. Mahmoud (1984), on the other hand, concluded that forecasters can rely on MSE instead of using Gardner's I value to determine the accuracy of any forecasting model relative to the naive model.

Because of the problems inherent in the MSE measure, some managers prefer to use the mean absolute percentage error (MAPE) and/or the median absolute percentage error (MdAPE) (Gardner 1983). Other techniques are also used such as the mean percentage error (MPE), the Theil's U-Statistics, the root mean squared error (RMSE), the mean error (ME), mean absolute deviation (MAD), and R-squared (Bretschneider and Carbone 1979, Armstrong 1978, Makridakis and Hibon 1979).

Conclusions

Forecasting is a subject that has been a constant and great concern to many scholars (e.g., Makridakis et al. 1982, Mahmoud 1982, 1984, Armstrong 1978, 1985, Makridakis et al. 1986). The existence of several forecasting methods raise a controversial question. Managers are questioning the accuracy of these techniques and are asking which method provides more accuracy than others.

A wide range of methods is available to assist managers in predicting the future. Various types of qualitative techniques are used (e.g. jury of executive opinion, sales force composite, management judgment, the Delphi approach), as well quantitative univariate and multivariate quantitative methods (time series and causal). Results have been mixed when these two techniques are compared. For example, studies such as Makridakis and Hibon (1979) and Mahmoud (1984) found that quantitative methods were superior to management judgment. On the other hand, several studies (e.g., Mabert 1976, Staelin and Turner 1973, Dalrymple 1987) recognize the potential benefits of subjective forecasts. Others (Carbone and Gorr 1985) reported that revised judgment forecasts are more accurate than initial judgment.

Combining quantitative and qualitative forecasting methods has been investigated extensively in the forecasting literature (e.g., Winkler and Makridakis 1983, Dalrymple and Parsons 1983, Moriarty and Adams 1984, Lawrence et. al 1986, Mahmoud and Makridakis 1989). Most of these studies showed that more accuracy can be obtained when these techniques are combined. Moriarty (1985), however, combined time series and management judgment and found no significant improvement in accuracy. These inconsistencies suggest that more investigations of the accuracy of combining forecasts are warranted (Mahmoud 1984, Mahmoud and Makridakis 1989).

Results have also been mixed when combining techniques are compared. Some studies found the simple average method is superior to weighted technique (e.g., Makridakis et al. 1982, Mahmoud 1982). On the other hand, studies such as Newbold and Granger (1969), Granger and Ramanathan (1984) suggested that the weighted average method is more accurate.

The proposed research has evolved from the contradictory results shown in the reviewed literature. The major goal of this study is to investigate the accuracy of combining quantitative and management judgment forecasts. In addition, the proposed study will examine the difference in accuracy level between initial judgmental forecast and revised judgmental forecasts. Finally, a comparison between the simple average and the weighted average combining techniques will be made.

CHAPTER III

METHODOLOGY

The purpose of this study is to investigate the accuracy of forecasting over time. Focus is placed on combining quantitative and qualitative forecasting techniques. Of particular interest is whether combining exponential smoothing and management judgment techniques provides better forecasts than those of the individual models. This case study also investigates whether a weighted average combination is superior to the simple average. Finally, the study compares the forecasts generated by the econometric model currently used by a corporation with the constituents forecasts generated by different time series methods.

The Company

The company under investigation is a market leader in the cosmetics industry. It produces a variety of products with a total product range comprising in excess of 200 individual items. Short-term forecasting for individual products within the company takes place on a monthly basis, using qualitative methods. A single econometric forecasting model is used to generate forecasts for all products.

The Data

The data used in the study consist of empirical time series. Thirty data sets were used to forecast sales. All series represent monthly sales from January 1985 to December 1989. In addition, monthly forecasts for the same thirty products generated by the management's qualitative method were obtained. This qualitative method utilizes the expertise of managers from different departments who get together periodically to discuss sales. It is purely subjective, and depends on the managers' expectations. Gross sales forecasts from January 1988 to June 1990 were generated by the company using econometric models. All data sets exhibited seasonality and trend (see Appendix B for data patterns).

Forecasting Methods

Six time series methods, one causal model, one qualitative method, and their combinations are investigated in this study. The six time series techniques tested here are: single exponential smoothing (SINGLE), Holt's two parameter linear model (HOLT), Winters' three-parameter trend and seasonal (WINTERS), adaptive response rate exponential smoothing (ARRES), Brown's one-parameter quadratic method (BROWNQ), and Carbone-Makridakis (CMFS).

Several criteria were considered in the selection of these particular methods. First, they are widely used in the literature. Second, the models chosen as accurate models from a number of comparative studies. Third, they were selected based on both their accuracy and simplicity. Finally, these selected methods provide forecasts quickly. This is very important these days when forecasts may need to be generated daily. These techniques, along with their strengths are summarized in Appendix C. The equations of these selected models are presented in Appendix D.

Six combination forecasts were selected from these six single techniques, resulting in three three-technique simple average combinations and three three-technique weighted average combinations. Although more combinations could have been investigated, earlier studies state that accuracy is not significantly affected by the selection of techniques in the combination (e.g. Makridakis et al. 1982, Makridakis and Winkler 1983, Winkler and Makridakis 1983, Sanders and Ritzman 1989). Furthermore, the benefits of combining have been shown to decrease when the number of techniques included in the combination exceeds four (Makridakis and Winkler 1983). Another study (Lawrence et al. 1986) concluded that combinations of three forecasts are more accurate than those using only two forecasts. All possible combinations were first investigated and the following six were selected for this study:

Simple Average:

1. COMB1s: Carbone-Makridakis (CMFS), Holt's Linear Exponential Smoothing (HOLT), and Single Exponential Smoothing: An Adaptive Approach (ARRES).
2. COMB2s:Carbone-Makridakis (CMFS), Holt's Linear Exponential Smoothing (HOLT), and Single Exponential Smoothing (SINGLE).
3. COMB3s: Carbone-Makridakis (CMFS), Single Exponential Smoothing: An Adaptive Approach (ARRES), and Single Exponential Smoothing (SINGLE).

Weighted Average Based Upon Actual Forecast Error:

1. COMB1w: Carbone-Makridakis (CMFS), Holt's Linear Exponential Smoothing (HOLT), and Single Exponential Smoothing: An Adaptive Approach (ARRES).
2. COMB2w: Carbone-Makridakis (CMFS), Holt's Linear Exponential Smoothing (HOLT), and Single Exponential Smoothing (SINGLE).
3. COMB3w: Carbone-Makridakis (CMFS), Single Exponential Smoothing: An Adaptive Approach (ARRES), and Single Exponential Smoothing (SINGLE).

The forecasts for the combinations were obtained period by period by taking both the simple average and a weighted average (based upon actual forecast error) of the forecasts obtained by the individual techniques that were included in the combination.

The forecasts generated by the causal model were provided by the corporation. The company uses econometric models to forecast gross sales for all of its products.

Measuring Forecast Accuracy

The accuracy measures used in this study are Mean Percentage Error (MPE), Mean Absolute Percentage Error (MAPE), and Root Mean Squared Error (RMSE). Managers are recommended to use more than one comparative measure because no one universally approved measure exists (Gardner and Dannenbring 1980, Mahmoud 1984). Therefore, three accuracy measures are used in order to evaluate better the accuracy of the various forecasting methods in this study. These three measures were selected because of their common use (Makridakis et al. 1978, Mahmoud 1987, Mahmoud et al. 1990).

Research Design

The proposed study involves several phases. First, in testing the accuracy of the individual models, and in order to examine whether the accuracy of a method is consistent and stable over time, the data series were partitioned. For each series which includes 60 data points, the first 30 data points were used to fit the model and forecast ahead 6 months. Then, 6 more data points were added so 36 data points were used to refit the model and forecast ahead 6 months. Doing this continued until 54 data points were employed in the fitted phase. This division of data was used for all the time series models. This partitioning process has been widely used (e.g., Makridakis et al. 1982 and Mahmoud et al. 1990). The accuracy of the fitted phases were compared to the accuracy of the forecasted values provided by the six time series models used in this study. This comparison was made for the three consecutive forecasting phases and the most accurate model (s) was selected and used for comparison and combining with management judgment forecasts.

Second, six different three-model combinations were developed and tested for accuracy using three accuracy measures (MPE, MAPE, and RMSE). The results of the combinational models are then compared with the individual methods. Two combining techniques were used for this purpose. The first is the simple average and the second is a weighted average based on the actual error (the MAPE was employed as a base).

Third, in order to compare whether forecasting accuracy is affected by the time horizon of the forecast, the same partitioning process was repeated for three periods and for one period ahead. For example, for three-period ahead forecast, the first 30 data points were used to fit the model and forecast three periods ahead. Then three data points were added to refit the model and forecast ahead three months. The same procedure was used for the short time horizon (one month ahead). The accuracy of the three different time horizons (six, three, and one month ahead) were then compared.

Fourth, to test whether subjective methods are more accurate than quantitative methods, the management judgment forecasts were tested and compared with the corresponding forecasts generated by the six time series models.

The fifth step in the study was to combine the management judgment forecast with the quantitative methods selected in step one. A weighted combining technique, based on the actual error, was used for this purpose. Then, the combining forecasts were tested and compared with the individual forecasts.

Finally, gross sales forecasts were generated by the best four time series methods selected in step one. Those forecasts were then compared with the forecasts developed by the econometric model currently used by the corporation.

Statistical Analysis

The possibility that the difference in performance among the techniques was due to chance was tested using nonparametric statistical tests. The Wilcoxon matched-pairs signed-ranks test and Friedman nonparametric analysis of variance were carried out on the forecasts generated by both the individual and the combinational models. Given the relatively small sample, these nonparametric tests are preferred to the parametric t-tests because of their less restrictive assumptions and their insensitivity to outliers (Moriarty and Adams 1984). Several studies comparing forecasting accuracy of different techniques also have used these tests (e.g. Armstrong and Grohman 1972, Carbone et al. 1983).

All six time series techniques were executed in an automatic mode using FUTURECAST, an interactive program developed by Makridakis and Carbone (1984).

Statistical Hypotheses

The primary interest in the study is to investigate whether combination of forecasts produces lower forecast error than the single best model. Based on the four steps described above, the following statistical hypotheses will be tested:

Hypotheses 1 (Ho1):

Combination of forecasts from several quantitative methods does not lead to more improvements in accuracy. Specifically, combining two or more time series methods does not produce lower forecast error than either (or any) of the separate methods.

Hypotheses 2 (Ho2):

The simple average combining technique is superior to the weighted average method. Specifically, the simple average combining is better than a weighted average based upon actual forecast error.

Hypotheses 3 (Ho3):

In general, subjective methods are superior to quantitative methods. Specifically, management judgment forecasts are more accurate than forecasts produced using time series methods.

Hypotheses 4 (Ho4):

Combination of forecasts from quantitative and subjective methods does not lead to more improvements in accuracy. Specifically, combining time series methods and revised management judgment methods is not superior to the individual forecasts.

Hypotheses 5 (Ho5):

The accuracy level of the quantitative forecasts does not change when the time horizon of the forecasts changes. Specifically, when the time horizon of the forecast changes from six months to three months, to one month, the accuracy level does not improve.

Hypotheses 6 (Ho6):

In general, causal methods generate more accurate forecasts than do time series methods.

CHAPTER IV

RESULTS

This chapter begins with an examination of the accuracy of combining several quantitative methods. The results of the simple average and the weighted average combining techniques are presented next, followed by a discussion of the forecasts generated from both quantitative and qualitative methods. Then, forecasts generated from combining quantitative and subjective methods are analyzed and discussed, followed by presenting forecasting performance with different time horizons. Finally, the results of both time series and causal models are presented. The chapter concludes with a summary of the findings.

Combination of Quantitative Forecasts: (Ho1)

To test whether combining quantitative forecasts improves accuracy over the constituent forecasts, the accuracy of six time series models and three combinations were tested and compared. The results are shown in tables 3 to 6.

Table 3 ranks the six individual forecasting models on their overall performance for the 30 time series using all three accuracy measures. Shown are the mean percentage error (MPE), mean absolute percentage error (MAPE), and root mean squared error (RMSE) scores for each technique in each of the forecasted phases individually, and in aggregate. The several similarities among the rankings of the three accuracy measures are interesting. For example, the three are consistent in ranking Winters' and Brown's as the least accurate models. However, noting that no one time series method is most accurate in all instances is important. For example, observe the values of Mean Percentage Error (MPE) and Mean Absolute Percentage Error (MAPE) for Adaptive Response at the first (37-42 data points), the second (43-48), the third (55-60), and the fourth (55-60) forecasted phases.

The possibility that the difference in accuracy between these models was due to chance was tested using Friedman's nonparametric analysis of variance (see Seigel 1956). The null hypothesis that no difference existed between the six time series models was rejected at the 0.01 level of significance. Table 4 presents mean ranks of the individual forecasting techniques. The chi square statistics reported in table 4 reveal strong significant differences in the accuracy of the six methods, with the Holt's model being the most accurate, followed by CMFS, ARRES, Single, Winters, and Brown, in order of decreasing accuracy.

Table 3.-- Ranking of Forecasting Techniques BY MPE, MAPE, and RMSE, According To the Performance of Each Method (Selected Series)

Forc. Phase	Acc. Measure	ARRES (R)	HOLT (R)	CMFS (R)	BROWN (R)	SINGLE (R)	WINTERS (R)
		Model					
37-42	MPE	-24.4 (5)	-11.2 (2)	-8.7 (1)	-24.2 (4)	-25.6 (6)	-23.9 (3)
	MAPE	37.8 (3)	36.4 (1)	37.2 (2)	40.1 (5)	38.2 (4)	40.2 (6)
	RMSE	9816 (1)	10094 (3)	10141 (4)	10586 (6)	9929 (2)	10170 (5)
43-48	MPE	-3.5 (2)	0.05 (1)	8.8 (4)	-21 (6)	-8.5 (3)	-10.7 (5)
	MAPE	15.7 (1)	23.1 (4)	17 (2)	32.6 (6)	19.5 (3)	27.6 (5)
	RMSE	5454 (1)	7504 (4)	5913 (2)	9767 (6)	6554 (3)	8376 (5)
49-54	MPE	-59.2 (3)	-47.9 (2)	-35.6 (1)	-68.3 (6)	-60.4 (4)	-67.8 (5)
	MAPE	73.2 (5)	69.4 (1)	72.5 (2)	80.0 (6)	72.6 (3)	72.7 (4)
	RMSE	8056 (2)	9060 (4)	10286 (6)	10169 (5)	8039 (1)	9039 (3)
55-60	MPE	-13.8 (4)	-7.3 (2)	0.46 (1)	-19.2 (6)	-10.2 (3)	-13.8 (5)
	MAPE	25.0 (4)	19.9 (1)	22.5 (3)	29.5 (5)	21.6 (2)	32.1 (6)
	RMSE	5916 (1)	6989 (4)	6273 (3)	7122 (5)	6091 (2)	8050 (6)
AVG.	MPE	-25.5 (3)	-16.6 (2)	-8.7 (1)	-33.2 (6)	-26.2 (4)	-29 (5)
	MAPE	37.8 (3)	37.2 (1)	37.3 (2)	45.5 (6)	37.9 (4)	43.1 (5)
	RMSE	7310 (1)	8412 (4)	8154 (3)	9411 (6)	7653 (2)	8909 (5)

Note: R = Rank
MPE = Mean Percentage Error
MAPE = Mean Absolute Percentage Error
RMSE = Root Mean Squared Error
ARRES = Adaptive Response Rate Exponential Smoothing
HOLT = Holt's Linear Exponential Smoothing
CMFS = Carbone-Makridakis
BROWN = Brown's One-Parameter Quadratic
SINGLE = Single Exponential Smoothing
WINTERS= Winters' Trend and Seasonality

Table 4.-- Friedman Test Results for Differences in Accuracy Between individual Methods (by MPE, MAPE, and RMSE)

Forecasting Techniques	Mean Ranks						
	ARRES	HOLT	CMFS	BROWNQ	SINGLE	WINTERS	Chi Square
	2.6	2.4	2.5	5.6	3.1	4.9	40.94*

* denotes significant difference at 0.01 level.

Also, the three measures show that the combining techniques are more accurate than the individual techniques in the combination. Table 5 ranks the individual forecasting models and their weighted average combinations on their overall performance for the 30 time series. Presented are the MPE, MAPE, and RMSE scores for each technique in each of the four forecasted phases individually, and in aggregate.

Table 5. Errors of Individual and Combinational Forecasting Techniques BY MPE, MAPE, and RMSE

Forc. Phase	Acc. Measure	ARRES	HOLT	CMFS	BROWN	SINGLE	WINTERS	COMB1w	COMB2w	COMB3w
37-42	MPE	-24.4	-11.2	-8.7	-24.2	-25.6	-23.6	-12.4	-12.4	-15.4
	MAPE	37.8	36.4	37.2	40.1	38.2	40.2	36.0	36.1	36.2
	RMSE	9816	10094	10141	10586	9929	10170	9859	9869	9754
43-48	MPE	-3.5	0.05	8.8	-21.0	-8.5	-10.7	4.18	3.09	2.73
	MAPE	15.7	23.1	17.0	32.6	19.5	27.6	16.06	16.69	15.01
	RMSE	5454	7504	5913	9767	6554	8376	5678	5815	5404
49-54	MPE	-59.2	-47.9	-35.6	-68.3	-60.4	-67.8	-43.3	-43.3	-45.1
	MAPE	73.2	69.4	72.5	80.0	72.6	72.7	68.7	68.2	69.1
	RMSE	8056	9060	10286	10169	8039	9039	9052	8995	8761
55-60	MPE	-13.8	-7.3	0.46	-19.2	-10.2	-13.8	-4.27	-3.62	-4.5
	MAPE	25.0	19.9	22.5	29.5	21.6	32.1	20.69	20.1	21.5
	RMSE	5916	6989	6273	7122	6091	8050	6180	6211	5959
AVG.	MPE	-25.5	-16.6	-8.7	-33.2	-26.2	-29.0	-13.9	-14.1	-15.6
	MAPE	37.8	37.2	37.3	45.5	37.9	43.1	35.5	35.4	35.6
	RMSE	7310	8412	8154	9411	7653	8909	7692	7723	7470

Table 6.-- Friedman Test Results for Differences in Accuracy Between Individual and Combinational Methods (by MPE, MAPE, and RMSE)

Mean Ranks									
ARRES	HOLT	CMFS	BROWNQ	SINGLE	WINTERS	COMB1w	COMB2w	COMB3w	CHI SQUARE
4.6	4.8	4.7	8.5	5.5	7.9	3.13	3.07	2.8	66.72 *

* denotes significant difference at 0.01 level.

Tables 3 to 6 shed considerable light on the issue of forecasting accuracy. The resultant forecasting errors show that the combinations generally outperformed the individual models across all three accuracy measures. Important to note, however, is that the accuracy of various methods differs sometimes, depending upon the accuracy measure being used and the time period of the forecast. For example, observe the values of the MPE, MAPE, and RMSE for single exponential smoothing at the first (37-42), the second (43-48), the third (49-54), and the fourth (55-60) forecasted phases in table 5. Clearly, this supports other studies (e.g. Mahmoud et al. 1990, Winkler and Makridakis 1983) which concluded that different forecasting procedures perform differently over various time periods.

Tables 5 and 6 also show that the accuracy of combined forecasts depends on the specific methods being combined. For example, the best results can be achieved when Single, ARRES, and CMFS models are combined. When Holt's was included, the accuracy level decreased. This was also concluded by Makridakis and Winkler (1983).

Simple Average vs. Weighted Average Combining: (Ho2)

To test whether weighted average combination of forecasts gives more accurate results than simple average combination, the accuracy of the six combinational models was tested. In table 7 the models are ranked on the bases of the three accuracy measures used. Table 8 presents the results of the Wilcoxon signed ranks tests. The z-scores reported indicate significant difference in MPE, MAPE, and RMSE between the two types of combining (simple and weighted averages), thus leading to the conclusion that the weighted average technique is better than the simple average.

The null hypothesis that no difference existed in accuracy between a simple average and a weighted average combinations was also tested by using the Friedman nonparametric test (see Seigel 1988). Table 9 presents mean ranks of MPE, MAPE, and RMSE of each combinational method for selected series. The chi square statistics reported in table 9 reveal strong significant differences in the accuracy of the two combining techniques for the three combinational models. The null hypothesis was rejected at the 0.5 level, which means a weighted average, based upon actual error, of three methods performs very well overall and better than the simple average technique.

Table 7.-- Ranking of Combinational Forecasting Techniques BY MPE, MAPE, and RMSE (Selected Series)

Series (products)		Model					
		COMB1s	COMB2s	COMB3s	COMB1w	COMB2w	COMB3w
1	MPE	4	5	6	1	3	2
	MAPE	4	5	6	1	3	2
	RMSE	4	6	5	2	3	1
4	MPE	4	6	5	1	3	2
	MAPE	4	6	3	2	5	1
	RMSE	4	6	3	2	5	1
10	MPE	5	6	4	2	3	1
	MAPE	6	5	4	1	3	2
	RMSE	5	6	2	3	4	1
16	MPE	3	5	6	1	4	2
	MAPE	4	6	5	1	3	2
	RMSE	4	6	5	1	3	2
30	MPE	5	4	6	3	2	1
	MAPE	6	5	4	3	2	1
	RMSE	6	5	4	3	2	1

Note: COMB1s (simple average): Carbone-Makridakis (CMFS), Holt's Linear Exponential Smoothing (HOLT), and Single Exponential Smoothing: An Adaptive Approach (ARRES).

COMB2s (simple average): Carbone-Makridakis (CMFS), Holt's Linear Exponential Smoothing (HOLT), and Single Exponential Smoothing (SINGLE).

COMB3s (simple average): Carbone-Makridakis (CMFS), Single Exponential Smoothing: An Adaptive Approach (ARRES), and Single Exponential Smoothing (SINGLE).

COMB1w (weighted average): Carbone-Makridakis (CMFS), Holt's Linear Exponential Smoothing (HOLT), and Single Exponential Smoothing: An Adaptive Approach (ARRES).

COMB2w (weighted average): Carbone-Makridakis (CMFS), Holt's Linear Exponential Smoothing (HOLT), and Single Exponential Smoothing (SINGLE).

COMB3w (weighted average): Carbone-Makridakis (CMFS), Single Exponential Smoothing: An Adaptive Approach (ARRES), and Single Exponential Smoothing (SINGLE).

Table 8.-- Wilcoxon Tests Results for Differences in Accuracy Between Combinational Methods

	COMB1w	COMB2w	COMB3w!
COMB1s	-3.41 *	-2.47 **	-3.41 *
COMB2s	-3.41 *	-3.41 *	-3.41 *
COMB3s	-3.24 *	-2.13 **	-3.41 *

* denotes significant differences at 0.01 level
** denotes significant differences at 0.05 level
! the weighted average used in the combination is based upon the actual historical error (MAPE). Each model is given a weight equals to its average MAPE, divided by the sum of the average MAPE of all models included in the combination.

Table 9.-- Friedman Test Results for Differences in Accuracy Between Individual Methods (by MPE, MAPE, and RMSE)

Mean Ranks						
COMB1S	COMB2S	COMB3S	COMB1W	COMB2W	COMB3W	Chi Square
4.5	5.5	4.5	1.8	3.2	1.5	56.2 *

* denotes significant difference at 0.01 level.

Subjective vs. Quantitative Methods: (Ho3)

To test whether subjective methods provide more accurate forecasts than quantitative methods, the accuracy of management judgment (subjective) and four time series (quantitative) models were compared. To accomplish this comparison the management judgment forecasts for the thirty products were compared with the corresponding forecasts generated by ARRES, CMFS, HOLT, and SINGLE, (the best four time series models were selected for this comparison). The MPE, MAPE and RMSE from each of these five models are presented in table 10.

Table 11 presents the results of the Wilcoxon signed ranks tests. The z-scores reported indicate significant difference in MPE, MAPE, and RMSE between the two types of forecasts (Quantitative and Subjective), thus leading to the conclusion that management judgment forecasts are less accurate than time series models.

Table 10.-- Ranking of Average MPE, MAPE, and RMSE for Quantitative and Subjective Methods (Selected Series)

SERIES (products)		R	ARRES	R	CMFS	R	HOLT	R	SINGLE	R*	QUAL.
7	MPE	5	-6.59	2	4.99	3	5.00	1	-2.59	4	-6.36
	MAPE	4	16.98	2	15.85	3	15.87	1	14.06	5	25.03
	RMSE	4	7408	2.5	7162	2.5	7162	1	6706	5	12794
13	MPE	5	-8.67	1.5	0.17	1.5	0.17	3	-4.00	4	-8.16
	MAPE	5	22.37	2	19.25	3	19.29	1	18.95	4	19.60
	RMSE	5	4268	2.5	3725	2.5	3725	1	3588	4	4215
15	MPE	4	2.18	2	-2.46	3	-2.47	1	-0.69	5	5.87
	MAPE	3	14.06	1	16.43	2	16.47	4	15.88	5	21.35
	RMSE	1	6106	3.5	6435	3.5	6435	2	6354	5	7164
1	MPE	4	-32.72	2	-27.45	3	-28.68	1	-20.51	5	-71.36
	MAPE	4	53.29	2	57.75	3	57.87	1	48.26	5	90.58
	RMSE	2	7559	3.5	8227	3.5	8227	1	7161	5	11502
5	MPE	4	-28.27	1.5	-7.00	1.5	-7.00	3	-15.14	5	89.15
	MAPE	4	38.55	2	31.58	3	31.62	1	28.11	5	96.28
	RMSE	2	2234	3.5	2604	3.5	2604	1	2071	5	4980
6	MPE	1	-323.6	2	-324.4	3	-324.5	4	-326.9	5	-634.7
	MAPE	1	336.46	2	339.50	3	339.57	4	343.02	5	636.66
	RMSE	4	8839	1.5	6313	1.5	6313	3	7758	5	13194
2	MPE	4	-9.54	2	6.62	3	6.65	1	-5.15	5	-11.70
	MAPE	4	20.47	2	19.79	3	19.83	1	19.51	5	30.83
	RMSE	1	4994	3.5	5266	3.5	5266	2	5023	5	8617
3	MPE	1	-4.85	4	-6.76	4	-6.76	2	-5.33	4	6.75
	MAPE	1	24.92	3.5	26.26	3.5	26.26	2	22.81	5	29.90
	RMSE	4	12965	2.5	12951	2.5	12951	1	11772	5	21338
26	MPE	1	-4.96	4.5	-9.28	4.5	-9.28	3	-7.53	2	-5.72
	MAPE	2	29.66	3.5	29.70	3.5	29.70	5	30.54	1	26.52
	RMSE	1	7395	2.5	7616	2.5	7616	4	7774	5	8390
29	MPE	3	-13.65	1.5	-4.29	1.5	-4.29	4	-13.95	5	-42.12
	MAPE	1	27.91	3.5	29.81	3.5	29.81	2	29.52	5	47.34
	RMSE	1	6892	3.5	8023	3.5	8023	2	7380	5	16962
AVG.	MPE	4	-43.07	1	-36.99	2	-37.11	3	-40.18	5	-67.84
	MAPE	3	58.60	2	58.59	4	58.63	1	57.17	5	102.41
	RMSE	4	6866	2.5	6832	2.5	6832	1	6559	5	11316
Mean Ranks		2.94		2.45		2.91		2.06		4.64	

* R= Rank

Table 11.-- Wilcoxon Tests Results for Differences in Accuracy Between Quantitative and Subjective Methods

	Forecasting Model			
	ARRES	CMFS	HOLT	SINGLE
Management Judgment	-4.12 *	-4.48 *	-4.12 *	-4.47 *

* denotes significant differences at 0.01 level

Combination of Forecasts from Quantitative and Subjective Methods: (Ho4)

To test whether combining quantitative and subjective methods lead to more accurate forecasts, an examination was made of combining one time series and one subjective (management judgment) methods. Table 12 shows for selected series the MPEs, MAPEs, and RMSEs of the Holt's, the management judgment, and the combined forecasts. Table 13 shows the z-scores of the Wilcoxon matched-pairs signed-ranks tests and reveals that a combination of judgmental and quantitative forecasts improved accuracy over the constituent forecasts-thus rejecting Ho5 at the 0.1 level.

Importantly, few instances of some accuracy measures of the combined forecast being worse than those of its constituent elements were noted. For example, the RMSE of the combinational model for series 7 ranks second, indicating that Holt's method is more accurate than the combinational method in terms of this accuracy measure. Examining the individual values of the accuracy measures for each series is thus recommended.

Table 12.-- Ranking of Quantitative, Subjective, and Combinational Forecasting Techniques BY MPE, MAPE, and RMSE (Selected Series)

Series	Acc. Measure	Model: HOLT	Rank	Management Judgment	Rank	Comb.	Rank
7	MPE	5	2	-6.36	3	1.02	1
	MAPE	15.87	2	25.03	3	15.42	1
	RMSE	7162	1	12796	3	8198	2
13	MPE	0.17	1	-8.16	3	-2.75	2
	MAPE	19.29	2	19.60	3	13.81	1
	RMSE	3725	2	4215	3	3331	1
15	MPE	-2.47	2	5.87	3	0.45	1
	MAPE	16.47	2	21.35	3	15.23	1
	RMSE	6435	2	7164	3	6380	1
1	MPE	-28.68	1	-71.36	3	-43.61	2
	MAPE	57.87	2	90.58	3	56.64	1
	RMSE	8227	2	11502	3	7616	1
5	MPE	-7.00	1	89.15	3	-35.74	2
	MAPE	31.62	1	96.28	3	47.44	2
	RMSE	2604	2	4980	3	2530	1
6	MPE	-324.48	1	-634.74	3	433.07	2
	MAPE	339.57	1	636.66	3	440.16	2
	RMSE	6313	1	13194	3	8442	2
2	MPE	6.65	2	-11.70	3	0.22	1
	MAPE	19.83	2	30.83	3	19.31	1
	RMSE	5266	2	8617	3	5145	1
3	MPE	-6.76	3	6.75	2	-2.03	1
	MAPE	26.26	2	29.90	3	21.73	1
	RMSE	13951	2	21338	3	13377	1
26	MPE	-9.28	3	-5.72	1	-8.03	2
	MAPE	29.70	3	26.52	2	24.45	1
	RMSE	7616	2	8390	3	7130	1
29	MPE	-4.29	1	-42.12	3	-17.53	2
	MAPE	29.81	2	47.34	3	28.22	1
	RMSE	8023	1	16962	3	8431	2
Mean Ranks			1.8		2.9		1.4

Table 13.-- Wilcoxon Tests Results for Differences in Accuracy Between Quantitative, Subjective and Combinational Methods

	Forecasting Model	
	HOLT	Management Judgment
Combinational	-1.80 *	-4.64 **

* denotes significant differences at 0.1 level
** denotes significant differences at 0.05 level

To test whether combining on the bases of period by period ahead provides better results than combining on the average, an examination was conducted of one series using four different combinational techniques: 1) period by period; 2) average of two periods; 3) average of three periods; and 4) average of six periods. The results of this comparison are presented in tables 14 to 16. The z-values of Wilcoxon signed-rank test in table 16 comparing the four combination techniques show that combining on the average of two periods ahead provides better forecasts.

Table 14.-- Results of Combining Quantitative and Subjective Forecasting Techniques BY: 1) Period by Period, 2) Average of Two Periods, and 3) Average of Three Periods (Selected Series)

Phase	MPE(1)	MPE(2)	MPE(3)	MAPE(1)	MAPE(2)	MAPE(3)	RMSE(1) (000)	RMSE(2) (000)	RMSE(3 (000)
1	-30.28			30.28			144993		
	-27.82	-29.05		27.82	29.05		139325	142159	
	14.04		-14.69	14.04		24.05	60895		115071
	-24.34	-5.15		24.34	19.19		77754	69324	
	-13.14			13.14			30626		
	3.15	-4.99	-11.44	3.15	8.15	13.54	2398	16512	36926
2	-2.80			2.80			991		
	-4.52	-3.66		4.52	3.66		2775	1883	
	11.06		1.25	11.06		6.13	23105		8957
	10.06	0.50		10.06	10.56		20499	21802	
	14.82			14.82			67047		
	2.81	8.81	2.52	2.81	8.81	9.23	1940	34494	29829
3	-28.83			28.83			107446		
	-30.24	-29.5		30.24	29.53		108355	107901	
	5.09		-17.99	5.09		21.38	5638		73813
	7.26	6.17		7.26	6.17		8480	7059	
	32.77			32.77			270364		
	25.84	29.31	21.96	25.84	29.31	21.96	223387	246875	167410
4	4.51			4.51			3345		
	16.45	10.48		16.45	10.48		40468	21907	
	25.79		15.58	25.79		15.58	126067		56627
	27.81	26.80		27.81	26.80		283284	204675	
	5.35			5.35			8218		
	-2.71	1.32	10.15	2.71	4.03	11.95	1805	5011	97769

Table 15.-- Mean Ranks of Quantitative, Subjective, and Combinational Forecasting Techniques.

Technique	Mean Ranks		
	HOLT	Management Judgment	Combinational
One period	1.8	2.5	1.7
Two periods	1.9	2.7	1.5
Three periods	2.0	2.5	1.6
Six periods	1.6	3.0	1.3

Table 16.-- Wilcoxon Tests Results for Differences in Accuracy Between Quantitative, Subjective and Combinational Methods on the Bases of 1, 2, 3 and 6 Periods.

	Forecasting Model	
	HOLT	Management Judgment
Combinational:		
one period	-0.60	-4.93 **
two periods	-1.82 *	-4.67 **
three periods	-1.59	-3.26 **
six periods	-1.80 *	-4.64 **

* denotes significant differences at 0.1 level
** denotes significant differences at 0.05 level

Effects of Forecasting Time Horizons: (Ho5)

To test whether forecasting methods perform differently under different time horizons, an examination was made of the six time series models as the forecast horizon was shortened from six periods to three periods, and then to one period ahead.

As is to be expected, the forecasting accuracy improves as the time horizon decreases. Tables 17, 18, 19, and 20 list and rank the accuracy measures for each of the four time series models over the three time horizons for selected series. Clearly, on the basis of the ranks, the one-period ahead procedure provides the most accurate forecasts among the three time horizons.

Table 17.-- Ranking of Average MPE, MAPE, and RMSE for Different Time Horizons - ARRES

SERIES (products)		R	ARRES.6M	R	ARRES.3M	R	ARRES.1M
7	MPE	3	-9.00	2	-6.66	1	-6.59
	MAPE	1	15.67	3	17.37	2	16.98
	RMSE	3	8382.00	2	8257.00	1	7408.00
13	MPE	3	-16.90	2	-11.67	1	-8.67
	MAPE	2	22.44	3	25.96	1	22.37
	RMSE	2	5354.00	3	5600.00	1	4268.00
15	MPE	1	-1.41	2	1.97	3	2.18
	MAPE	2	14.94	3	16.23	1	14.06
	RMSE	3	7540.00	2	7100.00	1	6106.00
1	MPE	3	-49.88	2	-41.26	1	-32.72
	MAPE	3	68.04	2	64.90	1	53.29
	RMSE	2	9353.00	3	10534.00	1	7559.00
5	MPE	3	-62.79	2	-44.44	1	-28.27
	MAPE	3	67.78	2	57.82	1	38.55
	RMSE	2	2997.00	3	3534.00	1	2234.00
6	MPE	3	-408.35	2	-388.37	1	-323.60
	MAPE	3	413.37	2	404.61	1	336.46
	RMSE	3	11493.00	2	9015.00	1	8839.00
2	MPE	3	-14.26	2	-10.25	1	-9.54
	MAPE	2	21.28	3	22.25	1	20.47
	RMSE	3	6283.00	2	6081.00	1	4994.00
3	MPE	3	-9.75	1	-4.81	2	-4.85
	MAPE	3	27.49	2	26.46	1	24.92
	RMSE	3	17259.00	2	15706.00	1	12965.00
26	MPE	3	-5.72	2	-4.97	1	-4.96
	MAPE	1	26.34	2	29.16	3	29.66
	RMSE	3	7672.00	2	8110.00	1	7395.00
29	MPE	3	-16.57	2	-14.73	1	-13.65
	MAPE	1	27.40	3	28.88	2	27.91
	RMSE	3	8157.00	2	8304.00	1	6892.00
AVERAGE	MPE	3	-59.46	2	-52.52	1	-43.07
	MAPE	3	70.47	2	69.36	1	58.60
	RMSE	3	8449.00	2	8224.00	1	6866.00

Table 18.-- Ranking of Average MPE, MAPE, and RMSE for Different Time Horizons - CMFS

SERIES (products)		R	CMFS.6M	R	CMFS.3M	R	CMFS.1M
7	MPE	1	0.76	2	2.97	3	4.99
	MAPE	1	14.98	3	768.23	2	15.85
	RMSE	3	7636.00	2	7534.00	1	7162.00
13	MPE	3	45.22	2	24.47	1	0.17
	MAPE	3	55.87	2	36.58	1	19.25
	RMSE	3	12030.00	2	7944.00	1	3725.00
15	MPE	2	-0.87	1	-0.61	3	-2.46
	MAPE	3	16.50	2	16.48	1	16.43
	RMSE	3	8119.00	2	7522.00	1	6435.00
1	MPE	3	-41.95	2	-38.23	1	-27.45
	MAPE	3	64.86	2	65.95	1	57.75
	RMSE	2	9568.00	3	10138.00	1	8227.00
5	MPE	3	-17.27	2	-12.07	1	-7.00
	MAPE	3	39.69	2	35.21	1	31.58
	RMSE	3	3666.00	2	3138.00	1	2604.00
6	MPE	3	-358.06	2	-353.61	1	-324.43
	MAPE	3	368.12	2	365.94	1	339.50
	RMSE	3	8551.00	2	7605.00	1	6313.00
2	MPE	1	4.9	2	6.04	3	6.62
	MAPE	2	21.56	3	21.89	1	19.79
	RMSE	3	6979.00	2	6416.50	1	5266.00
3	MPE	2	1.78	1	1.40	3	-6.76
	MAPE	3	30.09	2	26.88	1	26.26
	RMSE	3	9593.00	2	16309.00	1	12951.00
26	MPE	3	10.38	1	3.17	2	-9.28
	MAPE	3	29.73	1	27.99	2	29.70
	RMSE	3	9974.00	2	8755.00	1	7616.00
29	MPE	2	3.83	1	0.82	3	-4.29
	MAPE	2	26.80	1	26.65	3	29.81
	RMSE	3	9324.00	2	8629.00	1	8023.00
AVERAGE	MPE	1	-35.12	2	-36.57	3	-36.99
	MAPE	3	66.82	2	139.21	1	58.59
	RMSE	3	9544.00	2	8399.00	1	6832.00

Table 19.-- Ranking of Average MPE, MAPE, and RMSE for Different Time Horizons - HOLT

SERIES (products)		R	HOLT.6M	R	HOLT.3M	R	HOLT.1M
7	MPE	3	6.50	2	6.27	1	5.00
	MAPE	3	16.85	2	16.57	1	15.87
	RMSE	3	8903.00	2	8316.00	1	7162.00
13	MPE	2	-1.33	3	-2.03	1	0.17
	MAPE	3	28.21	1	9.15	2	19.29
	RMSE	3	6008.00	2	4085.00	1	3725.00
15	MPE	3	-6.84	2	-3.94	1	-2.47
	MAPE	2	15.84	1	15.41	3	16.47
	RMSE	3	7706.00	2	6790.00	1	6435.00
1	MPE	3	-53.66	2	-37.75	1	-28.68
	MAPE	3	71.07	2	70.20	1	57.87
	RMSE	3	12158.00	2	11159.00	1	8227.00
5	MPE	3	-7.83	2	-7.42	1	-7.00
	MAPE	3	33.37	2	33.18	1	31.62
	RMSE	3	3473.00	2	3130.00	1	2604.00
6	MPE	3	-341.08	2	-338.40	1	-324.48
	MAPE	3	354.25	2	353.02	1	339.57
	RMSE	3	7623.00	2	6806.00	1	6313.00
2	MPE	1	5.44	3	6.68	2	6.65
	MAPE	2	21.96	3	22.72	1	19.83
	RMSE	3	7198.00	2	6695.00	1	5266.00
3	MPE	3	-22.90	2	-7.26	1	-6.76
	MAPE	3	43.22	2	33.00	1	26.26
	RMSE	3	27354.00	2	17610.00	1	13951.00
26	MPE	1	-4.57	2	-6.24	3	-9.28
	MAPE	1	26.71	2	27.99	3	29.70
	RMSE	3	8211.00	2	8173.00	1	7616.00
29	MPE	2	2.55	1	-1.02	3	-4.29
	MAPE	1	28.99	2	29.41	3	29.81
	RMSE	3	9941.00	2	9279.00	1	8023.00
AVERAGE	MPE	3	-42.37	2	-39.11	1	-37.11
	MAPE	3	64.05	2	62.06	1	58.63
	RMSE	3	9857.00	2	8204.00	1	6832.00

Table 20.-- Ranking of Average MPE, MAPE, and RMSE for Different Time Horizons - SINGLE

SERIES (products)		R	SINGLE.6M	R	SINGLE.3M	R	SINGLE.1M
7	MPE	3	-8.94	2	-4.80	1	-2.59
	MAPE	2	15.00	3	15.48	1	14.06
	RMSE	3	7908.00	2	7492.00	1	6706
13	MPE	3	-24.02	2	-10.20	1	-4
	MAPE	3	28.96	2	26.15	1	18.95
	RMSE	3	6523.00	2	5752.00	1	3588
15	MPE	3	-5.31	2	-1.70	1	-0.69
	MAPE	3	15.90	2	16.04	1	15.88
	RMSE	3	7905.00	2	7155.00	1	6354
1	MPE	3	-52.75	2	-36.00	1	-20.51
	MAPE	3	65.54	2	61.63	1	48.26
	RMSE	3	9916.00	2	11474.00	1	7161
5	MPE	3	-59.74	2	-31.59	1	-15.14
	MAPE	3	66.94	2	46.35	1	28.11
	RMSE	3	3115.00	2	3429.00	1	2071
6	MPE	3	-380.72	2	-373.24	1	-326.86
	MAPE	3	386.70	2	383.06	1	343.02
	RMSE	3	9100.00	1	7650.00	2	7758
2	MPE	3	-20.44	2	-9.87	1	-5.15
	MAPE	3	26.62	2	24.57	1	19.51
	RMSE	3	7559.41	2	6885.00	1	5023
3	MPE	3	-26.16	2	-8.70	1	-5.33
	MAPE	3	33.01	2	31.26	1	22.81
	RMSE	3	20650.00	2	18109.00	1	11772
26	MPE	1	0.30	2	-3.48	3	-7.53
	MAPE	1	25.06	2	26.13	3	30.54
	RMSE	3	7911.00	1	7674.00	2	7774
29	MPE	3	-15.06	2	-14.96	1	-13.95
	MAPE	1	26.58	2	29.17	3	29.52
	RMSE	3	7822.00	2	8470.00	1	7380
AVERAGE	MPE	3	-59.28	2	-49.45	1	-40.18
	MAPE	3	69.03	2	65.98	1	57.17
	RMSE	3	8841.00	2	8409.00	1	6559

To test whether the difference between the three time horizons is significant, Wilcoxon matched pairs signed-ranks tests were conducted. Table 21 reports the z-values of these tests.

Looking at table 21, note that 10 out of the 12 cells have statistically strong significant z-values (at 99% significance level) inferring a strong difference in the accuracy among the three time horizons. Only one cell (ARRES 6 vs. 3 months) has significant z-value at 90% significance level. What is interesting to observe is that CMFS was the only model with no significant difference in the errors between three-months and one-month forecast horizon. This result is expected due to the nature of this procedure that utilizes both short term and long term forecasting horizons (see Makridakis 1986).

Table 21.-- Wilcoxon Tests Results for Differences in Accuracy Between Methods for Three Different Time Horizons

	Forecasting Model			
Time Horizon	ARRES	CMFS	HOLT	SINGLE
6 vs. 3 months	-1.65 **	-3.06 *	-3.00 *	-3.87 *
6 vs. 1 months	-4.06 *	-3.41 *	-3.75 *	-4.02 *
3 vs. 1 months	-4.26 *	-1.58	-2.81 *	-3.54 *

* denotes significant differences at 0.01 level
** denotes significant differences at 0.1 level

Time Series vs. Causal Models: (Ho6)

To test whether time series forecasting procedures provide better forecasts than causal models, a comparison between the econometric (a causal model used by the company to forecast gross sales) and the four time series (HOLT, CMFS, ARRES, and SINGLE) models was conducted. The results of this comparison are given in Tables 22 to 24.

Table 22 shows the accuracy of the five models at the four forecasted phases using gross sales. Note that, as expected, for macro-level data the causal model provided better forecasts than the time series methods. This is consistent with other studies. For example, McNeese (1974, 1975, 1979, 1981, 1986) investigated several organizations and tested the forecast accuracy for macroeconomic variables over different time periods. He concluded that econometric models are most accurate when generating long term forecasts for macroeconomic variables. Importantly, however, a successful implementation of causal models require continuous judgmental adjustment. This leads to an important question, whether the superiority of econometric models, if any, justifies their cost (Makridakis and Wheelwright 1977). Note also that Series 31 (gross sales) is short for time series analysis. This might have affected the accuracy of the forecasts generated by the time series models. Tables 23 and 24 present the mean ranks and the z-values of Wilcoxon signed-ranks test. The chi square statistic reported in table 23 reveals strong significant differences in the accuracy for the two types of forecasts. The negative entries in table 24 denote comparatively better forecasts on the part of the econometric model.

Table 22.-- Comparative Analysis Between Time Series and Econometric Models of Forecasting: Gross Sales (Monthly Data)

Technique & Accuracy Measures	Forecasted Phases (Data Points) 19-21	22-24	25-27	28-30	Average
HOLT					
MPE	-5.86	-9.40	-1.19	6.94	-2.38
MAPE	5.86	23.00	11.20	6.94	11.75
RMSE	2098.7	8085.58	4096.03	4213.48	4616.70
CMFS					
MPE	-3.30	-7.80	-0.87	7.92	-1.01
MAPE	4.30	21.40	11.52	7.92	11.29
RMSE	596.04	7661.75	4186.49	4653.19	4524.37
ARRES					
MPE	-7.07	-4.66	7.25	14.40	2.48
MAPE	7.07	19.96	12.43	14.40	13.46
RMSE	3121.00	7648.88	4946.14	6722.00	5609.50
SINGLE					
MPE	-4.44	-5.36	4.03	10.75	1.24
MAPE	5.26	20.32	11.52	10.75	11.96
RMSE	2015.26	7651.98	4251.72	5640.22	4889.79
Econometric *					
MPE	-0.49	-2.52	1.40	4.08	0.62
MAPE	2.92	6.00	3.35	4.08	4.09
RMSE	066.49	2107.78	1241.84	2907.46	1830.89

* Generated by the company for gross sales

Table 23.-- Friedman Test Results for Differences in Accuracy Between Time Series and Causal Methods (by MPE, MAPE, and RMSE)

Mean Ranks					
HOLT	CMFS	ARRES	SINGLE	Causal	Chi Square
3.27	2.7	4.4	3.5	1.13	35.13*

* denotes significant difference at 0.01 level.

Table 24.-- Wilcoxon Tests Results for Differences in Accuracy Between Time Series and Causal Methods

	Time Series Models			
Causal Model	HOLT	CMFS	ARRES	SINGLE
Econometric	-3.21 *	-2.9 *	-3.41 *	-3.41 *

* denotes significant differences at 0.01 level

Summary

Six hypotheses were proposed about forecasting accuracy. These suggested that combining several quantitative methods is more accurate that individual methods; that combining using a weighted average based on actual errors is more accurate than the simple average; that time series methods are more accurate than management judgment; that combining quantitative and qualitative methods provide more improvement in accuracy; that forecasting for one period ahead is more accurate than forecasting for three periods ahead, which in turn is more accurate than forecasting for six periods ahead; and that causal methods are more accurate than time series methods when dealing with macroeconomic data. Prior evidence on these hypotheses was mixed. However, they did receive strong support in this study.

CHAPTER V

DISCUSSION, CONCLUSIONS AND RECOMMENDATIONS

Though micro time series is commonly found in business, the forecasting literature has not given this type of data the attention it deserves (Sanders and Ritzman 1989). A few investigations are made at a micro level, such as dealing with data on individual products. Most empirical studies have investigated macro time series such as gross sales data on a firm or industry.

The study focused on forecasting accuracy of several individual and combinational models over time. Contradictory results have been found regarding which forecasting method is more accurate. For example, studies such as Makridakis and Hibon (1979) and Mahmoud (1984) found that quantitative methods were more accurate than management judgment. Others (e.g., Mabert 1976, Dalrymple 1987, Staelin and Turner 1973) concluded that subjective forecasts are superior to purely quantitative methods. Moreover, studies by Winkler and Makridakis (1983), Moriarty and Adams (1984), Lawrence et al. (1986), Mahmoud and Makridakis (1989), Zbib and Savoie (1989) recognize the potential benefits of combinational forecasts. No evidence was found in these studies to support any of these conclusions.

This study has evolved from the mixed results shown in the reviewed literature and from the lack of sufficient forecasting research dealing with micro data. The major purpose of this study has been to investigate and identify the accuracy of both quantitative and qualitative techniques implemented by the company under study, and to test the accuracy of different time series models for microeconomic data. Focus has been placed on testing the combining as a tool to improve forecasting accuracy. Of particular interest is whether combining time series and judgmental forecasts provide more accurate results than individual methods. Another purpose has been to compare forecasting accuracy for different time horizons. Three different time horizons have been investigated: (1) six months, (2) three months, and (3) one month ahead.

Thirty-one data sets were used in this study to forecast sales. Series 1 to 30 represented monthly sales for individual products from January 1985 to December 1989. Series 31 comprised monthly gross sales in thousands of dollars from January 1988 to June 1990. Use of series 31 permitted the comparison of the time series forecasts generated in this study with the econometric forecasts generated by the company.

The substantial contribution made by this study has implications for both theoretical and practical contexts. The finding's theoretical importance is in expanding understanding of the complex process of forecasting accuracy by supporting the combinational models of forecasting. The practical significance is the potential for substantially improving forecasting accuracy of the company under study in particular and organizations in general. The intent of this study was to explore the inconsistencies in the forecasting literature and to provide information of practical interest to forecasters, managers, and scholars.

Combining Quantitative Methods

From all analysis of 30 series, conclusions can be drawn that the performance of various time series methods differs sometimes, depending upon the series tested and the accuracy measure being used. The results show that no single method can be used for all products. This is especially true when products change due to characteristics. This supports and extends the conclusions suggested by Makridakis et al. (1982) and Schnaars (1984). Therefore, for a particular product, one needs to follow closely the change in data and suggest different models at different time intervals. For the company under study, it is recommended that at least four different methods should be used if the company seeks to improve accuracy. These are: 1) Adaptive Response, 2) Holt's, 3) Carbone-Makridakis, and 4) Single Exponential.

In addition, this study provides empirical evidence that regardless of the combining method used (e.g. weighted or simple average), any combination of these quantitative techniques can be expected to give more accurate results than the individual models. This is in agreement with prior research (for example, Makridakis and Winkler 1983, Flores and White 1989, Makridakis et al. 1982). However, the results of this study point out that the accuracy of the combinational models depends upon the models included in the combination. For example, Table 9 shows that COMB3w (a combinational model that includes Adaptive Response, Single Exponential, and Carbone- Makridakis) generates better forecasts than COMB1w (CMFS, Holt, and ARRES) and COMB2w (CMFS, Holt, and Single). Regardless, the results provide strong evidence that combining is better than using the best single model not only when dealing with macro data, but also when forecasting micro data as well.

Note that the chosen combinational model (COMB3w) excludes the best single model (Holt). This leads to the conclusion that perhaps three simpler and less expensive models can produce better combined forecasts than those generated from a fourth but more expensive model.

Simple Average vs. Weighted Average Combining

This study provides strong evidence that combining using weighing by historical accuracy is more accurate than combining using the simple average. Specifically, the results show a clear difference in accuracy between weighing based on actual Mean Absolute Percentage Error (MAPE) and the simple mean. In this regard, the results support previous research (e.g. Russell and Adams 1987). However, the base forecast used in this study is different from those used in previous studies (for example, Russell and Adam's employed the Mean Square Error).

Importantly, even though the weighted average was found to be superior to the simple mean overall, for some series the simple average performed better. Thus, before deciding on which combining technique to use, one should consider testing both, and then use the one that is more accurate.

Subjective vs. Quantitative Methods

Given the subjective nature of the management judgment technique, perhaps not surprisingly, this qualitative method has been shown to be less accurate than quantitative methods. Previous studies (e.g. Makridakis and Wheelwright 1977) showed that management judgment forecasts provide better forecasts for longer time horizons. The forecasters in the company under investigation may be applying this method to inappropriate time horizons. Other studies (e.g. Hogarth and Makridakis 1981) state that judgmental forecasts in general are less accurate than quantitative methods because of the biases inherent in information-processing.

The conclusion is that any time series method would seem to offer more accurate forecasts than may be obtained from the judgmental method currently employed by the firm to predict micro sales data. In short, the firm is suggested to either use time series models or a combination of judgmental and one or more time series methods. The advantages of integrating subjective and quantitative methods are explained below.

Combining Quantitative and Qualitative Models

The results of this study show the benefits that can be gained from combining judgmental and time series forecasts. Several combinational models that integrate management judgment with several time series models have been tested and compared. The results show that the best forecast can be generated by combining Holt's and management judgment using a weighted average on the base of the actual historical error.

Significantly, even though the proposed combinational model was shown to yield forecasts of superior accuracy when compared to any of the individual models, few instances are found of some accuracy measures of the Holt's model being better than those of the combinational method. Thus, the individual values of the accuracy measures for each series should be examined carefully before any model selection is made. In fact, Schnaars (1984) states that some products are less predictable than others.

In addition, the results suggest that combining on the basis of the average of two periods provides better forecasts. One series was tested for this purpose and the results showed significant difference between forecasts generated by combining on the average of two periods and those produced by other combining techniques (e.g. period by period, average of three periods, and average of six periods).

Effects of Forecasting Time Horizons

The results of this study support the superiority of the one period ahead procedure for all of the models tested. This conclusion is drawn from the fact that accuracy decreased with longer time horizons. The accuracy was tested for three different periods (six, three, and one month ahead) and it was concluded that the one month-ahead procedure performed best for all three accuracy measures. The results generally support previous findings which report that accuracy is relatively high for short range forecasts (e.g. Mentzer and Cox 1984, McLeavey et al. 1981).

In addition, the results show that the choice of forecasting horizon generally affects the relative performance of the combinational model. Prior evidence on this conclusion was not strong. Indeed, these results contradict the conclusions suggested by Russell and Adam (1987) which reported that the accuracy of the combinational models is not affected by length of the forecasting period.

Time Series vs. Causal Models

Econometric models seem to provide better forecasts than those obtained from other commonly used methods--namely, time series and management judgment when forecasting macro variables. This conclusion is in agreement with previous studies which suggested the relative superiority of the causal model when generating longer range aggregate forecasting (e.g. McNeese 1974; 1981; 1986, Armstrong and Grohman 1972, Mentzer and Cox 1984).

Several reasons exist for the difference in performance between time series and causal models in previous studies. According to Mahmoud et al. (1990), these reasons include the type of series being forecast, the time horizon of the forecast, and whether or not the forecast is adjusted. Although the results of this study show that the causal model outperformed the other forecasting techniques in this study, it is suspected that this superiority might have been the result of the small amount of gross sales data that was available for the comparison. Some authors suggested that more accurate forecasts are possible when a greater amount of data is available (e.g. Michael 1979, Chambers et al. 1971). Therefore, the gross sales series (series 31) might be short for time series analysis.

A successful implementation of causal models requires continuous feedback and adjustment, making the technique more expensive and time consuming. The implementation also requires high skills and expertise which make its use unjustifiable in many cases (Fildes 1985).

Summary and Recommendations

Six main findings emerge from this study. First, no single method can be used for all products. Products change due to characteristics and accuracy changes over time from one series to another and from one model to another. As a result, we need to follow closely the changes in data for a particular product, and use different models at different time intervals. The results suggest that we need to use at least four different time series methods if the corporation seeks to improve accuracy.

In addition, some products were observed to be related. This relationship should be examined carefully to see if similar products can be grouped together. For this corporation, grouping five or six products, and selecting one technique that would be appropriate for the same group, might be worthwhile. If this is feasible, the corporation can save both time and money.

Second, accuracy is affected by the time horizon of the forecast. The findings suggest that accuracy is relatively higher for short range forecasts (one period).

Third, combinations of three techniques (excluding the best model) yield better results. In addition, the study concludes that a weighted average combining, based on historical accuracy, is more accurate than combining using the simple average.

Fourth, objective methods are more accurate than subjective methods. In fact, a highly significant difference was found between time series and management judgment methods.

Fifth, combinations of quantitative and subjective methods improve forecasting accuracy. This study has shown the benefits that can be gained from combining time series and judgmental forecasts and suggests the superiority of combining on the basis of an average of two periods.

Sixth, causal models are more accurate than time series methods for only aggregate forecasts. The evidence on this hypothesis is not strong however.

The study also suggests the importance of monitoring the accuracy very closely. Errors can be reduced by examining the accuracy periodically and adjusting the estimated values.

Assuredly, the results of the study were constrained by the data series employed and by the limited number of methods compared. This limitation is especially true for hypothesis six. Data series with few observations would doubtless make time series methods look inferior to causal models.

The proposed combinational model can be used to improve forecasting accuracy in comparison to individual models. However, additional research regarding the application of this model is suggested. Specifically, this model should be tested over a wider range of time series than those used in this study to determine its reaction to trend and seasonality. Also, more theoretical and empirical research is required to define the best technique for combining forecasting methods, and which techniques should be included in the combination (Mahmoud 1984). In a recent study, Mahmoud and Makridakis (1989) suggested that future studies should investigate how combining could help managers learn and improve individual forecasting methods.

Since the difference in performance between the simple and weighted average did not consistently favor weighing in this study, other weighted average combining techniques should be investigated using the same series to see if further improvement can be achieved. Specifically, other weighing basis should be tested and compared to the one used in this study. A combinational weighing technique which incorporates an adjustment for bias could also be developed and tested for accuracy, as could a combinational model that includes other subjective techniques. Finally, the set of individual models included in the combination in this study could be extended to include other time series methods.

Without doubt, this study needs to be repeated using a variety of companies in order to test the generalizability of the results. Longitudinal studies in which the adjustment process is observed may also be useful. This appears to be important for understanding when and how often an adjustment is needed.

The fact that the findings of this study are company-specific should not negate the importance of the results. Indeed, the objective of this study is to test forecasting accuracy for micro variables. This raises the question of whether some of the findings suggested by previous cross-industry/cross-company studies can also be applied when micro sales are being forecast. Another question raised by this study is whether a company possesses a unique set of forecasting characteristics and, if so, what these characteristics are.

Future Research

Future research should focus on the reasons for the differences in accuracy achieved by the different forecasting techniques (Makridakis et al. 1982, Mahmoud et al. 1990). In order to do this, more quantitative and qualitative techniques should be tested at both macro and micro levels. Further research in this direction may set the stage for providing consistent results which are lacking in the forecasting literature.

In particular, more empirical studies concentrating on different demographic data are warranted to confirm the results of this study. For example, a need to replicate this study to see if there is a difference in accuracy among different demographic data sets is indicated. The results of such studies would be helpful in selecting the appropriate forecasting models for specific situations.

Another question that deserves further consideration is how to assist forecasters in improving the techniques they are currently using rather than suggesting what methods they should choose. As indicated before, the judgmental method currently used by the corporation is inferior to any of the other models tested in this study. Future research should examine if the currently used method can be improved without investing in costly alternatives. As suggested by Moriarty (1985), there are unique forces within organizations that sometimes create pressures causing bias and inaccurate forecasts. These forces need to be investigated by researchers in order to suggest improvement in the forecasting methods being used.

Finally, note the signficance of judging the accuracy of the forecasting techniques on the bases of the average of the accuracy measures for the forecasted phases sometimes shows different results from those suggested by each phase. Mahmoud et al. (1990) warn against using this procedure and suggest that forecasters should examine carefully each accuracy measure at each phase to avoid misleading results. Thus, developing a unique and accurate method of averaging is warranted.

APPENDIX A

A SUMMARY OF SELECTED STUDIES IN THE AREA OF FORECASTING ACCURACY

A Summary of Selected Studies In the Area
of Forecasting Accuracy

Topic	Major Findings	Source
	A. Quantitative Methods	
Human forecasts versus Winters' method	Winters' method provided more accurate results than human forecasts.	Adam & Ebert (1976)
Time series methods versus sales opinions and corporate opinions	Forecasts based on opinions of corporate executives and sales people are less accurate and more expensive than those based on other quantitative methods.	Mabert (1975)
Eyeball extrapolation vs. objective methods	Objective methods gave more accurate results than eyeball extrapolation.	Carbone & Gorr (1985)
Exponential smoothing vs. Box-Jenkins	Concluded that the Box-Jenkins method was more accurate than Holt and Winters	Newbold & Granger
	The results of this study showed simple time series models to be better than the Box-Jenkins.	Koehler (1985)
Survey of Research: time series and econometric models	Of the 20 studies included in this work, 15 showed econometric methods to be more accurate, three showed equivalence, two showed econometric techniques to be less accurate than other methods.	Fildes (1985)
Time series & econometric models	Econometric models are superior to time series models.	Christ (1975), Armstrong (1985)
Box-Jenkins & econometric models	These studies indicated box-Jenkins models are stronger than econometric models	Cooper (1972), Nelson (1976), Reid (1971-5), Schmidt (1979)

A Summary of Selected Studies In the Area of Forecasting Accuracy (continued)

Topic	Major Findings	Source
	This study indicated that the performance of both techniques is equivalent.	Kinney (1978)
Sophisticated vs. simple time series techniques	These studies concluded that sophisticated methods are not better than simple time series techniques.	Groff(1973), Makridakis & Hibon(1979), Makridakis et al. (1982), Carbone et al. (1983)
Comparing smoothing models	This study found that exponential smoothing performed better for short term forecasting.	Gross & Ray (1965)
	Found a multiple exponential smoothing model to have a number of structural and performance advantages over simple exponential smoothing.	Enns et al. (1982)
	This study investigated how companies prepare sales forecasting, finding that the naive method was most popular, followed by the moving average, while the exponential smoothing was the least popular.	Dalrymple (1987)
	This study reported that deseasonalized single exponential smoothing performed well when a pattern took place at the end of the data.	Carbone & Makridakis (1986)

A Summary of Selected Studies In the Area of Forecasting Accuracy (continued)

Topic	Major Findings	Source
	This study indicated that exponential double smoothing was most accurate for studies with low noise level.	McLeavy et al. (1981)
	This study extended the single exponential and the Holt's methods to the case of irregular time intervals. It was found that this extended model is more efficient and easy to use.	Wright (1986)
	This study found that for forecasting retail sales, time series models outperform judgment and econometric models. It was also concluded that exponential smoothing techniques are better than Box-Jenkins in forecasting department store sales.	Geurts & Kelly (1986)
	This study indicated that single exponential smoothing techniques are very accurate for monthly data. However, for yearly and quarterly data, the Lewandowski's method is superior. No difference was found between Holt's and Holt-Winters' methods.	Makridakis et al. (1982)
	<u>B. Qualitative Methods</u>	
Delphi technique	This study indicated the forecasting errors reduced from 20% to less than 4% when the Delphi technique was used.	Basu & Schroeder (1977)

A Summary of Selected Studies In the Area of Forecasting Accuracy (continued)

Topic	Major Findings	Source
Sales force composite/ executive opinion	This survey showed that these two techniques were widely used by American companies.	Dalrymple (1987)
Judgment of experts	This study suggested that the judgment of experts is necessary to evaluate relevant data indirectly and to obtain the results needed in a standard setting.	Winkler (1987)
	In this study, the authors noted that quantitative techniques are not commonly used for certain types of sales forecasting such as industrial marketing.	Mahmoud et al. (1988)
	After analyzing a sample of 111 time series, this study found that judgmental forecasts were as accurate as statistical techniques.	Lawrence et al. (1985)
	These studies reported that, if given accurate information, analysts can predict better than quantitative methods.	Jonston & Schmitt (1974), Critchfield et al. (1978), Brandon & Jarrett (1979)
Judgmental adjustment	Using MBA students and a sample of 10 time series, this study concluded that judgmental adjustment improved the accuracy of the objective forecasts.	Carbone & Gorr (1985)

A Summary of Selected Studies In the Area of Forecasting Accuracy (continued)

Topic	Major Findings	Source
Comparing different judgmental techniques	This study found that causal judgmental methods were more accurate than naive judgmental techniques. It was also concluded that subjective judgmental methods were less accurate than objective judgmental methods.	Armstrong (1975)
	This study indicated that management judgmental forecasts are more accurate than analysts' judgmental forecasts.	Armstrong (1984)
	Investigated whether multiple scenarios improve the accuracy of judgmental sales forecasts. No evidence of any improvement was shown.	Schnaars & Topol (1987)
	C. <u>Combining Forecasts</u>	
Combining qualitative techniques	This study indicated that more accuracy was obtained when a number of subjective forecasts made by advertising sales executives were combined.	Ashton & Ashton (1985)
	The conclusion was that the accuracy level was always improved when a set of judgmental methods was aggregated.	Lawrence et al. (1986), Flores & White (1987)
Combining quantitative techniques	Used 111 time series to combine 14 quantitative methods. Using the simple average in the combination, the researchers concluded that the accuracy of	Makridakis & Winkler (1983)

A Summary of Selected Studies In the Area of Forecasting Accuracy (continued)

Topic	Major Findings	Source
	combined forecasts was influenced by the number and the type of the methods included in the combination.	
	Applied 10 forecasting techniques to 1001 time series. It was concluded that the accuracy was improved when the methods were combined.	Winkler & Makridakis (1983)
	Combined 6 methods using A) simple average, and B) a weighted average based on the sample covariance matrix of fitting errors. The authors concluded that both combining methods performed better than the individual techniques included in the combination. It was also found that the simple average performed better than the weighted average.	Makridakis et al. (1982, 1984)
Combining quantitative & qualitative techniques	Reported an improvement in accuracy when statistical and judgmental forecasts are combined.	Lawrence et al. (1986), Zbib & Savoie (1989)
	Combined time series forecasting with subjective predictions from open-market operators. It was concluded that more accuracy can be obtained when these techniques are combined.	Pereira et al. (1989)
	Combined several quantitative and qualitative methods to forecast livestock prices. It was reported that the the combining method reduced	Brandt & Bessler (1985)

A Summary of Selected Studies In the Area of Forecasting Accuracy (continued)

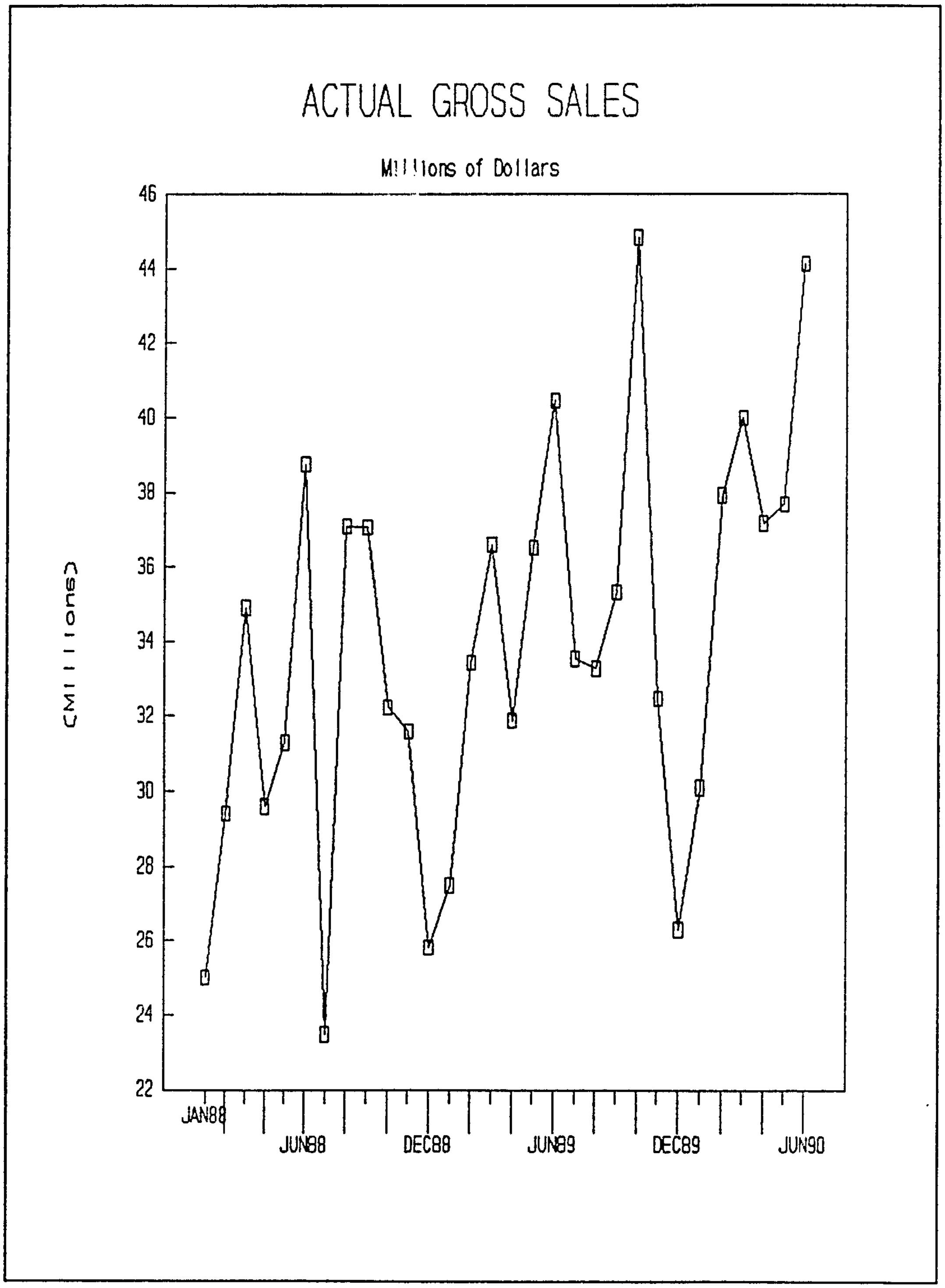
Topic	Major Findings	Source
	large forecasting errors.	
	Suggested a combinational model that includes both systematic and judgmental forecasts.	Moriarty & Adams (1984)
	Combined management judgment and time series. No significant improvement in accuracy was found.	Moriarty (1985)
	Reported that managers should prepare a judgmental forecast separately and then formally combine it with other quantitative methods.	Mahmoud & Makridakis (1989)
	<u>D. Combining Methods</u>	
Simple average	These studies supported the simple average.	Makridakist et al. (1982), Einhorn (1972), Gupta & Wilton (1978), Mahmoud (1982), Ashton (1982), Carbone et al. (1983), Winkler and Makridakis (1983), Figlewski & Urich (1983), Lawrence et al.(1986), Clemen & Winkler (1986), Kang

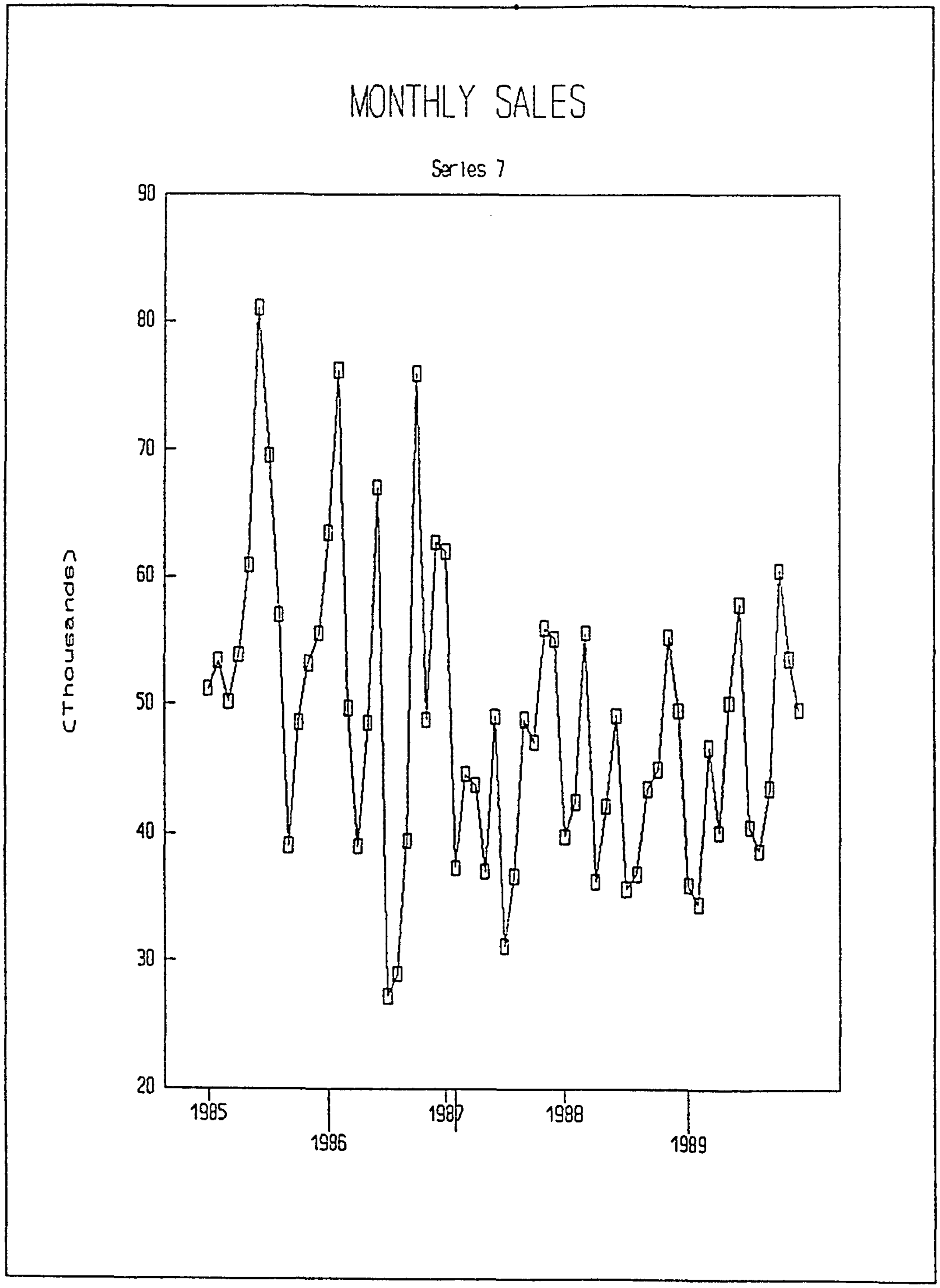
A Summary of Selected Studies In the Area of Forecasting Accuracy (continued)

Topic	Major Findings	Source
		(1986), Holden & Peel (1986)
Odds-Matrix Method	This study indicated that the OM method is highly robust and superior to the simple average.	Gupta & Wilton (1987)
Linear combination	These studies concluded that a linear combination provides more accuracy than other methods, especially the simple average.	Nelson (1972), Dickinson (1975), Diebold & Pauly (1987), Bunn & Seigal (1983)
Subjective combining	Compared the accuracy of subjective and objective combining methods. The results favored the subjective approach.	Flores & White (1989)
	This study indicated that the combining methods that include local bias adjustment are superior to the simple average method.	Sessions & Chatterjee (1989)
N- Step combinations	This method involves combining the combined forecasts resulted from from several combination methods employed at the preceding step. The results showed that more accuracy can be obtained when this concept is employed.	Gunter & Aksu (1989)
Weighted average based on the sample covariance matrix	These studies indicated that this technique is superior to the simple average.	Bates & Granger (1969), Newbold & Granger (1974), Makridakis & Winkler (1983)

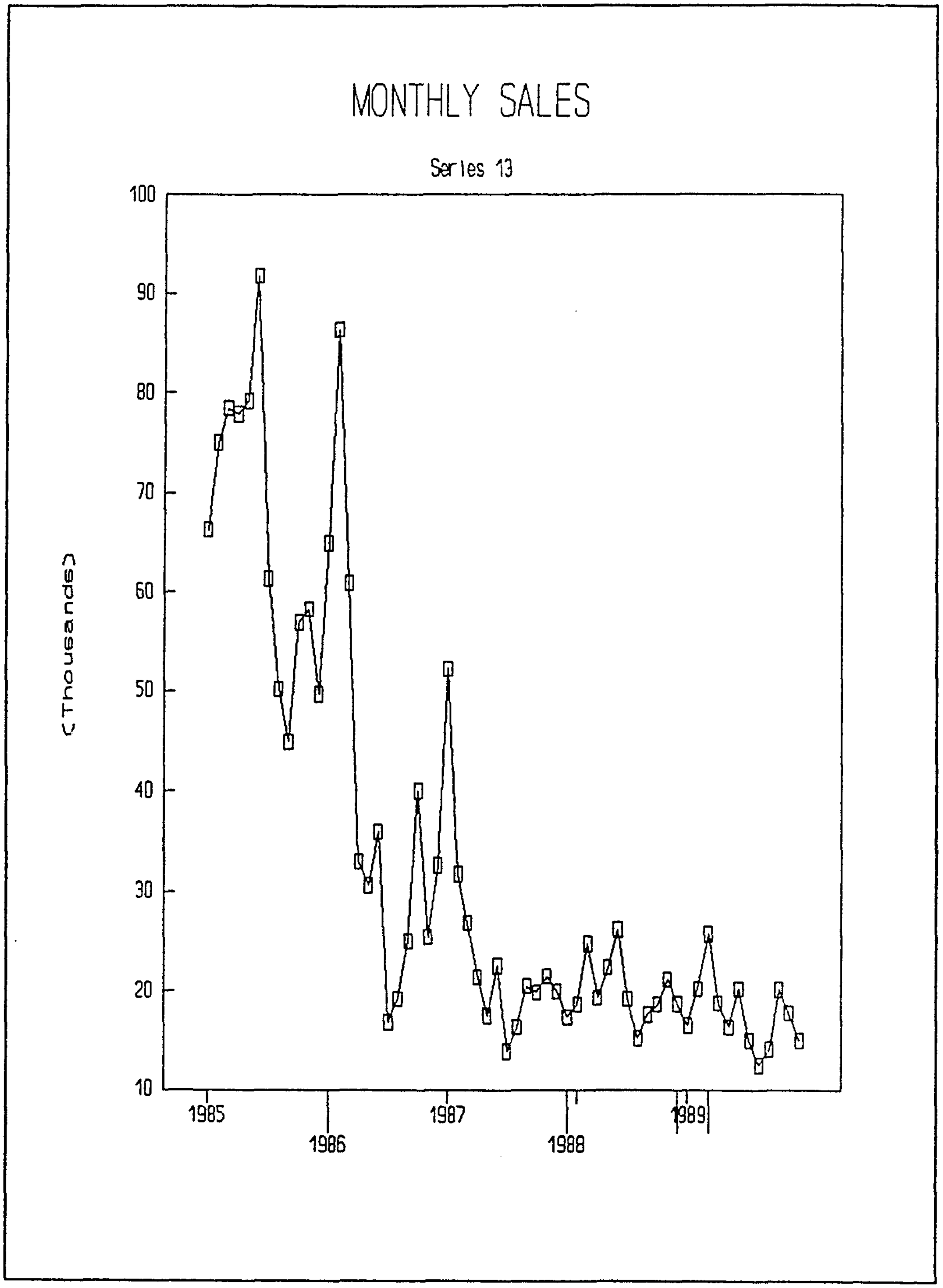
APPENDIX B

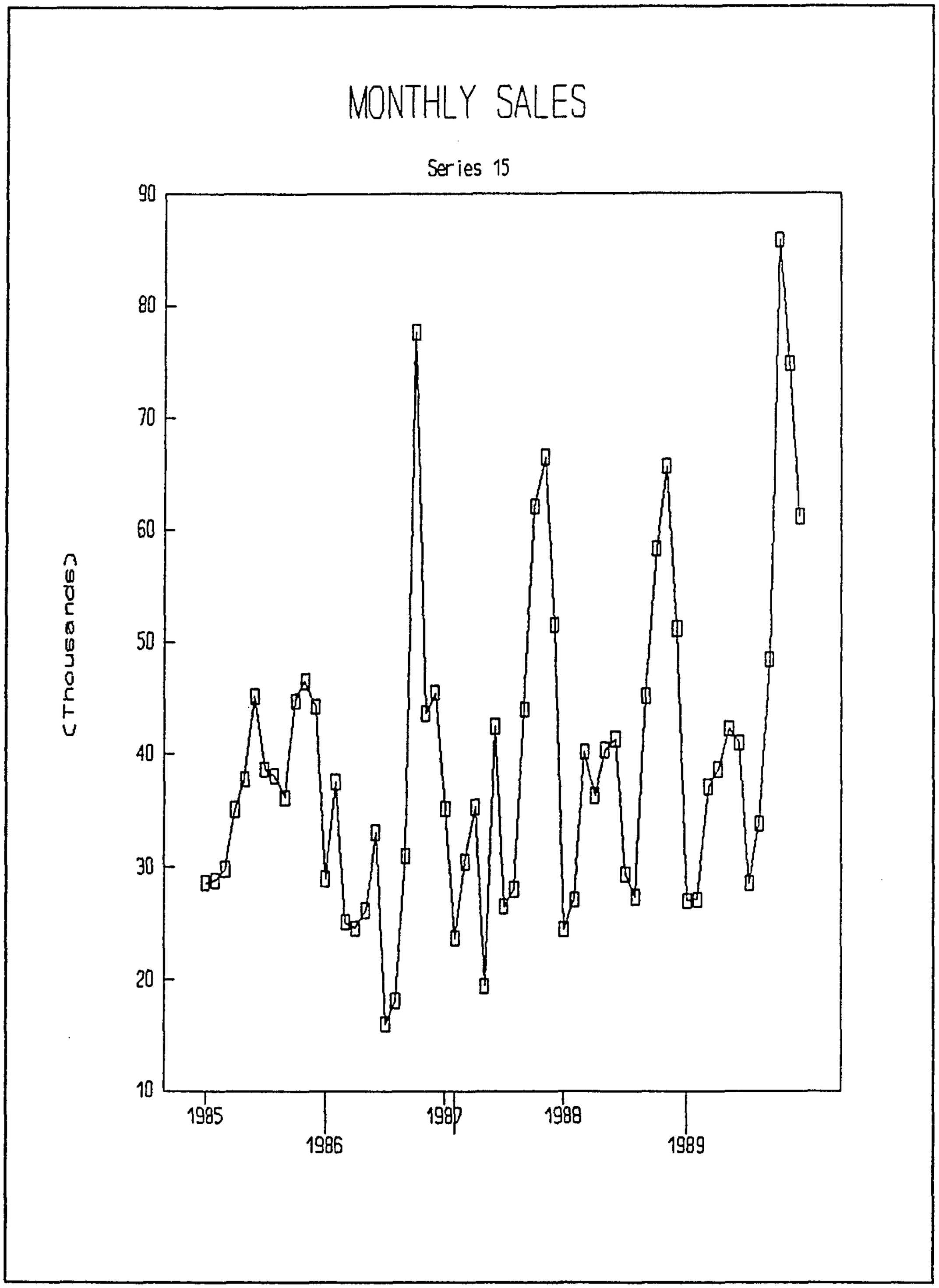
GRAPHICAL PRESENTATION OF THE DATA PATTERN FOR SELECTED SERIES

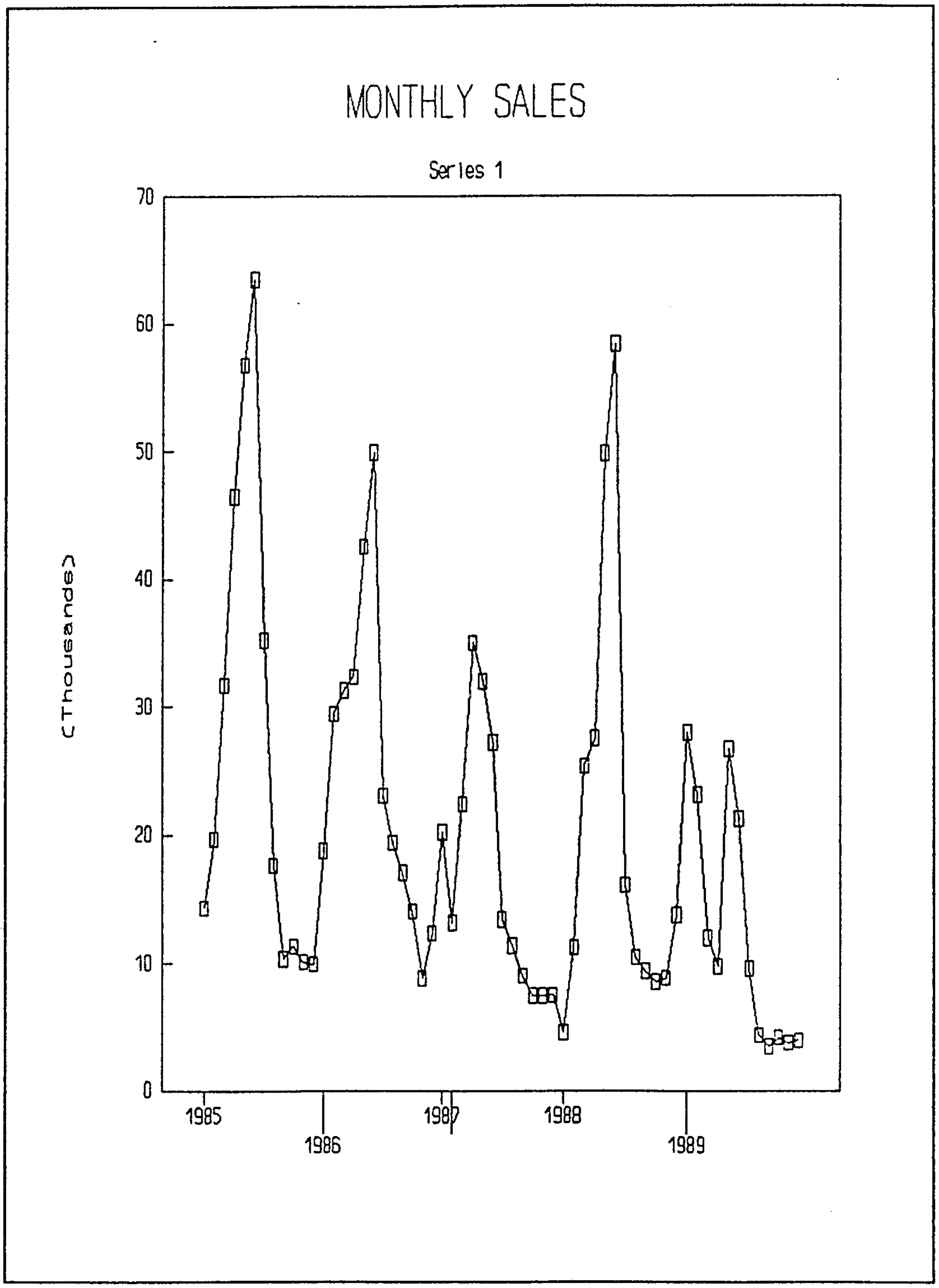

ACTUAL GROSS SALES
Millions of Dollars
(Millions)
46
44
42
40
38
36
34
32
30
28
26
24
22
JAN88
JUN88
DEC88
JUN89
DEC89
JUN90

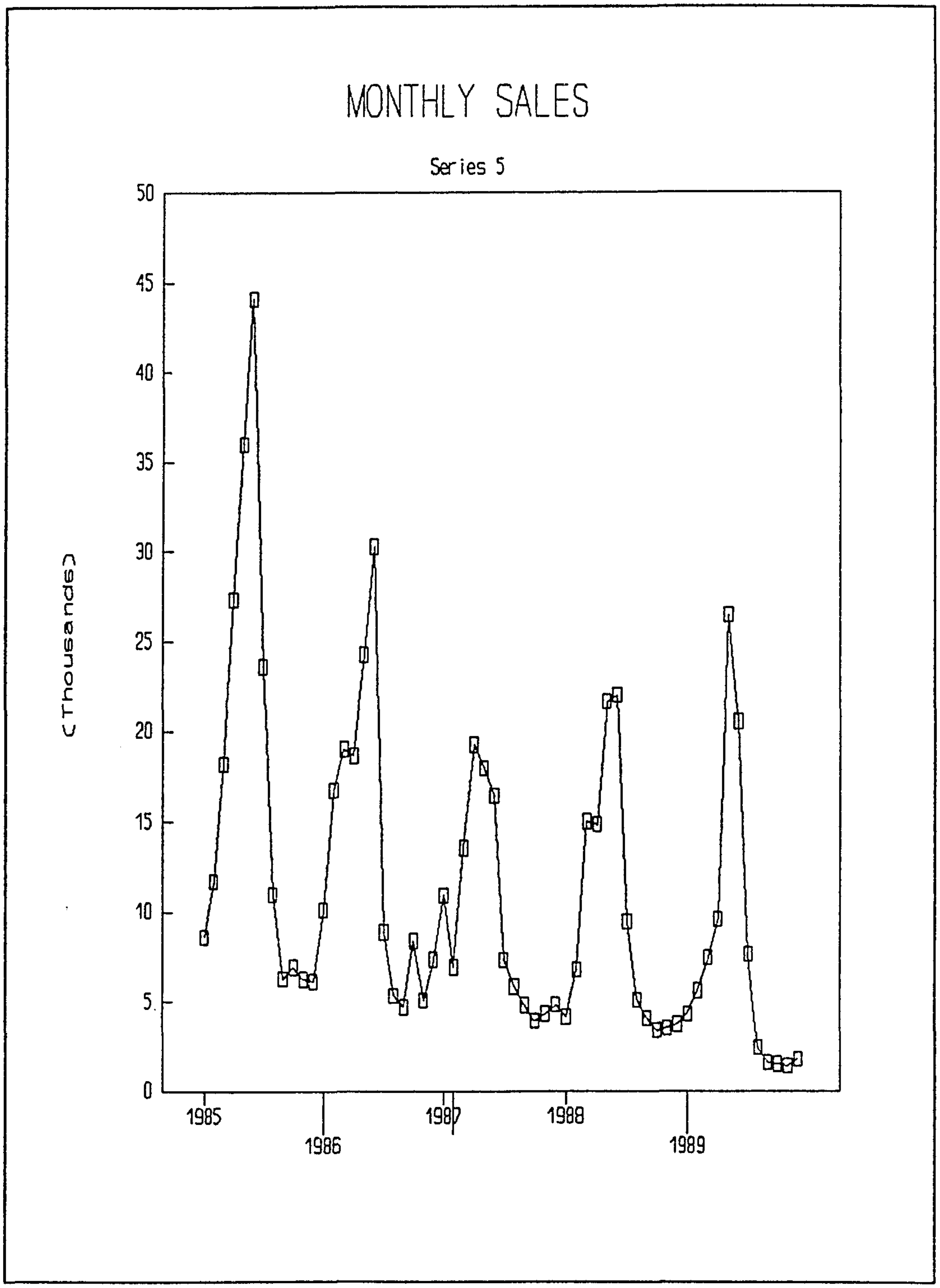


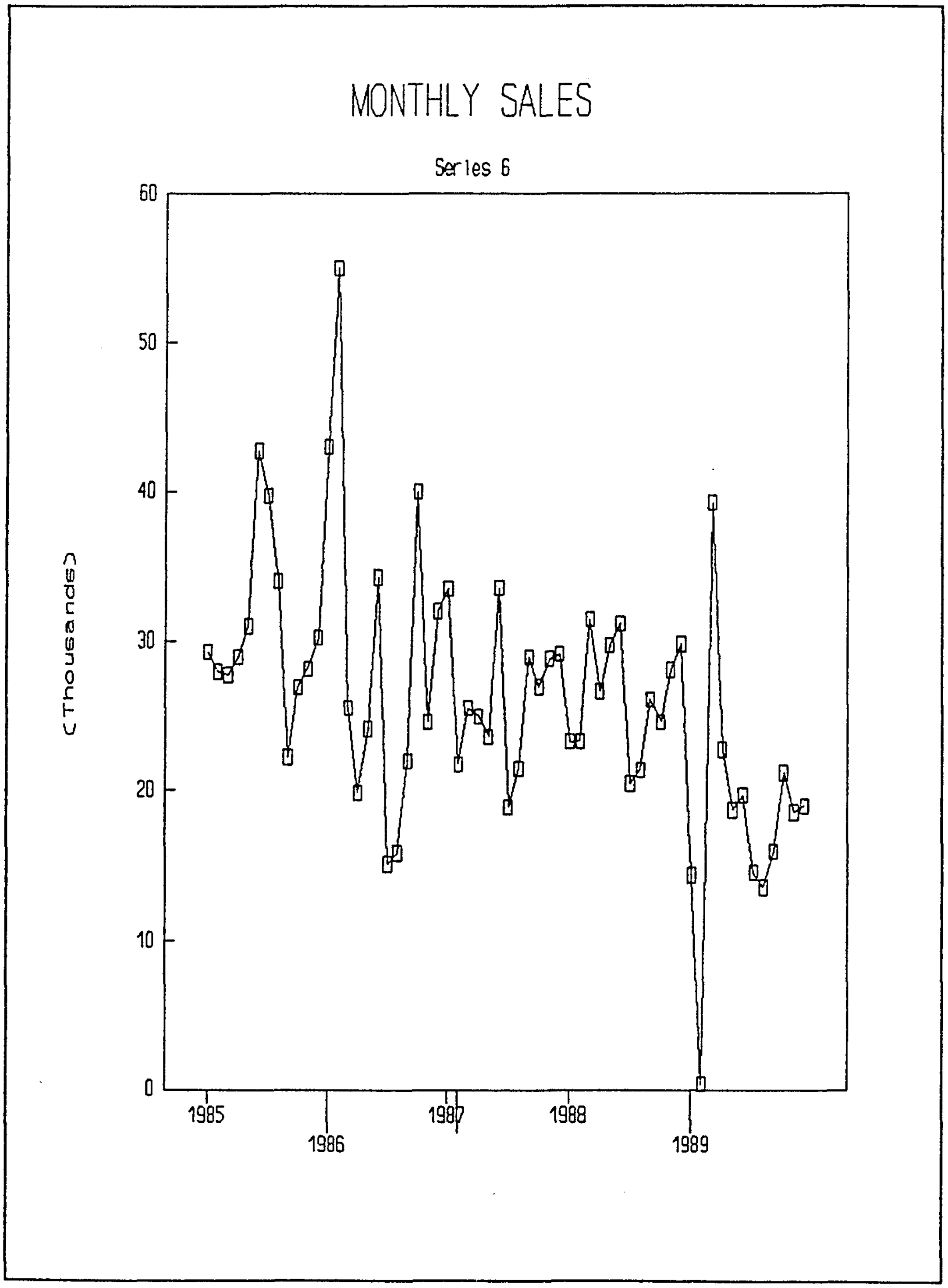
MONTHLY SALES
Series 7
90
80
70
60
50
40
30
20
(Thousands)
1985
1986
1987
1988
1989

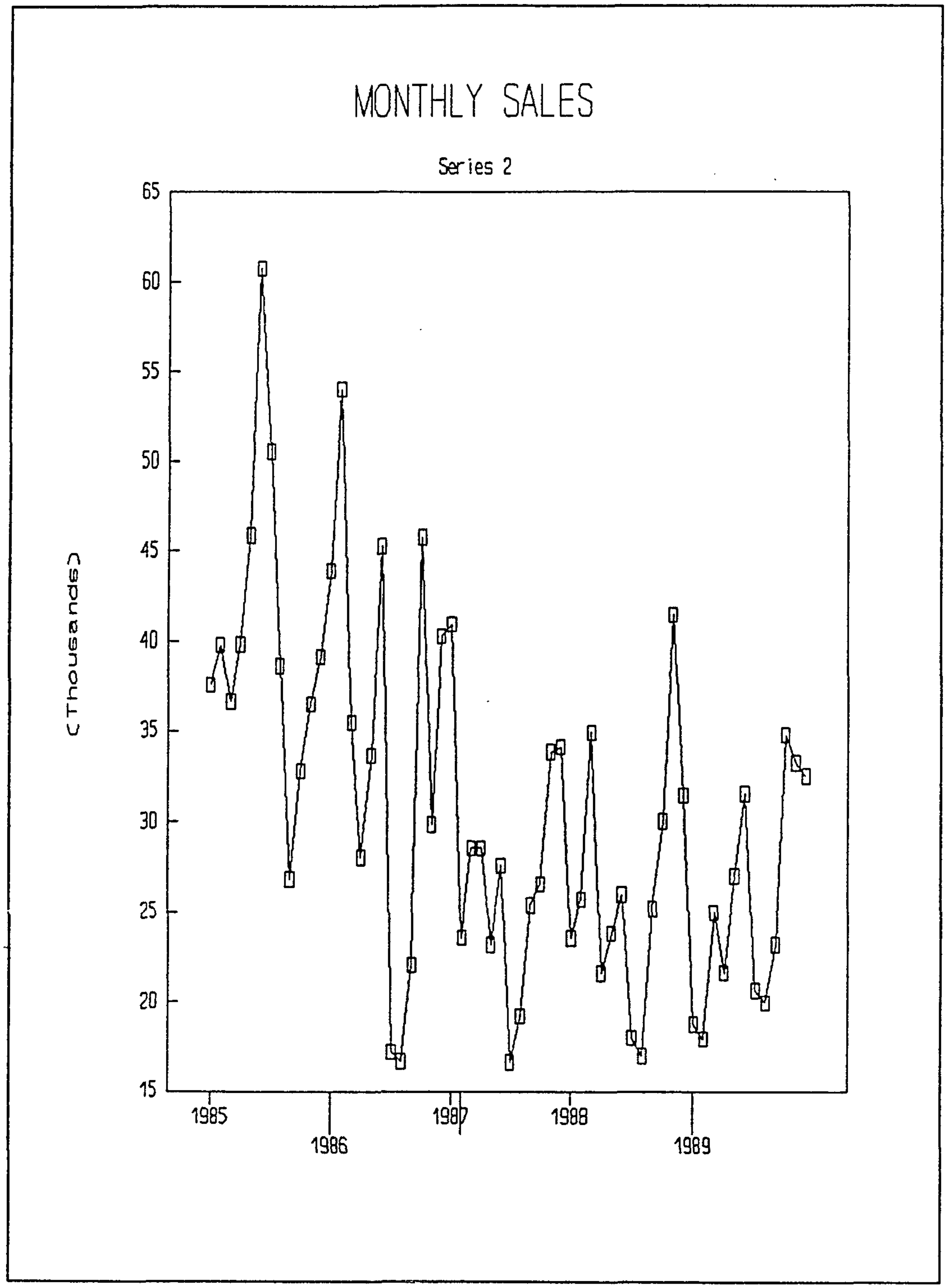

MONTHLY SALES
Series 13
(Thousands)
100
90
80
70
60
50
40
30
20
10
1985
1986
1987
1988
1989

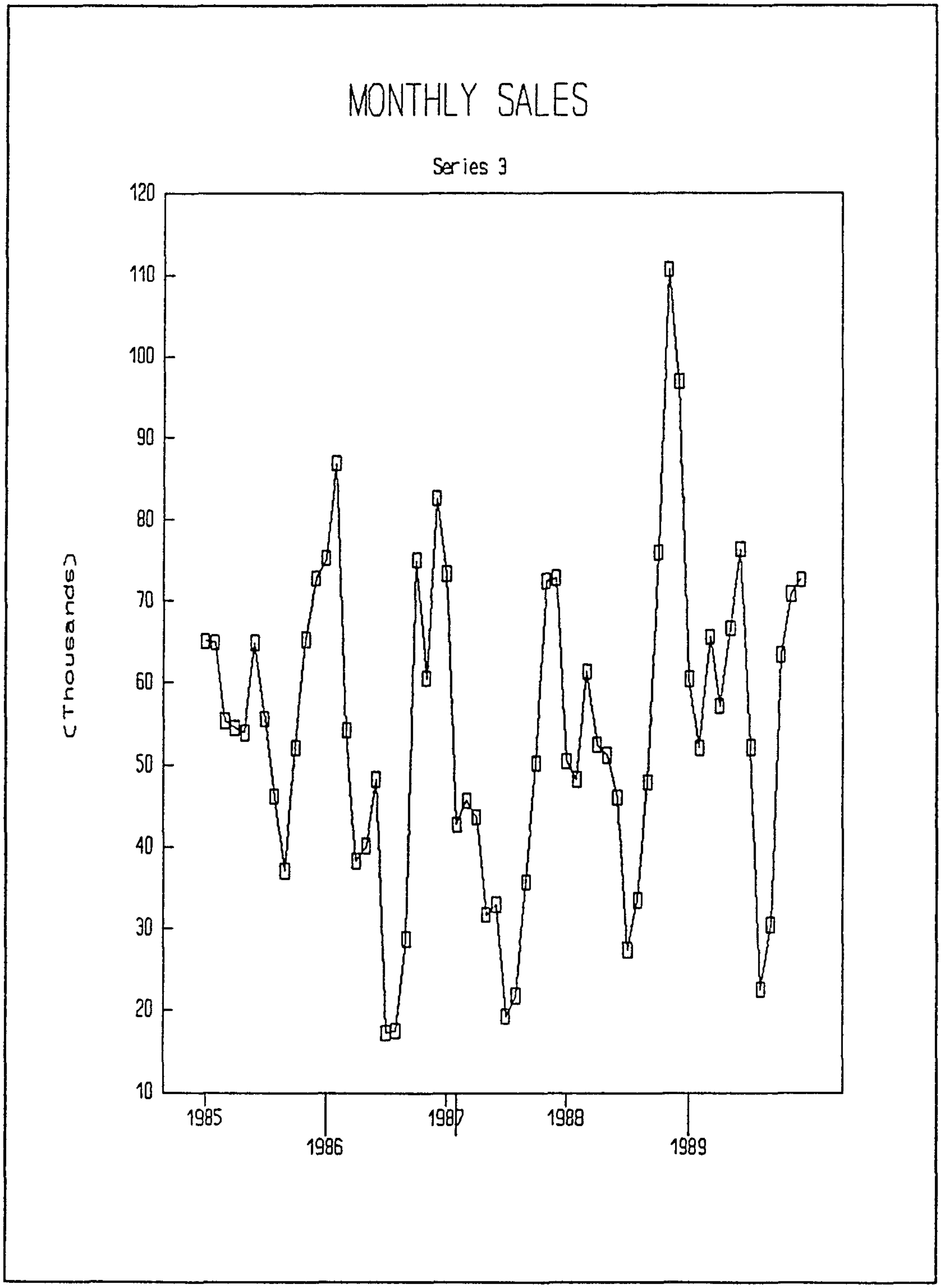

MONTHLY SALES
Series 15
(Thousands)
90
80
70
60
50
40
30
20
10
1985
1986
1987
1988
1989

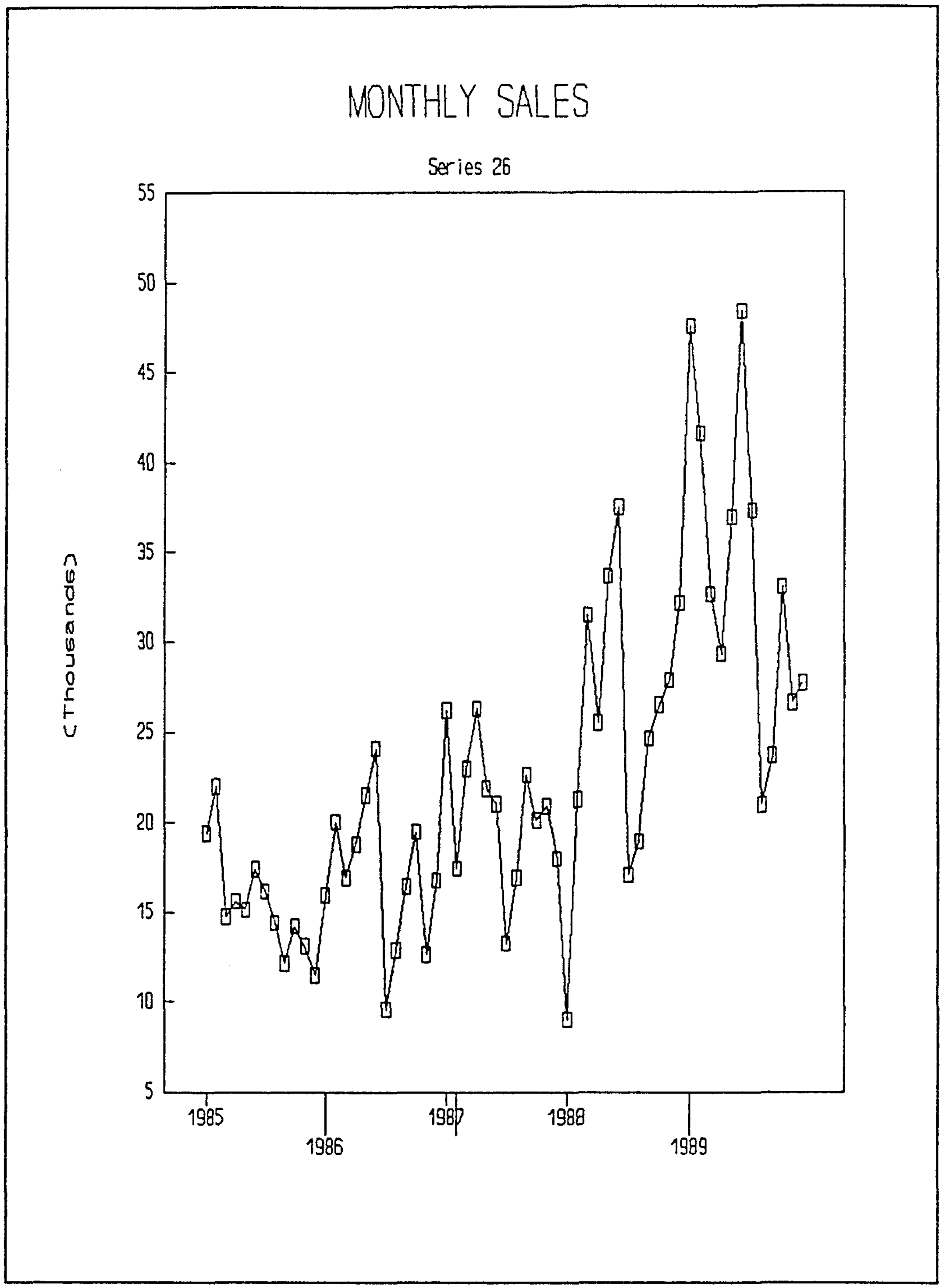

MONTHLY SALES
Series 1
(Thousands)
70
60
50
40
30
20
10
0
1985
1986
1987
1988
1989

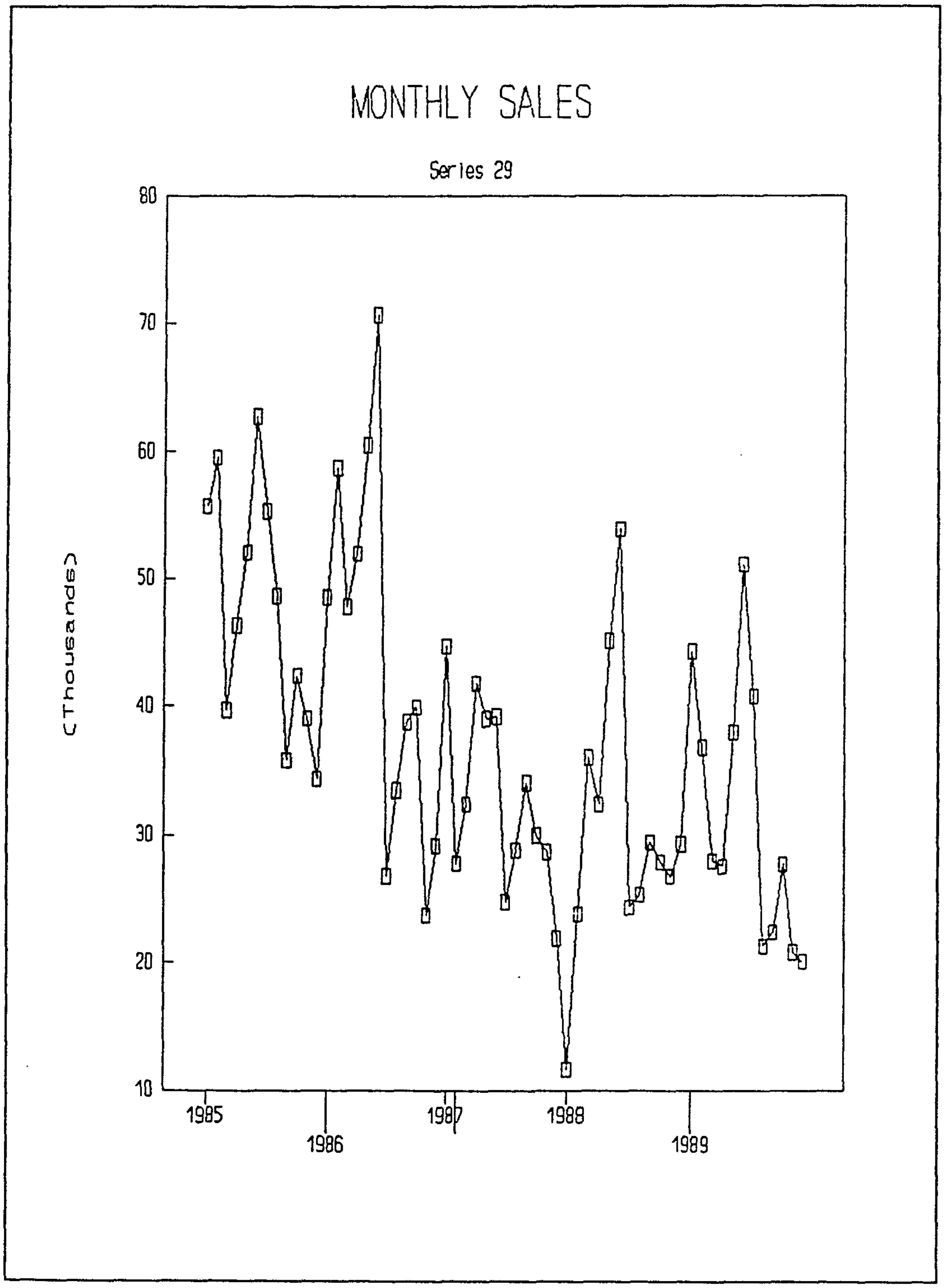

MONTHLY SALES
Series 5
(Thousands)
50
45
40
35
30
25
20
15
10
5
0
1985
1986
1987
1988
1989


MONTHLY SALES
Series 6
(Thousands)
60
50
40
30
20
10
0
1985
1986
1987
1988
1989


MONTHLY SALES
Series 2
65
60
55
50
45
40
35
30
25
20
15
(Thousands)
1985
1986
1987
1988
1989


MONTHLY SALES
Series 3
(Thousands)
120
110
100
90
80
70
60
50
40
30
20
10
1985
1986
1987
1988
1989


MONTHLY SALES
Series 26
(Thousands)
55
50
45
40
35
30
25
20
15
10
5
1985
1986
1987
1988
1989


MONTHLY SALES
Series 29
(Thousands)
80
70
60
50
40
30
20
10
1985
1986
1987
1988
1989

APPENDIX C

SUMMARY OF SIX TIME SERIES FORECASTING TECHNIQUES

Summary of Six Time Series Forecasting Techniques

Method	Description	Strength
Single Expon. Smoothing	- Implies exponentially decreasing weights as the observations get older. - Requires one smoothing parameter. - Appropriate for stationary data.	- Requires little storage. - Requires few and simple computations - Trails any trend in the actual data.
Adaptive Response Rate Expon- ential Smoothing	- Implies exponentially decreasing weights as the observations get older. - Requires one smoothing parameter. - Appropriate for stationary data. - Allows parameter value to change when the data pattern changes. - Appropriate when thousands of items are involved.	- The parameter value changes automatically when the data pattern changes. - Requires little storage. - Requires few and simple computations. - Trails any trend in the actual data.
Holt's Linear Expon. Smoothing	- Implies exponentially decreasing weights as the observations get older. - Requires two smoothing constants.	- Smooth the trend values separately. This provides more flexibility.
Brown's One- Parameter Quadratic	- Implies exponentially decreasing weights as the observations get older. - Requires three smoothing constants.	- Picks up the linearity. - The initiali- zation process can be very simple.

Summary of Six Time Series Forecasting Techniques (continued)

Method	Description	Strength
Winters' Trend and Season-ality	- Implies exponentially decreasing weights as the observations get older. - Requires three smoothing constants.	- Captures the seasonality element.
Carbone-Makridakis	- Differentiates between two models: a short and long term. These two models are reconciled to produce final forecasts.	- Utilizes both short term and long term forecasting models. Enables the forecaster to adapt to changes in data patterns as they occur. - Captures the long-term trend.

APPENDIX D

EQUATIONS OF SIX TIME SERIES FORECASTING TECHNIQUES

1- Single Exponential Smoothing (SINGLE):

$$F_{t+1} = F_t + \alpha(X_t - F_t).$$

where F_{t+1} = forecast or period t+1
F_t = forecast for period t
$(X_t - F_t)$ = forecast error
α = smoothing parameter

2- Holt's Two Parameter Linear Model (HOLT):

$$S_t = \alpha X_t + (1 - \alpha)(S_{t-1} + b_{t-1}),$$

$$b_t = \gamma(S_t - S_{t-1}) + (1 - \gamma)b_{t-1},$$

$$F_{t+m} = S_t + b_t m.$$

where S_t = smooth component
b_t = trend component
α = smoothing parameter
γ = smoothing parameter (trend)
F_{t+m} = forecast for m periods ahead

3- Winter's Three-Parameter Trend and Seasonal (WINTERS):

$$F_{t+m} = (S_t + b_t m)I_{t-L+m}.$$

where L = length of the seasonality
b = trend component
I = seasonal adjustment factor
F_{t+m} = forecast for m periods ahead

4- Adaptive Response Rate Exponential Smoothing

$$F_{t+1} = \alpha_t X_t + (1 - \alpha_t)F_t,$$

The basic equation for this method is similar to the single exponential smoothing except that the smoothing parameter changes automatically when the data pattern changes.

5- Brown's One-Parameter Quadratic Method (BROWNQ):

There are three smoothing parameters here

$$S'_t = \alpha X_t + (1 - \alpha)S'_{t-1} \quad \text{(first smoothing)},$$
$$S''_t = \alpha S'_t + (1 - \alpha)S''_{t-1} \quad \text{(second smoothing)},$$
$$S'''_t = \alpha S''_t + (1 - \alpha)S'''_{t-1} \quad \text{(third smoothing)},$$
$$F_{t+m} = a_t + b_t m + \tfrac{1}{2}c_t m^2.$$

6- Carbone-Makridakis Forecasting System (CMFS):

Combination of Short and Long term forecasts

source: Makridakis et al. (1983)
Makridakis and Carbone (1984)

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