# SAP ${ }^{\circledR}$ 'S UNIVARIATE SALES 

## FORECASTING FUNCTIONALITY:

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Wherever this thesis draws on the work of others, such sources are clearly acknowledged: $\qquad$
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## ABSTRACT

The accuracy of sales forecasts is a major determinant of inventory costs and service level driven revenues. Failure to establish future customer demand without a reasonable degree of certainty often leads to poor levels of customer service and/or high levels of the wrong inventory and resulting reductions in company profitability. Enterprise resource planning (ERP) systems such as SAP are widely adopted and typically contain sales forecasting functionality. The sales forecasting accuracy of ERP systems can have a critical impact on business profitability and empirical research into the effectiveness of ERP offerings should be considered a valuable endeavour. However, commonly adopted measures of forecast accuracy, such as mean absolute error (MAE) and mean absolute percentage error (MAPE), do not provide explicit costs associated with forecast errors.

This thesis adopts a quantitative case study methodology to evaluate the nine forecasting models ( 2 moving average and 7 exponential smoothing) of $\mathrm{SAP}^{\circledR 1}{ }^{\text {S }}$ enterprise resource planning system (SAP ${ }^{\circledR}$ ERP). The SAP forecast models are evaluated against both common statistical measures and commercial measures of forecast error, using a 24 month and 60 month product sales data set provided by a New Zealand based importer and retailer of electrical products. The forecast models are a combination of SAP default smoothing parameters, fitted smoothing parameters, baseline statistical forecasts, and event management adjusted forecasts resulting in a total of 38 forecast model combinations. The 38 forecast models are assessed using a rolling-origin holdout approach and evaluated against mean absolute error (MAE), mean absolute percentage error (MAPE), revenue-weighted mean absolute percentage error
(RW-MAPE), and two new measures developed by the author; margin-weighted mean absolute percentage error (MW-MAPE) and cost of forecast error (CFE).

The findings of the case study support the fitting of forecast smoothing parameters using historical data, the selection of forecasting models based on historical time series characteristics, i.e. level, trend, and seasonality, and length of available history. The study also supports the evaluation of sales forecasts with cost of forecast error (CFE) as a more commercially useful measure than the widely adopted mean absolute error (MAE) and mean absolute percentage error (MAPE) measures. Event management adjustment of baseline statistical forecasts was not found to be statistically significant. However, an argument is presented that significance testing should be deemphasised in favour of effect size (forecast error cost reduction in the case of this study). However, the results should be viewed as case specific and reflect the particular time series characteristics, costs, and margins of the company in question.

The study concludes with methodological recommendations for practitioners, ERP vendors, and academics which are supported by the specific case study results and the reviewed literature.

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The following software was used in the data analysis and write up of this thesis:
SAP ${ }^{\circledR}$ ERP Enterprise Core Component (ECC) 5.0, Microsoft ${ }^{\circledR}$ Excel ${ }^{\circledR}$ 2003, Microsoft ${ }^{\circledR}$
Word $^{\circledR}$ 2003, Microsoft ${ }^{\circledR}$ Visio $^{\circledR}$ 2003, EndNote ${ }^{\circledR}$ 7.0.

### 1.0 INTRODUCTION AND RESEARCH AIMS

"Although journals are the primary means for reporting scientific advances in forecasting, software programs are the critical paths for implementation"
(Tashman \& Hoover, 2001, p. 652)

This study evaluates the sales forecasting models of $\mathrm{SAP}^{\circledR}$, enterprise resource planning system (SAP® ERP) using a case study methodology, details of which are explained in the following sections.

The historical sales data set used to assess the $S A P ~^{\circledR}$ forecasting models in this case study was obtained from a privately owned, medium sized electrical products retaildistribution company (referred to as "the company"). It operates 22 stores throughout New Zealand, employing 140 staff, with annual sales revenue of approximately NZ\$24 million. The company imports the majority of its products from China via sea freight. Although profitable, the company faces growing competition from other specialist retailers and "big box" hardware stores.

In April 2003 the company commenced implementation of SAP ${ }^{\circledR \text {, }}$ s All-in-One* enterprise resource planning system, with the primary aim of achieving higher stockturns and increased availability of core products. The inventory management improvements would be achieved via $S A P^{\circledR,}$ s material requirements planning (MRP) functionality. In order to realise the benefits of MRP it is necessary to accurately forecast demand, a subject area that is explored in the subsequent literature review.

[^0]aim of the system is to provide a preconfigured ERP solution that is tailored to SMEs providing a less complex and less costly implementation. For the purpose of both clarity and relevance I will refer to the system as $\mathrm{SAP}^{\circledR}$ ERP throughout this document.

This Chapter provides an executive summary of the research. A selective examination of the literary context of the research subsequently details knowledge in the field.

### 1.1 The Company's Supply Chain

The company's supply chain network consists of 22 retail stores located throughout New Zealand, which are serviced by a central distribution centre located in Auckland. Replenishment of product to the stores from the distribution centre is achieved via re-order points for each product, with inventory levels against the re-order points reviewed daily by the SAP ${ }^{\circledR}$ MRP module. Store stock found to be below the set re-order point results in the creation of a minimum stock transport order which generates a delivery document to enable picking and despatch from the central distribution centre. The store re-order points are frequently set at levels higher than true customer demand (within the distribution centre replenishment lead-time) to accommodate visual merchandising requirements, i.e. the requirement for stock to be attractively presented in store. The company sources 66\% of its product from China, 32\% from New Zealand, and 2\% from Italy. The Chinese product is sourced from five major suppliers, including one agent that deals with in excess of 20 manufacturing plants. The mean delivery leadtime from placement of orders with Chinese suppliers is 77 days.

Overseas purchasing requirements for the distribution centre are determined by producing a statistical forecast based on the aggregate sales history of all 22 retail stores. Net product requirements are then calculated as follows: uncommitted stock on
hand + planned receipts (purchase orders) - requirements (forecast sales) over the entire three month planning horizon, being the company's procurement lead-time from China and Italy which includes manufacturing and sea freight. Details of the company's sales and operations planning process are described next.

### 1.1.1 Sales and Operations Planning Process

Establishing an accurate product sales forecast is critical to the company's profitability. Understating future demand leads directly to lost sales. Corsten and Gruen's (2004) study of more than 600 retailers revealed that when a precise product demanded by the customer is not available fewer than half on average will make a substitute purchase. Conversely, overstating future demand leads to overstocking of products with the associated tying up of capital, additional warehousing requirements, and ultimately the carrying of obsolete items that may require sale at heavily discounted prices.

In order to maximize long-term company profitability through the effective balancing of product supply and demand, the company operates a monthly Sales and Operations Planning (SOP) process. The details of the company's SOP process are commercially sensitive, however it is important to introduce the key elements in order to appreciate the impact of product sales forecasting on the business. The monthly SOP process commences with statistical sales forecasting performed by the SAP ${ }^{\circledR}$ system. Forecasts are then judgmentally adjusted for new products, store openings and promotions. Following sign-off of the procurement plan by the company directors, in the monthly SOP meeting, the SAP generated purchase requisitions are converted to purchase orders and emailed to the overseas suppliers. The process is constrained by supplier lead-time and therefore is concerned with supply and demand a full three months ahead. The critical protection period consists of an average lead-time of 77 days
plus the monthly review period of 30 days (107 days total). It should be noted that the review period of one month is arbitrary.

### 1.2 Theoretical Basis and Importance of the Study

The accuracy of sales forecasting is a major determinant of inventory costs, service levels, scheduling and staffing efficiency, and many other measures of operational performance (T. Lee, Cooper, \& Adam, 1993). Product sales forecasting is also a critical starting point for mobilising a company's resources, be they labour, capital, or equipment (Sengupta \& Turnball, 1996). Once a realistic demand distribution for a product is established then customer service levels and inventory levels can be determined. Failure to establish future customer demand without a reasonable degree of certainty often leads to poor levels of customer service and/or high levels of the wrong inventory. According to Cecere (2005) "Forecast accuracy is the most important and advantageous supply chain metric. According to our benchmarking research, a one-point improvement in demand forecast accuracy could yield a two-point improvement in perfect order performance. Organizations with better forecasts gain competitive advantage with a $35 \%$ shorter cash-to-cash cycle time."

Theoretical contributions to univariate forecasting frequently appear in a number of established disciplines, namely; operations research, operations management, management science, managerial economics, and the emerging discipline of supply chain management (defined in the literature review) all of which apply quantitative techniques to business problems in an effort to improve decision-making. However, based on a five year review of operations management articles, Wacker (1998) states that empirical case studies are underrepresented in the literature. Wacker concludes that "there is a lack of studying causality in the empirical world which hinders the development of verified relationships that are assumed to be true", i.e. a lack of theory
development and/or validation through empirical data. However, support for empirical forecasting research is relatively common in the forecasting literature and is epitomised by the three "M" (Makridakis) forecasting competitions (Makridakis et al., 1982; Makridakis et al., 1993; Makridakis \& Hibon, 2000). One of the primary motivations for conducting empirical forecasting research is the requirement for organisations to identify and apply accurate, cost effective forecasting methods (Armstrong, 1997; Makridakis, 1993b). This empirical case study is also motivated by the need to identify and apply an accurate, cost effective forecasting method for informing business decision making in an ERP environment. In the context of ERP sales forecasting it has been reported that ERP adopters admit to not fully utilising their forecasting systems (Vega, 2001).

The research approach detailed in the subsequent sections can serve as a template for businesses wishing to evaluate their ERP based forecasting systems and potentially gaining higher levels of customer service at a reduced inventory holding cost.

### 1.3 Relevance of SAP to the Case Study

Enterprise resource planning (ERP) systems have seen widespread adoption in business largely due to what O'Leary (2002) says is the appeal of integrating disparate functions. SAP ${ }^{\circledR}$ (Systeme, Anwendungen, Produkte in der Datenverarbeitung, English translation - Systems, Applications and Products in Data Processing) was founded in 1972 by five former IBM $^{\circledR}$ employees. Headquartered in Walldorf, Germany, the company currently has 39,300 employees, 38,000 customers, and 79,800 worldwide installations. In 2006, SAP ${ }^{\circledR}$ s worldwide enterprise application vendor share was $24 \%$ (ORACLE ${ }^{\circledR} 9 \%$, Microsoft ${ }^{\circledR} 5.2$, rest of market $61.8 \%$ ). Revenue in 2006 was $€ 9.4$ billion (SAP, 2007).

For the purpose of providing a 'flavour' of $\mathrm{SAP}^{\circledR}$ 's offering, the primary product portfolio is listed below (see http://www.sap.com for further information).

SAP ${ }^{\circledR}$ for Industry: (Industry specific solutions, i.e. tailored ERP systems)
SAP ${ }^{\circledR}$ Business Suite: ( $S A P ®$ ${ }^{\circledR} C R M$ (Customer Relationship Management), $S A P ®$ ERP (Enterprise Resource Planning Core Component), SAP® PLM (Product Lifecycle Management), SAP® SCM (Supply Chain Management), SAP® SRM (Supplier Relationship Management))

SAP ${ }^{\circledR}$ Solutions for Midsize and Small Businesses: (SAP® All-in-One, $S A P ®$ Business Suite, SAP ${ }^{\circledR}$ Business One)

SAP ${ }^{\circledR}$ NetWeaver ${ }^{\circledR}$ : $\left(S A P^{\circledR}\right.$ Enterprise Portal, SAP ${ }^{\circledR}$ Master Data Management, SAP ${ }^{\circledR}$ Composite Application Framework, SAP ${ }^{\circledR}$ Business Intelligence, SAP ${ }^{\circledR}$ Mobile Infrastructure, SAP ${ }^{\circledR}$ Exchange Infrastructure, SAP ${ }^{\circledR}$ Web Application Server)

SAP ${ }^{\circledR}$ has a dominant customer base within Global 500 companies (SAP ${ }^{\circledR}$, 2007) and to facilitate further growth has an active go-to-market strategy of obtaining SME market share (SAP, 2005). Released in 2002, SAP® All-in-One had a customer base of 4,600 by the end of 2003.

The widespread use of $S A P^{\circledR}$ provides fertile ground for empirical research to support the 12 million worldwide users of $S A P^{\circledR}$ products. The application of relevant prior research to practical problems is clearly an important activity to assist SAP ${ }^{\circledR}$ practitioners, with the lack of empirical research in the context of SAP ${ }^{\circledR}$ software identified in the literature review in Chapter 3.

The forecasting models used by $\mathrm{SAP}^{\circledR}$ are also in common use in other systems. The results of the case study are not limited to $\mathrm{SAP}^{\circledR}$ practitioners and methodology should generalise to similar business tools.

### 1.4 Limitations

1. The case study is limited to products that are imported by the company. A distinguishing feature of these products is delivery lead-times of up to three months due to overseas manufacture and subsequent shipping.
2. Where possible all data processing and analysis is conducted using SAP $^{\circledR}$ functionality. The rationale for this limitation was to ensure that other SAP ${ }^{\circledR}$ practitioners could replicate or apply the results of the case study in their particular environments, without the need to utilise additional statistical packages (e.g. SPSS, Minitab, SAS). However, the determination of optimized smoothing parameters, along with statistical analysis of the results, was performed using the widely available Microsoff ${ }^{\circledR}$ Excel ${ }^{\circledR}$.
3. All forecasting takes a "bottom up" approach, i.e. forecasting at stock keeping unit (SKU) level, being the convention adopted in the major forecasting studies such as the M-Series (Makridakis \& Hibon, 2000). For an evaluation of "bottom up" versus "top down" forecasting approaches see Fliedner (2001).

Having introduced the setting and limitations of the case study the next Chapter will detail the research aims, working hypotheses, and questions.

### 1.5 Research Aims

The primary aim of the case study is to identify and evaluate the $S A P^{\circledR}$ sales forecasting method that provides the "best-fit" for the company's sales forecasting requirements, within the constraints of the company's ERP system. SAP ${ }^{\circledR \text {, }}$, ERP forecasting functionality includes nine time series forecast models as well as event management (causal forecast adjustment). The forecast serves to provide planned independent requirements (forecast sales) for the $S A P ~^{\circledR}$-based material requirements planning process of the company. Improved forecasting accuracy is reported as leading to increased levels of customer service and reduced inventory costs (Enns, 2002; Gardner, 1990; Tyagi, 2002). The fundamental choices that the "company" has to make in order to utilise the SAP forecasting functionality are: choice of forecasting strategy (forecast model), selection of smoothing parameters (or use of the SAP default parameters), and adjustment of baseline statistical forecasts for known events (e.g. sales promotions). The working hypotheses are:

Based on tests of statistical significance; (1) Fitted forecast smoothing parameters will outperform the SAP default smoothing parameters, (2) event management adjusted forecasts will outperform baseline statistical forecasts, (3) one of the 38 forecasting model/parameter combinations will produce a statistically significantly more accurate (better fit) forecast across all products, and (4) that SAP's forecast error measures do not reflect the commercial impact of forecast errors.

Further research aims are to evaluate the SAP ERP forecasting functionality in relation to the literature and to provide methodological recommendations for practitioners to help better leverage their ERP demand forecasting packages.

The following are the specific research questions that correspond to the previous hypotheses:

1. Do the default $S A{ }^{\circledR}$ forecast smoothing/weighting parameters provide the "Bestfit" forecast for the company and is any performance differential statistically significant? (Matched t-test applied to MAE and CFE)
2. Does the combination of event management (causal factors) with time series techniques provide a "Better Fit" than the time series techniques alone and is any performance differential statistically significant? (Matched t-test applied to MAE and CFE)
3. Which of the nine available $S A P^{\circledR}$ time series (univariate) forecasting models provides the "Best-fit" for the company and is any performance differential statistically significant? (repeated measures ANOVA applied to MAE and CFE)
4. Are the forecast error measures utilised by $S A P^{\circledR}$ indicative of the commercial impact of the resulting forecast errors? (Coefficient of determination $\left(r^{2}\right)$ applied to ranked forecast error measures)

Having presented the research aims, working hypotheses, and questions, the next Chapter will review the relevant literature.

The review of the literature introduces the role of information and communication technologies (ICT) in supply chain management and then identifies the importance of sales forecasting as the primary input into supply chain management activities.

A review of forecasting techniques and methods relevant to $S A P ~^{\circledR}{ }^{\circledR}$ s offering then follows, including a critique of previous forecasting studies. The review of the literature concludes with a critique of relevant $\mathrm{SAP}^{\circledR}$ literature.

### 2.1 Information and Communication Technology enabled Supply Chain Management

The application of computing to commercial supply chain management (SCM) problems first appeared in the 1950s with use of mainframe systems to automatically calculate re-order points for inventory items. In 1961 Joseph Orlicky, an IBM ${ }^{\circledR}$ engineer, successfully applied material requirements planning (MRP) within J.I Case Company, a farm machinery manufacturer. MRP is defined by the American Production and Inventory Control Society (APICS, 2002) as:

[^1]accomplished by exploding the bill of materials, adjusting for inventory quantities on hand or on order, and offsetting the net requirements by the appropriate lead times" (p. 70).

By 1971 approximately 150 companies were using MRP systems, with the 1970s seeing widespread adoption of MRP systems by manufacturing companies (Plossl, 1994). By the mid nineties in excess of 60,000 MRP implementations were in world-wide use (AMR, 1995). Reported benefits of MRP include reductions in stock levels (work in progress and finished goods) and higher delivery date performance (Braglia \& Petroni, 1999). Reported limitations include lack of capacity requirements planning, problems with bill of material accuracy and implementation time, lack of options for influencing the system behaviour with respect to strategic and operational goals, internal focus, thus addressing only one node of the supply chain, limited decision support capabilities, scheduling decisions based on a priori specified lead-times, making insufficient use of information about the current situation on the shop floor, insufficient consideration of potential bottlenecks, and inadequate plant data collection (Knolmayer, Mertens, \& Zeier, 2002). The major limitation of MRP systems concerning capacity planning was addressed during the 1980s with the development of Manufacturing Resource Planning (MRPII) systems. APICS (2002) define Manufacturing Resource Planning as:


#### Abstract

"A method for the effective planning of all resources of a manufacturing company. Ideally, it addresses operational planning in units, financial planning in dollars, and has a simulation capability to answer what-if questions. It is made up of a variety of processes, each linked together: business planning, production planning (sales and operations planning), master production scheduling, material requirements planning, capacity requirements planning, and the execution


support systems for capacity and material (shop floor control). Output from these systems is integrated with financial reports such as the business plan, purchase commitment report, shipping budget, and inventory projections in dollars. Manufacturing resource planning is a direct outgrowth and extension of MRP" (p. 68).

The relationships between the various modules contained in an MRPII system are shown in Figure 1.


Figure 1. MRPII System Modules (Vollmann, Berry, \& Whybark, 1992)

Enterprise resource planning systems (ERP) evolved directly from manufacturing resource planning (MRPII), with the term ERP being coined in the early nineties. However, apart from industry standard MRPII functionality, the major ERP offerings are limited in their ability to plan resources as suggested by Davenport and Brooks (2004) who state that early ERP systems were concerned with the integration and execution of
internal business functions, not the planning of wider supply chain activities. As a result of the planning limitations of traditional ERP systems, supply chain management systems grew in popularity from the mid-nineties with vendors such as i2 Technologies, Manugistics, and Red Pepper (later acquired by Peoplesoft) offering specialist SCM solutions. The last five years has seen sophisticated advanced planning and scheduling (APS) systems offered by traditional ERP vendors including SAP ${ }^{\circledR}$, ORACLE ${ }^{\circledR}$, and Peoplesoft ${ }^{\circledR}$ (acquired by ORACLE ${ }^{\circledR}$ ). In a study of leading ERP system adopters, Davenport, Harris, and Cantrell (2002) found that supply chain initiatives were cited in executive interviews more than any other application domain.

Kumar (2001) provides a framework (Figure 2) for supply chain activities that are supported by current ERP systems and their recently incorporated advanced planning and scheduling systems. The framework shows the specific supply chain activity, e.g. make or sell, the corresponding ICT enabled process, e.g. production scheduling, along with the organisational level of such processes, i.e. operational, tactical, or strategic.


Figure 2. Functional Domains of Advanced Planning \& Scheduling Systems (Kumar, 2001)

Kumar identifies demand planning as a tactical process concerned with the sales function. Although not made explicit in Kumar's framework, demand planning is the
fundamental starting point for mobilising a firm's resources. Demand planning is, of course, inherently difficult, as it is deals with uncertainty, i.e. what the future holds. In contrast, supply planning is generally a straightforward resource allocation problem, albeit often subject to multiple constraints and trade-offs that lend themselves to optimisation or heuristic techniques, i.e. linear programming (Render \& Stair, 1997) or genetic algorithms (Knolmayer et al., 2002).

### 2.1.1 ICT Enabled Supply Chain Management and Demand Forecasting

The APICS (2002) definition of supply chain management (SCM) includes "synchronising of supply with demand", the basis of such synchronization being the determination of customer demand (firm orders and/or forecast requirements) and the review of demand against available capacity (machinery, labour, cash, etc.). Determination of demand in make-to-stock environments (i.e. those that require a leadtime greater than customer requirements, such as retail settings where customers expect to be able to take immediate possession of goods) requires demand forecasting. Short to medium term demand forecasting is a primary input to manufacturing/procurement planning and control systems. Even make-to-order environments usually require demand forecasting for raw materials, parts, or subassemblies, so that end customer requirements for finished goods can be provided in a timely manner.

In summary, ICT enabled SCM first appeared in the 1950s with the calculation of simple reorder points. In the 1960s MRP was developed and saw significant growth through the 1970s, later being extended in the 1980s to include capacity planning and financial management functionality and termed MRPII. The 1990s saw further advances with the full extension of MRPII into business-wide functionality (sales and distribution, finance and accounting, materials management, production planning, human resource
management, quality management, asset management, and plant maintenance) to form ERP. The late 1990s through to the present have seen ERP systems augmented with advanced planning and scheduling (APS) systems.

Irrespective of the SCM model or technology (MRP, MRPII, ERP, or APS), demand forecasting is a critical requirement for mobilising a company's resources. This observation is clearly stated by Vollmann et al. (1992) "Providing adequate inventory to meet customer's needs throughout the distribution system and to maintain desired customer service levels requires detailed forecasts". The economic impact of forecasting is the subject explored in the next section.

### 2.2 Economic Impact of Forecasts

"Few C-Level executives care about forecasting accuracy. What they care about is the impact of improved forecasting on shareholder value" Mentzer (1999)

Improved forecast accuracy plays a pivotal role in increasing shareholder value (Mentzer \& Moon, 2005). The relationship of forecast accuracy to shareholder value is shown in Figure 3, which is an elaboration of Mentzer and Moon's (2005, p. 68) "Impact of Forecasting Improvements on Shareholder Value". However, the majority of forecast error measures are not representative of financial impact, the one identified exception being Mentzer and Moon's aggregate MAPE.


Figure 3. Forecast Accuracy and Stakeholder Value (Adapted from SAP ${ }^{\circledR}$, 2006)

A number of authors have highlighted the need to assess the economic consequences of forecast error. Fildes and Beard (1992), state "Ideally a forecasting method should be chosen in order to minimize unnecessary costs such as stock holding". Flores, Olson and Pearce (1993) state "the statistical criteria may not be the most suitable because statistical measures of forecast accuracy are not designed to capture the economic implications associated with managing an inventory system". Roberts and Whybark (1974) consider forecast cost implications as "probably the most essential measure" of forecast model performance. Gardner (1990) applies inventory investment and customer service "trade off" curves to determine forecast model performance, claiming that traditional forecast accuracy measures such as MAPE and MSE do not provide an estimate of investment and customer service levels. Lee, Cooper and Adam (1993) employ total cost as a "much more relevant" error measure compared with bias, MAD, and MSE.

To assess the economic impact of forecast accuracy it is necessary to at least determine the costs of forecast error in terms of both inventory costs and the costs of poor service (Flores et al., 1993). However, the impact of improved forecasting can extend throughout the value chain and have major consequences on production, procurement, transportation/distribution, storage, and marketing costs. Conversely, the forecasting activity itself incurs costs associated with software, training, recognition of performance, and direct personnel expenses (Mentzer, 1999).

The nature of attempting to forecast sales demand is that forecasts will invariably contain a degree of error. In the context of sales forecasting there is a vital need to mitigate forecast error to maintain the desired level of customer service while minimizing the costs associated with excess inventory. This balance is achieved using safety stock. Safety stock is defined by APICS (2002) as "...a quantity of stock planned to be in inventory to protect against fluctuations in demand or supply. A more involved and
arguably more useful definition is provided by Silver, Pyke and Peterson (1998): "Safety stock is the amount of inventory kept on hand, on the average, to allow for the uncertainty of demand and the uncertainty of supply in the short run. Safety stock is not needed when the future rate of demand and the length of time it takes to get complete delivery of an order are known with certainty. The level of safety stock is controllable in the sense that this investment is directly related to the desired level of customer service (that is, how often customer demand is met from stock)".

The balancing of service level and required inventory has been referred to as the "sweet spot" and can result in "dramatic bottom line improvements" (Smart, 2004).

### 2.2.1 Customer Service Level

The importance of safety stock for maintaining customer service is highlighted by Lowson's (2002, p. 198) concept of "shadow demand" where customers make decisions regarding unavailable items and such decisions are remarkably difficult for the supplying business to quantify. Examples include backorder and accept a late delivery, substitute the product, or leave the purchase situation. Lowson's estimates of outcomes equate to the retailer losing a full $25 \%$ of sales in a stock-out situation. Corsten and Gruen's (2004) subsequent article "Stock-Outs Cause Walkouts" surveys more than 71,000 consumers worldwide and conclude that in retail settings $31 \%$ of customers will leave the store to buy an item at another store and $9 \%$ do not make a purchase at all. These findings equate to a $40 \%$ loss in purchase to the particular retailer if a desired item is unavailable. The study also shows that world-wide stock out rates sit at approximately 8\%.

The longer-term effects of stock-out situations are difficult to quantify but it would be reasonable to assume that customer loyalty is negatively impacted and the likelihood of repeat business diminished. Considering the work of Lowson (2002), and Corsten
and Gruen (2004) the importance of maintaining stock availability is clear. However, how does one define stock availability for managerial purposes? Silver, Pyke and Peterson (1998, p. 245) define three forms of availability as follows:
$P_{1}$ : Specified probability of no stock-out per replenishment cycle - Cycle Service Level.
$P_{2}$ : Specified fraction of demand to be satisfied routinely from the shelf - Fill Rate.
$P_{3}$ : Specified fraction of time during which net stock is positive - Ready Rate.

In summary, although the commonly employed measures of forecast accuracy, e.g. MAE, MAPE, serve an important purpose it is highly desirable to also determine the economic impact of different forecast methods so as to ensure that organisational objectives of sales forecasting will actually be achieved.

### 2.3 Forecasting Techniques

This section contains a review of reported forecasting techniques relevant to SAP ${ }^{\circledR}$,s offering, including parameter selection techniques, model identification and selection, and causal adjustment of statistical forecasts. The appropriate selection of forecasting methods can lead to major improvements in forecasting accuracy (Fildes \& Beard, 1992).

### 2.3.1 Forecasting Techniques Overview

Sales forecasting techniques can be broadly classified as qualitative or quantitative (see Figure 4). Qualitative approaches assume that certain people, e.g. management, experts, or customers, can determine what future demand will be. Qualitative techniques can range from informal, i.e. intuition, to quite structured approaches such as Delphi, where a panel of domain experts are iteratively consulted until a consensus forecast is obtained (Makridakis, Wheelwright, \& Hyndman, 1998, p. 595). Quantitative methods consist of time series (observations taken at regular intervals) and causal techniques. Time series techniques assume that historical demand is the best determinant of future demand and essentially seek to identify underlying patterns in the historical data and extrapolate these to form a forecast (Armstrong, 2001, p. 215). Causal techniques attempt to identify the factor(s) that determine demand, e.g. promotional activity, pricing, interest rates, market share, and use such factors as the basis of a model to forecast demand (Armstrong, 2001, p. 770). Sophisticated causal techniques are referred to as econometric models.


Figure 4. Overview of Forecasting Techniques

### 2.3.2 Forecasting Models

SAP ${ }^{\circledR}$ 's ERP provides both time series and event management (promotion planning) techniques, although forecast values can be obtained through judgmental approaches, via manual data entry of forecast values into the relevant planning table. SAP ${ }^{\circledR}$, ERP time series functionality consists of two moving average methods and seven exponential smoothing methods. The time series techniques adopted by $\mathrm{SAP}^{\circledR}$ are described and critiqued in this section. Other time series techniques are widely cited in the literature, e.g. Autoregressive integrated moving average (ARIMA) (Box, Jenkins, \& Reinsel, 1994), and neural network approaches (Alon, Qi, \& Sadowski, 2001; Ansuj, Camargo, Radharamanan, \& Petry, 1996; Kuo, Wu, \& Wang, 2002). However, given the focus on $S A P^{\circledR}$ functionality, other techniques are considered outside of the scope of this literature review. It should also be noted that the description of the time series methods are in the context of sales forecasting, however the reviewed forecasting methods are
not limited to the forecasting of sales, but can also be applied to other time series, e.g. recreational visitation numbers (R. J. Chen, Bloomfield, \& Fu, 2003) or hospital patient admissions (Soucy et al., 2005).

Notation: The following standard notation is used throughout this review*:
$Y_{t}=$ Actual sales value in period t
$F_{t}=$ Forecast sales value in period t conducted when period $\mathrm{t}-1$
$e_{t}=\operatorname{Error}\left(Y_{t}-F_{t}\right)$ in period t
$m=$ Periods ahead

Smoothing Parameters:
$\alpha \quad$ Alpha for the smoothing of level of historical sales
$\beta \quad$ Beta for the smoothing of trend of historical sales
$\gamma \quad$ Gamma for the smoothing of seasonality of historical sales

* This notation differs from that used by $\mathrm{SAP}^{\circledR}$ in their literature in favour of the more common notation used by Makridakis, Wheelwright, and Hyndman (1998).


## Moving Average Methods

The two moving average methods calculate the mean of a time series over a chosen number of observations and use this as the sales forecast. Moving average methods represent one of the simplest forms of time series methods and are simple to understand and calculate, however they do not account for trend and/or seasonality in the time series.

Simple moving average. The simple moving average applies an equal weighting, which sum to 1 , over the prescribed historical observations of sales. It is suitable for constant pattern data where the historical sales level is constant (Pegels, 1969).

$$
\begin{equation*}
F_{t+1}=\frac{Y_{t}+Y_{t-1}+Y_{t-2}+\ldots+Y_{t-n+1}}{n} \tag{1}
\end{equation*}
$$

Weighted Moving Average. The weighted moving average applies a weighting, which sum to 1 , to each historical observation of sales that enables a higher weighting on more recent observations. The advantage of the weighting is that the model responds more quickly to changes in level than the simple moving average if the weights are increasing in time (Makridakis et al., 1998).

$$
\begin{equation*}
F_{t+1}=W_{t}\left(Y_{t}\right)+W_{t-1}\left(Y_{t-1}\right)+\ldots+W_{t-n+1}\left(Y_{t-n+1}\right) \tag{2}
\end{equation*}
$$

where $W_{t}=$ weighting factor

Note: The simple moving average is a special case of the weighted moving average.

## Exponential Smoothing Methods

Exponential smoothing techniques have seen widespread adoption in industry, particularly in applications requiring regular sales forecasting of a large number of products (Box et al., 1994; Brown \& Meyer, 1961; Fildes \& Beard, 1992, Holt, 2004; Snyder, Koehler, \& Ord, 2002; Tersine \& Green, 1979; Winters, 1960).

The favourable characteristics of exponential smoothing are: declining weight is put on older data, extremely easy to compute, relative ease of use, ability to change smoothing parameters, and minimal data are required. The limitations of such methods include no consideration of: leading indicators, market conditions, econometric trends, or other external influences. Exponential smoothing seems better suited to short term forecasting as it tends to lag genuine changes in demand, e.g. turning points (Holt, 2004; Tersine \& Green, 1979).

Single exponential smoothing (SES). The single exponential smoothing model is appropriate for constant pattern data, as a lag will occur if a trend in sales is present. The model places an exponentially decreasing emphasis on older data, essentially a weighted moving average (Makridakis et al., 1998).

$$
\begin{equation*}
F_{t+1}=\alpha Y_{t}+(1-\alpha) F_{t} \tag{3}
\end{equation*}
$$

Adaptive Response Rate Single Exponential Smoothing (ARRSES). The ARRSES model (shown in equation 4) adapts the smoothing factor for each period through the use of a tracking signal. The tracking signal determines the degree of error between the last sales forecast and the actual sales value and adjusts the smoothing parameter accordingly. A number of empirical studies have raised doubts regarding the effectiveness of adaptive smoothing parameters, favouring constant parameters. The concerns regarding ARRSES relate to the over-sensitivity of the model to changes in level. (See Gardner (1985), Gardner and Dannenbring (1980), Makridakis and Hibon (1979), and Makridakis et al., (1982)). However, Mentzer and Gomes (1994) present an adaptive variant known as adaptive extended exponential smoothing methodology (AEES) which automatically adapts all of the Winter's parameters and was shown to be
successful using the M-Competition data set. Taylor (2004) also presents a new variant of ARRSES known as smooth transition exponential smoothing (STES) that is reportedly less sensitive than traditional ARRSES to sudden demand shifts, although Taylor's STES or Mentzer's AEES is not utilised by SAP ${ }^{\circledR}$.
$F_{t+1}=\alpha_{t} Y_{t}+\left(1-\alpha_{t}\right) F_{t}$
where $\alpha_{t}=\left|\frac{A_{t}}{M_{t}}\right|$

$$
\begin{aligned}
& A_{t}=\beta E_{t}+(1-\beta) A_{t-1} \\
& M_{t}=\beta\left|E_{t}\right|+(1-\beta) M_{t-1} \\
& E_{t}=Y_{t}-F_{t}
\end{aligned}
$$

Brown's One Parameter Linear Method. Brown's method is appropriate for data exhibiting trend (Gardner, 1985). The method performs an initial smoothing, equivalent to single exponential smoothing, and then performs a second smoothing which accounts for the trend in sales. Brown's method only requires that the alpha (level) parameter be determined.
$F_{t+1}^{(1)}=\alpha Y_{t}+(1-\alpha) F_{t}^{(1)} \quad$ Single smoothing
$F_{t+1}^{(2)}=\alpha F_{t+1}^{(1)}+(1-\alpha) F_{t}^{(2)} \quad$ Double smoothing

Holt's Two-Parameter Linear Method. Holt's method considers trend in the time series by calculating an estimate of level of historical sales and an estimate of trend in historical sales. The two estimates are then combined to form the forecast value. Holt's method requires that both alpha (level) and beta (trend) parameters be determined. The empirical evidence favours Holt's two-parameter method over Brown's one parameter method due to the additional flexibility of the two parameters, which allows for individual smoothing of both level and trend. (See Gardner (1985), Gardner and Dannenbring (1980), Makridakis and Hibon (1979), and Makridakis et al., (1982)).
$F_{t+m}=L_{t}+b_{t} m$
where $L_{t}=\alpha Y_{t}+(1-\alpha)\left(L_{t-1}+b_{t-1}\right) \quad$ Level

$$
b_{t}=\beta\left(L_{t}-L_{t-1}\right)+(1-\beta) b_{t-1} \quad \text { Trend }
$$

Holt-Winter's Method (Multiplicative Seasonality). The Holt-Winters multiplicative method is an extension of Holt's linear trend that incorporates seasonality of historical sales. The method uses a third smoothing equation, the gamma parameter, that produces a multiplicative seasonal index, i.e. forecast seasonality increases along with increases in trend (Makridakis et al., 1998).

$$
\begin{equation*}
F_{t+m}=\left(L_{t}+b_{t} m\right) S_{t-s+m} \tag{7}
\end{equation*}
$$

where $L_{t}=\alpha \frac{Y_{t}}{S_{t-s}}+(1-\alpha)\left(L_{t-1}+b_{t-1}\right) \quad$ Level

$$
b_{t}=\beta\left(L_{t}-L_{t-1}\right)+(1-\beta) b_{t-1} \quad \text { Trend }
$$

$$
S_{t}=\gamma \frac{Y_{t}}{L_{t}}+(1-\gamma) S_{t-s}
$$

Holt-Winter's Method (Additive Seasonality). The additive method differs from the multiplicative method in that seasonality remains constant irrespective of changes in historical sales trend (Makridakis et al., 1998).

$$
\begin{equation*}
F_{t+m}=L_{t}+b_{t} m+S_{t-s+m} \tag{8}
\end{equation*}
$$

$$
\begin{array}{rll}
\text { where } & L_{t}=\alpha\left(Y_{t}-S_{t-s}\right)+(1-\alpha)\left(L_{t-1}+b_{t-1}\right) & \text { Level } \\
b_{t}=\beta\left(L_{t}-L_{t-1}\right)+(1-\beta) b_{t-1} & \text { Trend } \\
S_{t}=\gamma\left(Y_{t}-L_{t}\right)+(1-\gamma) S_{t-s} & \text { Seasonal }
\end{array}
$$

### 2.3.3 Pegels' Classification

Pegels (1969) proposed a graphical framework to identify the most appropriate of nine exponential smoothing models. Pegels' framework depicts nine forms of historical data pattern, based on the combination of historical trend and seasonality. The specific combinations are: no trend and no seasonality, no trend and additive seasonality, no trend and multiplicative seasonality, additive trend and no seasonality, additive trend and additive seasonality, additive trend and multiplicative seasonality, multiplicative trend and no seasonality, multiplicative trend and additive seasonality, and finally multiplicative trend and multiplicative seasonality. The value of Pegels' classification is that exhaustive model selection testing can be bypassed and the most appropriate method selected based on the users understanding of the underlying pattern of historical sales, typically
through a visual inspection of the charted times series. The previously described univariate forecast models along with their appropriate time series characteristics are summarised in Table 1.

|  | NON-SEASONAL | SEASONAL |
| :--- | :--- | :--- |
| Simple moving average <br> Weighted Moving Average <br> Single exponential smoothing (SES) <br> Adaptive Response Rate Single Exponential <br> Smoothing (ARRSES) |  |  |
|  | Brown's One Parameter Linear Method <br> Holt's Two-Parameter Linear Method | Holt-Winter's Method (Additive Seasonality) <br> Holt-Winter's Method (Multiplicative Seasonality) |

Table 1. Summary of Forecast Models and Time-Series Characteristics

Gardner (1985) extended Pegels' classification to include damped trends, thereby providing three more exponential smoothing methods.

In addition to visual methods (time series charts), determination of the seasonality and /or trend component of a time series is covered in the next section.

### 2.3.4 Determining Underlying Patterns of a Time Series

Autocorrelation is the correlation between observations of a univariate time series separated by k time units (lags), e.g. months. Autocorrelation helps identify seasonality and cycles in a time series (Makridakis et al., 1998). The formula for autocorrelation is shown below:
$r_{k}=\frac{\sum_{t=k+1}^{n}\left(Y_{t}-\bar{Y}\right)\left(Y_{t-k}-\bar{Y}\right)}{\sum_{t=1}^{n}\left(Y_{t}-\bar{Y}\right)^{2}}$
where $r_{k}=$ autocorrelation at lag $k$.

The plot of the autocorrelation function or ACF is known as a correlogram. An example correlogram is shown in Figure 5.


Figure 5. Example Correlogram
Bars extending beyond the upper or lower limit correspond to statistically significant autocorrelations. In the example shown in Figure 5 a small degree of autocorrelation is apparent for lag 2.

## Detection and Estimation of Trends

Like cycles/seasonality, the detection and estimation of trend plays an important role in the selection of appropriate forecasting models. Brauner (1997) presents the advantages and disadvantages of trend detection and estimation methods in Table 2 below.

| Methods for Detection and Estimation of Trends. |  |  |  |  |
| :--- | :--- | :--- | :--- | :---: |
| Test <br> Procedure | Applicability | Notes | Reference(s) |  |
| Graphical <br> Methods | Visual estimate of <br> trend <br> presence/absence | No quantifiable results | (Makridakis <br> et al., 1998) |  |
| Linear <br> Regression | Provides an <br> estimate of slope, <br> confidence <br> interval, and <br> quantifies <br> goodness of fit | Allows quantified estimate of <br> influence of multiple independent <br> variables <br> Does not handle missing data <br> May be greatly affected by outliers <br> and cyclic data | (Makridakis <br> et al., 1998) |  |
| Box-Jenkins <br> Model | Test for trends in <br> long term, <br> regularly spaced <br> data | Requires large data set <br> Requires constant temporal <br> spacing of data sets | (Box et al., <br> 1994) |  |
| Mann-Kendall | Yes/No test for <br> existence slope | Non-parametric test <br> Allows missing data <br> Not affected by gross data errors <br> and outliers | (Mann, 1945) <br> (Kendall, |  |
| Sen's Method | Estimates value <br> and confidence <br> interval for slope | Allows missing data <br> Makes no assumptions on <br> distribution of data <br> Not affected by gross data errors <br> and outliers | (Sen, 1968) <br> (Theil, 1950) |  |
| Dickey-Fuller <br> test | A unit-root test <br> which determines <br> whether a time <br> series is <br> stationary | The evidence on the use of unit- <br> root tests is considered mixed. | Armstrong <br> (2001) |  |

Table 2. Methods for Detection and Estimation of Trends (Brauner, 1997)

In summary, the review of forecasting models describes the particular models that are suited to specific patterns of sales demand and should be selected and applied based on this principle. Having decided on an appropriate forecasting model there is a need to estimate appropriate smoothing parameters (Fildes \& Beard, 1992), the subject of the next section.

### 2.3.5 Exponential Smoothing Parameter Selection

Exponential smoothing methods require that smoothing parameters be selected (Makridakis et al., 1998), the exception being adaptive methods, e.g. Adaptive Response Rate Single Exponential Smoothing (ARRSES) which automatically adapt the smoothing factor each period through the use of a tracking signal.

The selection of smoothing parameters is commonly performed by fitting the method to historical data to minimise error measures such as mean squared error (MSE) or mean absolute error (MAE). However, Gardner (1985) refers to some studies that have fitted smoothing parameters to minimise inventory cost. Three approaches to fitting were tested by Fildes, Hibon, Makridakis and Meade (1998); (1) arbitrary, (2) optimise once, (3) optimise based on the available history each time a forecast is made (a rolling origin approach). Fildes et al. (1998) study found the best option to be optimising based for each successive horizon, i.e. rolling origin fitting. However, the major MAPE gains were achieved with moving from an arbitrary value to either optimise once or optimise each origin. Rasmussen (2004) recommends the use of a fitting period followed by an evaluation using holdout data to ensure that the model and parameters do provide an acceptable forecast outside of the fitting period. It is worth noting that a close fit to historical data does not necessarily result in an accurate forecast due to potential overfitting (Narayan Pant \& Starbuck, 1990). Over-fitting is due to the model incorporating "random fluctuations" that do not repeat themselves in the holdout or forecast periods (Rasmussen, 2004).

Fitting can be achieved via a simple grid search of smoothing parameter values, e.g. 0-1 in increments of 0.1, or through the use of a non-linear optimiser such as Microsoft ${ }^{\circledR}$ Excel's ${ }^{\circledR}$ Solver (Radovilsky \& Ten Eyck, 2000; Rasmussen, 2004), which utilises the Generalized Reduced Gradient (GRG2) algorithm.

Gardner (1985) suggests that a range of smoothing parameters should be entertained and that "parameters should be estimated from the data". In contrast to Gardner's suggestion, Silver, Pyke and Peterson (1998) observe that an alpha value greater than 0.3 for a constant model may indicate that a trend model is more appropriate.

Finally, Robb and Silver (2002) suggest that the shortening of product lifecycles has increased noise (random error) in time series and as a result establishing SKU level parameters may be less effective than establishing parameters at product group level.

### 2.3.6 Automatic Model Selection

The use of automatic selection of forecasting methods and subsequent generation of forecasts supports the large number of time series often encountered in business situations. In the case of inventory the number of SKUs is frequently in the thousands. Automatic forecasting systems take five general forms (Tashman \& Leach, 1991). A brief description of each follows:

1. Rule-Based Logic (expert system): A type of expert system that is applied to time series extrapolation. Rules based on forecasting expertise and domain knowledge are used to combine alternative extrapolations (Armstrong, 2001).
2. Automatic forecasting program (specification tests): A program that, without user instructions, selects a forecasting method for each times series under study. The method selection rules differ across programs but are frequently based on comparisons of the fitting or the forecasting accuracy of a number of specified methods (Armstrong, 2001).
3. Unified framework: The application of parameter optimisation to a unified framework, such as exponential smoothing models based upon 4 parameters:
level, trend, seasonal, and trend-modification parameters (Tashman \& Leach, 1991).
4. Forecasting contest: Automatic selection based on conducting a contest among a prescribed group of methods (Tashman \& Leach, 1991).
5. All possible specifications: Used for the selection of ARIMA models, all first and second order regular ARMA specifications are fit resulting in likely models for the user to then choose (Tashman \& Leach, 1991).

In addition to the automatic forecasting systems that exclusively incorporate the widely employed moving averages, exponential smoothing, regression, and ARIMA techniques, a heuristic methodology known as Focus Forecasting is widely adopted by practitioners. Focus forecasting was developed by Smith (1978) and is now embodied in a software product known as Demand Solutions. The Demand Solutions product uses 20 equations (Tashman \& Tashman, 1993), as follows in Table 3:

| No. | Method |
| :--- | :--- |
| 1 | Previous quarter plus a growth factor (GF) |
| 2 | Same quarter last year |
| 3 | Same quarter last year plus GF |
| 4 | Mean of the two most recent quarters |
| 5 | Mean of the two most recent quarters plus GF |
| 6 | Previous quarter weighted $2 / 3$ plus the preceding quarter weighted $1 / 3$ |
| 7 | Previous quarter weighted $1 / 2$ |
| 8 | Preceding two quarters each weighted $1 / 4$ |
| 9 | Previous quarter adjusted by the last year's difference |
| 10 | Mean of the corresponding quarters of the past 2 years |
| 11 | Previous quarter adjusted by corresponding differences of the past two years |
| 12 | Mean of the last 4 quarters |
| 13 | Mean of the last 4 quarters plus GF |
| 14 | Mean of the last 8 quarters |
| 15 | Mean of the last 8 quarters "seasonally adjusted" |
| 16 | Mean of the last 4 quarters weighted $2 / 3$ plus the mean of quarters $5-8$ weighted $1 / 3$ |
| 17 | Same as the previous one except "seasonally adjusted" |
| 18 | Simple exponential smoothing, Alpha =.1 |
| 19 | Simple exponential smoothing, Alpha $=.2$ |
| 20 | Simple exponential smoothing, Alpha specified by user or optimized by a grid search |

Table 3. Focus Forecasting Equations

The Demand Solutions software produces twelve one-step ahead forecasts for all 20 models and calculates the mean absolute percentage error (MAPE) resulting in a winner (recommended model).

Although Focus Forecasting has been widely adopted, 850 sites in 48 countries (Tashman and Tashman, 1993), it has not performed well in a number of empirical studies against damped-trend and seasonal exponential smoothing methods (Flores \& Whybark, 1986; Gardner \& Anderson, 1997; Gardner, Anderson-Fletcher, \& Wicks, 2001).

### 2.3.7 Event Adjustment of Statistical Forecasts

The use of promotional activities to stimulate demand is a frequently adopted industry practice (Caniato, Kalchschmidt, Ronchi, Verganti, \& Zotteri, 2005). Promotions are defined by Kotler (1994) as "a diverse collection of incentive tools, mostly short term, designed to stimulate quicker and/or greater purchase of particular products/services by consumers".

The impact of sales promotions can be determined in a variety of ways including techniques such as intervention analysis (Box et al., 1994) through to the judgmental adjustment of baseline statistical forecasts (Adya, Armstrong, Collopy, \& Kennedy, 2000; Goodwin, 2000). In forecasting terms, promotions can be considered "events", also known as interventions. Events are not limited to promotions but could include such changes to the time series as new laws, strikes, or even exceptional supplier delivery problems and as such can have either a positive or a negative effect on sales demand. Goodwin and Fildes (1999) state that "While statistical methods are superior at distilling information from historical data, management judgment can be used to assess the effect of exceptional events like promotions". A great deal of evidence supports the judgmental adjustment of statistical forecasts, if performed in a structured manner to avoid such
issues as bias and over-optimism (Goodwin, 2002; Nikolopoulos, Fildes, Goodwin, \& Lawrence, 2005). The structured judgmental adjustment of forecasts is particularly useful for unsystematic events and if the timing and impact of the event can be identified with reasonable accuracy (Armstrong, 2001).

Fildes, Goodwin, and Lawrence (2003) explore potential design features of forecasting decision support systems which includes the need to incorporate judgmental adjustment of statistical forecasts. AbdEIRehim (2004) presents a method of structuring managerial judgment and forecast combining known as modified progressive event exponential smoothing (MEPEES). MEPEES essentially quantifies an agents (persons) judgmental forecasting accuracy and weights judgmental adjustments of exponential smoothing forecasts accordingly.

In summary, the evidence supports the structured judgmental adjustment of statistical forecasts when events can be identified and quantified accurately through appropriate domain knowledge.

Having decided on an appropriate forecasting model, or combination of models, there is a need to evaluate the models' performance in terms of forecast accuracy (Makridakis \& Hibon, 2000).

### 2.4 Forecast Evaluation

Forecast accuracy measures can be classified as either standard or relative. Standard measures use the same unit of measure as the data in question, e.g. stock-keeping-units, or dollars. The problem with standard measures is that it can be difficult to interpret the magnitude of the error as a forecast containing large values could well produce a standard error that appears large but is, nevertheless, a relatively accurate forecast. The most common standard forecast accuracy measures, as described by Sanders (1997) and Makridakis et al. (1998), are: mean error (ME), mean absolute error (MAE), mean squared error (MSE), and root mean squared error (RMSE).

Relative measures provide forecast accuracy as a percentage, which allows easy interpretation of the relative accuracy of different periods and/or forecasts. The most common relative measures are: mean percentage error (MPE), mean absolute percentage error (MAPE), relative absolute error (RAE), and Theil's U. Other measures have been proposed in the literature (Z. Chen \& Yang, 2004), although practitioner adoption of such measures is very low (Carbone \& Armstrong, 1982). A description and critique of each common forecast accuracy measure, divided into standard and relative, follows.

### 2.4.1 Standard Forecast Accuracy Measures

The mean error (ME) provides an average of all forecast errors $\left(Y_{t}-F_{t}\right)$. The advantage of the mean error is that it allows the practitioner to evaluate any bias present in the forecast, i.e. the tendency for the model to over or under forecast. The disadvantage of mean error is that positive and negative errors could be present but cancelled by each other resulting in little information on overall accuracy (Makridakis et al., 1998, p. 43).

Mean Error:

$$
\begin{equation*}
M E=\frac{1}{n} \sum_{t=1}^{n} e_{t} \tag{10}
\end{equation*}
$$

The mean absolute error (MAE), also known as the mean absolute deviation (MAD), provides an average of all forecast errors, but does not offset positive with negative errors. The mean absolute error therefore overcomes the problems of the mean error. However, as a standard accuracy measure, it too suffers from the drawbacks of using the unit of measure with its inherent difficulty in interpretation. The MAE does however provide the practitioner with a good indication of the magnitude of forecast error (Makridakis et al., 1998, p. 43).

Mean Absolute Error:

$$
\begin{equation*}
M A E=\frac{1}{n} \sum_{t=1}^{n}\left|e_{t}\right| \tag{11}
\end{equation*}
$$

The mean squared error (MSE) provides the average of the squared forecast errors. The advantage of squaring the forecast errors is that the effect of positive and negative errors is cancelled. The main disadvantage with the mean squared error is that it can be difficult to interpret due to the measure potentially appearing large relative to the forecasting units. The inherent difficulty of interpreting mean squared error can be mitigated by calculating the root mean squared error (RMSE). The root mean squared error simply provides the square root of the mean squared forecast errors, which are easier to relate to the units being forecast (Makridakis et al., 1998, p. 43).

Mean Squared Error:
MSE $=\frac{1}{n} \sum_{t=1}^{n} e_{t}^{2}$

Root Mean Squared Error

$$
\begin{equation*}
R M S E=\sqrt{\frac{1}{n} \sum_{t=1}^{n} e_{t}^{2}} \tag{13}
\end{equation*}
$$

### 2.4.2 Relative Forecast Accuracy Measures

Mean percentage error (MPE) provides an average of all forecast errors as a percentage. The advantage of the mean percentage error is that, like mean error, it allows the practitioner to evaluate any bias present in the forecast. A second advantage is that as a relative accuracy measure it is unit-free allowing comparisons across different time series. The disadvantage of mean percentage error is that positive and negative errors could be present but cancelled by each other (Makridakis et al., 1998, p. 44).

Mean Percentage Error:
$M P E=\frac{1}{n} \sum_{t=1}^{n} P E_{t}$
where $P E_{t}=\left(\frac{Y_{t}-F_{t}}{Y_{t}}\right) \times 100$

The mean absolute percentage error (MAPE) shares the advantages of the mean percentage error, but overcomes the canceling of positive and negative values.

Makridakis (1993a) describes the mean absolute percentage error as a "measure that incorporates the best characteristics among the various accuracy criteria" due to its ease of interpretation by decision makers. Being a relative measure it can be used to compare the forecast accuracy of different time series and/or horizons. Two serious limitations of MAPE are that dividing numbers close to zero can cause large error values and division by zero returns infinity (Collopy \& Armstrong, 2000; Hyndman \& Koehler, 2005). However, variants of MAPE such as the unbiased absolute percentage error (UAPE) overcome such limitations (Makridakis, 1993a).

Mean Absolute Percentage Error:
$M A P E=\frac{1}{n} \sum_{t=1}^{n}\left|P E_{t}\right|$
where $P E_{t}=\left(\frac{Y_{t}-F_{t}}{Y_{t}}\right) \times 100$

Unbiased Absolute Percentage Error:
$U A P E=\frac{1}{n} \sum_{t=1}^{n}\left|P E_{t}\right|$
where $P E_{t}=\left|\frac{Y_{t}-F_{t}}{\left(Y_{t}+F_{t}\right) / 2}\right| \times 100$

Mentzer and Moon (2005) propose a variation of MAPE known as the aggregate MAPE which weights the individual product MAPEs by the revenue contribution (units $x$ price) of each product. The aim is to provide an aggregate forecast accuracy measure that is more representative of the financial impact of forecast accuracy.

Aggregate Mean Absolute Percentage Error (Revenue Weighted MAPE):
$R W-M A P E=\sum_{t=1}^{n} \operatorname{MAPE}_{p}\left(D_{p} / D_{T}\right)$
where $M A P E_{P}=$ MAPE for Product p
$D_{p}=$ Dollar demand revenue for Product $p$
$D_{T}=$ Total dollar demand revenue for all products

I have developed an example as follows:

| Product | Revenue (Units $\times$ Price) | MAPE | Weighting |  |
| :---: | :---: | :---: | :---: | :---: |
| A | $100 \times \$ 5=\$ 500.00$ | $12 \%$ | A. $0.12 \times(500 / 3,050)=0.020$ |  |
| B | $50 \times \$ 15=\$ 750.00$ | $9 \%$ | B. $0.09 \times(750 / 3,050)=0.022$ |  |
| C | $10 \times \$ 180=\$ 1,800.00$ | $18 \%$ | C. $0.18 \times(1,800 / 3,050)=0.106$ |  |
|  | Total Revenue | Average MAPE | Aggregate MAPE (A+B+C) |  |
|  | $\$ 3,050.00$ | $\mathbf{1 3 \%}$ |  | $\mathbf{1 4 . 8 \%}$ |

## Table 4. Aggregate Mean Absolute Percentage Error Example

The example shown in Table 4 demonstrates a higher RW-MAPE weighting applied based on product revenue, as opposed to the equally weighted (Average MAPE) method. Mentzer and Moon's (2005) Aggregate MAPE is clearly a more useful forecast accuracy measure for commercial decision making than average MAPE. However, product revenue does not necessarily reflect the importance of a product's financial impact. The reason being is that gross revenue is not as important as gross margin, i.e. a product could command high revenue but conceivably result in a low or even negative margin.

Theil's U-statistic compares the proposed method with a random walk via the root mean squared error (RMSE). Armstrong and Collopy (1992) argue that Theil's U-statistic is difficult for practitioners to interpret and communicate. However, the U-statistic has the advantage of always providing relativity with another forecasting method (random walk).

Theil's U-Statistic:
$U=\sqrt{\frac{\sum_{t=1}^{n-1}\left(F P E_{t+1}-A P E_{t+1}\right)^{2}}{\sum_{t=1}^{n-1}\left(A P E_{t+1}\right)^{2}}}$
where $F P E_{t+1}=\frac{F_{t+1}-Y_{t}}{Y_{t}}$
$A P E_{t+1}=\frac{Y_{t+1}-Y_{t}}{Y_{t}}$
Carbone and Armstrong (1982) found that both academics and practitioners rated forecast accuracy as the most important selection criteria for an error measure, with mean squared error (MSE) receiving the highest rating. Mean absolute percentage error was rated second by academicians, but third behind mean absolute error by practitioners. Following accuracy, ease of interpretation, and then cost/time were the most frequently reported criteria (Carbone \& Armstrong, 1982). Irrespective of the results of Carbone and Armstrong's (1982) study, the view of Makridakis (1993a) that mean absolute percentage error (MAPE) incorporates the "best characteristics" of forecast accuracy measures is that shared by the author. MAPE has also seen widespread adoption in forecasting competitions, subsequent to the publication of the Carbone and Armstrong (1982) study.

A fundamental weakness of the application of the average MAPE to large commercial (sales forecasting) data sets is that no weighting is provided based on the financial contribution of individual products. As stated by Armstrong and Collopy (1992) "relative error measures do not relate closely to the economic benefits associated with the use of a particular forecasting method". This shortcoming can be partially overcome by the use of Mentzer and Moon's (2005) Aggregate MAPE.

### 2.5 Empirical Forecasting Studies

Empirical studies of forecasting methods are common in the literature and a number of peer reviewed journals are dedicated to forecasting, e.g. International Journal of Forecasting, Foresight: The International Journal of Applied Forecasting, and The Journal of Forecasting Methods and Systems. Empirical studies have taken three general forms; simulated time series studies, case studies, and forecasting competitions. Simulated time series studies use data generated from statistical processes, e.g. Gaussian populations with different means, rather than actual sales data. Case studies employ real world data sets as do the major forecasting competitions. Given the applied nature of this research only case studies and forecasting competitions that use actual sales data will be reviewed. In an effort to contain the scope of this review, only frequently referenced and/or seminal works have been included, most notably the M Series of forecasting competitions conducted by Spyros Makridakis et al. from 1982 to 2000.

### 2.5.1 Case Studies and Field Experiments

A large number of case studies involving the assessment of exponential smoothing have been published in the peer-reviewed literature. Armstrong (1984) identifies and reviews 39 studies that assess exponential smoothing and concludes that more sophisticated methods do not provide benefits over simpler, pre-1960, methods. In essence, Armstrong suggests that extrapolative forecasting techniques developed between 1960 and 1984 have not yielded the anticipated gains. Armstrong concludes by stating that practitioners should adopt simpler methods, such as exponential smoothing, as opposed to more complex methods, such as Box-Jenkins. Armstrong also notes that Box-Jenkins is actually a technique for automatically identifying a "suitable" method, rather than a forecasting method itself.

Schnaars (1984) case study, "Situational factors affecting forecast accuracy", indicates that certain products have higher forecasting accuracy than others, namely nondurable goods compared with durable.

Gardner (2006) identifies 66 studies involving exponential smoothing and makes a number of generalisations as follows; The data were frequently seasonal. However, seasonal exponential smoothing methods were rarely used and should have been; many studies only used one exponential smoothing method, and damped trend methods which have performed well in large scale forecasting competitions were not often employed.

### 2.5.2 The $M$-Series

The most widely cited empirical studies are those of Spyros Makridakis, the MSeries forecasting competitions. The M-Series evolved from the work of Makridakis and Hibon (1979) in which the authors conducted a comparative accuracy study of forecasting methods using 111 time series that varied by country, time period, industry, and company. The Makridakis and Hibon (1979) study concluded that simple methods produced accurate forecasts.

An extension to the Makridakis and Hibon study was conducted by Makridakis et al. (1982) known as the M-competition. The M-competition compared the forecasting accuracy of 24 methods using 1001 time series of varying horizons, as follows: (1) Naïve, (2) Simple moving average, (3) Single exponential smoothing, (4) Adaptive response rate exponential smoothing, (5) Holt's two parameter linear exponential smoothing, (6) Brown's one parameter linear exponential smoothing, (7) Brown's one parameter quadratic exponential smoothing, (8) Linear regression trend fitting, (9-16) Deseasonalised variants of methods 1 to 8, (17) Holt-Winter's linear and seasonal exponential smoothing, (18) AEP (automatic) Carbone-Longini, (19) Bayesian forecasting, (20) Combining forecasts (simple average of methods (11), (12), (13), (14),
(17), and (18)), (21) Combining forecasts (weighted average of methods used in 20), (22) Box-Jenkins methodology, (23) Lewandoski's FORSYS system, (24) ARARMA methodology. The M-Competition concluded by confirming two significant hypotheses; statistically sophisticated methods do not perform better than simple models such as exponential smoothing, and the combining of forecasts outperforms the accuracy of the individual methods. The concept of combining forecast methods is taken up later in this discussion.

In 1987 Makridakis et al. (1993) commenced the M2-Competition which consisted of providing forecasting experts with industry data and having them produce a judgmentally-adjusted 15 month ahead forecast. A second 15-month ahead forecast was then submitted following the expert's review of the first round of actual results. Throughout the competition, the experts were free to request additional information from the participating companies that had provided the datasets to enable judgmental input to the forecasts. Forecasts were also produced by purely quantitative approaches, e.g. exponential smoothing and Box-Jenkins.

The M2-Competition concluded that simple methods proved more accurate than complex and judgementally adjusted methods. The competition also concluded that the combining of simple methods increased accuracy.

The final M-competition, the M3 (Makridakis \& Hibon, 2000), compared the relative accuracy of twenty four methods using 3003 time series. The series represented micro, industry, macro, finance, and demographic data over yearly, quarterly, and monthly periods. Each method was provided with historical data for fitting and then used to produce forecasts over various horizons. Ex-post values (actuals) were then used to evaluate each of the methods using the following accuracy measures: symmetric mean absolute percentage error, average ranking, percentage better, median symmetric absolute percentage error and median relative absolute error.

The results confirmed the conclusions of the two earlier M-Competitions and the Makridakis and Hibon (1982) study, being: complex methods (e.g. ARIMA and ARARMA) do not result in greater forecast accuracy than simple methods (exponential smoothing) and the combining of methods, on average, results in more accurate forecasts. Further conclusions were the relative performance of methods varies depending on the accuracy measures employed, and method accuracy varies depending on the forecasting horizon, i.e. methods do not typically perform equally well over all time horizons. The two later conclusions were also supported in the Fildes et al (1998) study that used both telecommunication and M-competition data.

The M-competitions have not been without criticism. One statistical review of the M3 competition results (Hibon \& Stekler, 2003) concluded that irrespective of forecast horizon, some methods consistently performed better or worse than average. Hibon and Stekler's statistical analysis did however allow methods to be ranked overall better than average even though for some horizons they were actually not significantly worse than average. Hibon and Stekler also state that the combination of methods produced mixed results depending on the time-series and therefore the M-competition conclusion that the combining of methods produces more accurate forecasts was not a valid hypothesis. Armstrong (2006) challenges the entire notion of using statistical significance testing in the context of forecast assessment, claiming that effect sizes are more important than statistical significance. Armstrong also points out that the combining of forecasts in the M3 competition resulted in a $4.7 \%$ error reduction over the component forecasts even though Hibon and Stekler (2003) found this finding not to be statistically significant. Armstrong concludes by stating that "practitioners should ignore tests of statistical significance". Clemen's (1989) review of 209 forecast combining studies also lends strong support to the validity of combining forecasts, as does more recent research such as that of Chan, Kingsman and Wong (1999). The weight of evidence, including

Armstrong's (2001) published principles of forecasting (discussed below) supports the combining of forecast methods.

Other criticisms of the M-competitions exist such as that of Newbold (1983), that large scale forecasting competitions do not adequately reflect practice and as such should be discontinued in favour of forecasting case studies. Clemen (2001), although generally supportive of the M -competitions, notes that forecasting is not limited to business and economic applications and that sophisticated methods (ARIMA) have produced valuable insight when applied in the natural sciences.

The most significant finding of the M -Competitions is that simple methods (exponential smoothing) tend to be equally accurate, if not more so, when compared with complex methods (Box-Jenkins, or adaptive parameter methods).

In an effort to summarise the findings of empirical forecasting studies, Principles of Forecasting: A Handbook for Researchers and Practitioners (Armstrong, 2001) was published. This book includes contributions from 40 leading experts and presents 139 forecasting principles covering the setting of objectives, structuring the forecasting problem, identifying information sources, collecting data, preparing data, selecting methods, implementing methods, integrating judgmental and quantitative methods, combining forecasts, evaluating methods, assessing uncertainty, and using forecasts (presentation/learning). All principles are supported by reference to peer reviewed published research.

The book also contains an assessment of forecasting software programs (Tashman \& Hoover, 2001) that rates spreadsheet add-ins, forecasting modules of statistical programs, neural networks, and dedicated business forecasting programs against the relevant forecasting principles (Table 5). Unfortunately, a fifth software category, forecasting engines for demand planning was to be evaluated, but due to an unwillingness of unnamed vendors to submit their products for review, was omitted.

Tashman and Hoover selected 30 principles that were considered relevant to forecasting software and also included 15 software features. The forecasting principles and software features were divided into data preparation, method selection, method implementation, method evaluation, assessment of uncertainty, forecast presentation, and forecasting a product hierarchy.

| Software <br> Category | Category <br> Rating | Individual <br> Rating |
| :--- | :---: | :---: |
| Spreadsheet Add-Ins | $\mathbf{0 . 1 6}$ |  |
| CB Predictor |  | 0.26 |
| Excel DAT |  | 0.03 |
| Insight.xla | $\mathbf{0 . 4 2}$ | 0.18 |
| Forecasting Modules of Statistical Programs |  |  |
| Minitab |  | 0.43 |
| SAS/ ETS |  | 0.77 |
| Soritec for W 95/NT | $\mathbf{0 . 3 8}$ | 0.25 |
| SPSS Trends |  | 0.25 |
| Neural Network Programs |  |  |
| NeuroShell Predictor | $\mathbf{0 . 6 0}$ | 0.35 |
| NeuroShell Professional Time Series |  | 0.54 |
| SPSS Neural Connection |  | 0.74 |
| Dedicated Business-Forecasting Programs |  | 0.70 |
| Autobox |  | 0.67 |
| Forecast Pro |  | 0.48 |
| SmartForecasts |  |  |
| Time Series Expert |  |  |
| tsMetrix |  |  |

Table 5. Assessment of Forecasting Software (Tashman and Hoover ,2001)

The assessment concluded that dedicated business forecasting software had the highest adoption of forecasting principles with an overall $60 \%$ best-practices score. Spreadsheet add-ins were found to have the poorest adoption of principles with a $16 \%$ best practices rating. The demand forecasting functionality of $S A P^{\circledR} E R P$ is reviewed next.

### 2.6 SAP ${ }^{\circledR}$ Demand Forecasting Functionality

SAP ${ }^{\circledR}$, ERP offering contains a logistics module (LO) with Sales and Operations Planning functionality (LO-SOP). Sales and Operations Planning (SOP) is described by SAP ${ }^{\circledR}$ (2006) as "a flexible forecasting and planning tool with which sales, production, and other supply chain targets can be set on the basis of historical, existing, and estimated future data" . The relationship between the SOP tool and other SAP ${ }^{\circledR}$ planning functions are shown in Figure 6.


Figure 6. Information Flow between SOP and other SAP® ERP Applications (Adapted from $S A P^{\circledR}$, 2006)

As can be seen in Figure 6, SOP is concerned with long and medium term planning of independent demand (finished goods, not components) and aggregate capacity. Demand management addresses medium term requirements at stock keeping unit (SKU) level. MPS/MRP addresses short term planning, including dependent demand items. Both production control and production order control are concerned with the execution and control of plans. Once planning in the SOP tool has been performed then planned independent requirements are transferred (either manually or automatically) to the demand management module for subsequent input to materials requirement planning (MRP). The planning process adopted by SAP ${ }^{\circledR}$ is very similar to that espoused by Vollmann, Berry and Whybark (1992) - See Figure 1.

### 2.6.1 SAP ${ }^{\circledR}$ Sales and Operations Planning Module

The SOP tool allows the planning of sales, production/purchasing, inventory, and forecasts, at various levels of aggregation, e.g. stock keeping units, product groups, or organizational levels. Balancing of supply with demand can then be planned in the preferred units of measure, i.e. units or dollars. The chosen organisational levels and units of measure are referred to as planning hierarchies.

SOP data such as period units (days, months, years), characteristics (e.g. company code, plant, materials), and key figures (e.g. sales forecast, actual sales, production/purchasing quantities, and inventory) are contained in information structures.

The SOP tool requires that a planning method is assigned to an information structure. The planning methods available are:

Consistent Planning: With consistent planning all data are stored at SKU level and changes at any level of aggregation are represented at all other levels.

Level-by-level Planning: With level-by-level planning all data are stored at all planning levels, independent of each other.

Delta Planning: With delta planning data are automatically aggregated to higher levels, but changes are not automatically disaggregated. This planning method does not require a planning hierarchy.

The use of planning hierarchies allows forecasting views at different levels of aggregation. Highly aggregate forecasts provide an efficient "view" of the data for senior executives, with lower levels of aggregation and/or SKU level providing the necessary detail for operational managers/users. Fliedner (2001) reviews the literature on hierarchical forecasting and discusses different methods of hierarchical forecasting depending on the user requirements and resulting needs in terms of level(s) of aggregation. Based on a review of the hierarchical forecasting literature one of Fliedner's (2001) conclusions is that proration based on hierarchy member fair share "works relatively well". The fair share approach is the same methodology used in SAP ${ }^{\circledR}$, ${ }^{\text {s }}$ consistent planning hierarchy. Given support from the literature, SAP ${ }^{\circledR 3}$ s adoption of planning hierarchies are an accepted and efficient means of viewing and manipulating forecasts at different levels.

### 2.6.2 The SOP Planning Table

Sales and operations planning is performed in the planning table (Figure 7). The planning table consists of a header that shows the material or product group information, and an input matrix where key figures and time buckets (periods) are displayed. The planning table also provides $\mathrm{SAP}^{\circledR}$ statistics graphic functionality (Figure 8).


Figure 7. SAP ${ }^{\circledR}$ Planning Table (transaction MC94) showing key planning figures


Figure 8. SAP $^{\circledR}$ Statistics Graphic showing forecast versus actual sales in units

The planning table references planning types that are customized views consisting of key figures, e.g. actual sales, forecast sales, production, and inventory. Like planning hierarchies, planning types are based on information structures.

Macros are also available to allow mathematical operations to be performed on key figures in a planning type e.g. forecast error and days supply of stock (stock / daily sales). Although the available macro operators are limited, more complex code can be developed as a functional enhancement in ABAP ${ }^{\text {TM }}$ (Advanced Business Application Programming), $\mathrm{SAP}^{\circledR}$, native programming language.

The SOP functionality also allows resource leveling to be performed to ensure that plans are feasible from a capacity perspective. With resource leveling, key work centers (bottlenecks), or product groups can be set up to show aggregate load and then adjusted if necessary.
$S A P^{\circledR}$, s use of a planning table provides a familiar user interface in that it resembles the commonly used Microsoft ${ }^{\circledR}$ Excel ${ }^{\circledR}$ format. However, user customisation of the planning table and development of macros requires specialist knowledge of the $S A P^{\circledR}$ configuration environment which is not intuitive. The application of $\mathrm{SAP}^{\circledR 3} \mathrm{~S}$ business graphics functionality allows the user to graphically display historical sales values and forecast values. Visual interpretation of the data are a valuable first step in selecting an appropriate forecasting method (Pegels, 1969) and evaluating the historical fit and future accuracy of the selected method. It is notable that the system does not provide basic time series tools such as correlograms for the assessment of cycles and seasonality. Forecast values can also be adjusted, via mouse, through the SAP ${ }^{\circledR}$ business graphics interface.

Unfortunately the default system does not allow for the graphical, or table, presentation of multiple forecasts. Such a feature would simplify comparative method and/or parameter evaluations.

### 2.6.3 SOP Forecasting and Event Management

SAP ${ }^{\circledR}$, ERP offering provides nine time series forecast models and event management. Table 6 shows the nine forecasting methods, along with parameters, and model initialisation requirements.
\(\left.$$
\begin{array}{|l|l|l|l|}\hline \begin{array}{l}\text { Time Series } \\
\text { Pattern }\end{array} & \text { Forecast Model } & \text { Parameters } & \text { Initialisation } \\
\hline \text { Constant } & \begin{array}{l}\text { Constant model } \\
\text { (1st-order exponential } \\
\text { smoothing) } \\
\text { Constant model with } \\
\text { smoothing factor adaptation - } \\
\text { ARRSES } \\
\text { (1st-order exponential } \\
\text { smoothing) } \\
\text { Moving average model }\end{array} & \text { Alpha factor } & \begin{array}{l}\text { All constant } \\
\text { models } \\
\text { require at } \\
\text { least one } \\
\text { period }\end{array} \\
\hline \text { Trend } & \begin{array}{l}\text { Weighted moving average } \\
\text { model }\end{array} & \begin{array}{l}\text { Nrend model } \\
\text { (1st-order exponential } \\
\text { smoothing) } \\
\text { values } \\
\text { Weighting group }\end{array} & \begin{array}{l}\text { Alpha and Beta } \\
\text { factors }\end{array} \\
\hline \begin{array}{l}\text { (2nd-order exponential } \\
\text { smoothing model) } \\
\text { Trend model } \\
\text { (2nd-order exponential } \\
\text { smoothing model with } \\
\text { parameter optimization) }\end{array} & \text { Alpha factor } & \text { Three periods } \\
\hline \begin{array}{l}\text { Seasonal model (Winter's } \\
\text { Method) }\end{array} & \begin{array}{l}\text { Alpha and Gamma } \\
\text { factors } \\
\text { Periods per season }\end{array} & \begin{array}{l}\text { One season, } \\
\text { e.g. 12 } \\
\text { months }\end{array} \\
\hline \text { Seasonal } & \begin{array}{l}\text { Alpha, Beta, and } \\
\text { Gamma factors } \\
\text { Periods per season }\end{array}
$$ <br>
plus three <br>

periods\end{array}\right]\)| Three periods |
| :--- |
| Seasonal <br> Trend |
| Seasonal trend model <br> (1st-order exponential <br> smoothing model) |

Table 6. SAP ${ }^{\circledR}$ Forecast Models and Parameters (Adapted from SAP ${ }^{\circledR}$, 2006)

In addition to the models shown in Table 6, the system allows users to adopt historical sales values as forecast values and also provides automatic forecast selection based on an ex-post forecast with tests for trend and/or seasonality (a tenth forecasting approach, yet based on an automatic selection of the nine models shown in Table 6).

### 2.6.4 SAP ${ }^{\circledR}$ Automatic Model Selection

If the user does not wish to specify a forecast model manually, the system can be instructed to make an automatic selection. With automatic selection, the system analyses the historical data and then selects the most suitable model. The following model categories are possible; constant, trend, seasonal, and seasonal trend. If the system cannot detect any regular pattern in the historical data (trend and/or seasonality), it automatically selects the constant model.
$S A P ® E R P$ provides two procedures for the automatic selection of forecasting methods as detailed below:

Procedure 1: Various statistical tests and test combinations are performed depending on the user's level of knowledge of the time series to be forecast.

Trend test: In the trend test, the system subjects the historical values to a regression analysis and checks to see whether there is a significant trend pattern.

Seasonal test: In the seasonal test, the system clears the historical values of any possible trends and then carries out an autocorrelation test.

Procedure 2: The system calculates the models to be tested using various combinations for alpha, beta, and gamma. The smoothing factors are also varied between 0.1 and 0.5 in intervals of 0.1. The system then chooses the model which displays the lowest mean
absolute deviation (MAD). Procedure 2 is more precise than procedure 1, but takes significantly longer.

The criteria for automatic model selection are based on the calculation of total error, mean absolute deviation (MAD), tracking signal, and Theil's coefficient (U-statistic) over the ex-post period $\left(\mathrm{SAP}^{\circledR}\right.$, 2006). However, it is not possible to view either the tracking signal or Theil's coefficient, nor determine the weighting given to each accuracy measure to arrive at an automatic selection through standard $S A P^{\circledR}$ reports. The lack of visibility of underlying analysis processes restricts the user's ability to assess the quality of the ex-post forecast. A further serious shortcoming of the SOP module is the lack of any error measure evaluation as standard key figures in the planning table. This lack of error measures also limits the ability of the user to easily assess historical forecast accuracy on an ongoing basis.
$S A P^{\circledR}$, adoption of simple methods, i.e. exponential smoothing, is in line with the empirical evidence on the relative accuracy of forecasting methods (Armstrong, 1984; Makridakis et al., 1982; Makridakis et al., 1993; Makridakis \& Hibon, 1979, 2000). However, the system does not allow for the combining of methods which has been shown to improve overall forecast accuracy (Armstrong, 1989; Clemen, 1989; Makridakis \& Hibon, 2000).

SAP ${ }^{\circledR}$ (2006) suggest that if forecast models are being manually selected, i.e. no systems test for trend and/or seasonality, then reference should be made to the following graphic (Figure 9):


Figure 9. SAP ${ }^{\circledR}$ Model Identification for Different Historical Patterns (Adapted from SAP ${ }^{\circledR}$, 2006)

Figure 9 appears to be a simplification of Pegels (1969) classification and as such provides a research-supported method for determining the appropriateness of the available forecasting method.

An extension to basing method selection on historical patterns in the data would be to provide criteria based on the required forecasting horizon. One of the conclusions of the M-Competitions was that the relative accuracy of forecasting methods appears to be dependent on the forecasting horizon in question (Makridakis \& Hibon, 2000).

The SAP system also provides functionality to correct outliers automatically in the historical data on which the forecast is based (Figure 10). The system calculates a tolerance lane for the historical time series by generating an ex-post forecast plus or minus a user defined sigma factor multiplied by the MAE. Historical data that lies outside
the tolerance lane is corrected so that it corresponds to the ex-post forecast value for that point in time.


Figure 10. $\mathrm{SAP}^{\circledR}$ Outlier Correction (Adapted from $\mathrm{SAP}^{\circledR}$, 2006)
"The width of the tolerance lane for outlier control is defined by the sigma factor: the smaller the sigma factor, the greater the control. The default sigma factor is 1 , which means that $90 \%$ of the data remains uncorrected. If you set the sigma factor yourself, set it at between 0.6 and $2^{\prime \prime}\left(S A P^{\circledR}, 2006\right)$.
2.6.5 Event management.

Events provide causal functionality so that the impact of future sales promotions can be applied to the time series forecast, either as cumulative or proportional values (Figure 11 \& Figure 12).


Figure 11. Promotional Event Curve (Adapted from SAP ${ }^{\circledR}$, 2006)


Figure 12. Event Planning Screen (transaction MC64)

The literature suggests that when both the timing and impact of future events is known then forecasts should be adjusted accordingly (Armstrong, 2001), therefore $S A P^{\circledR}{ }^{\infty} \mathrm{S}$ inclusion of event management is in line with the reported research. However, the system does not accommodate regression analysis and/or intervention analysis, or facilitate a structured judgmental approach to determine the historical impact of events, instead it is left to the user to either perform the required analysis outside of $S A P ~^{\circledR}$ or rely on a purely judgmental approach to determining the impact of past and future events.

### 2.6.6 Generation of Forecasts

SOP allows sales forecasts to be run online, from the planning table, and evaluated against the following criteria: Basic value, trend value, mean absolute deviation (MAD), and error total of forecast versus historical. The SOP forecasting functionality also includes forecast profiles (Figure 13) that allow forecast models and parameters to be saved and reused for multiple forecasting runs. Forecasts can also be saved as forecast versions to allow comparisons between different models and/or parameters. The running of forecast profiles and the subsequent saving as forecast versions can also be achieved via mass processing, which allows large jobs to be scheduled and run in the background.


Figure 13. Configuration of Forecast Profiles (transaction MC96)

The ability to generate and save multiple forecasts through forecast profiles and massprocessing jobs is a useful feature. However, as already stated, the system does not accommodate comparisons of multiple forecasts and/or parameters within the same planning table or graphical display.

In summary, the SAP® ERP SOP module utilises hierarchical forecasting concepts that are supported by the literature. However, the system is limited in its graphical presentation of forecasts and that could well inhibit both user acceptance and decision-making. In relation to forecast methods, the system uses accepted and proven forecasting methods (moving average and exponential smoothing) and applies a variation of Pegels' (1969) classification to the selection of methods. This conclusion regarding the suitability of the available forecast methods is of great importance as, irrespective of the somewhat limited user interface, a poor choice of available forecasting methods would render the SOP module ineffective in a business environment. As stated earlier, demand forecasting is a critical input to allocating and mobilising resources to
meet customer demand at least cost. Mistakes in demand forecasting can prove serious, both in terms of customer service (revenue) and inventory levels (cost). The ability to adjust forecasts based on foreseeable events, e.g. promotions, is also an important feature, which is supported by the research literature (Armstrong, 2001).

Table 5 provides a review and summary of the $S A P^{\circledR} E R P$ functionality using the Tashman and Hoover criteria (2001), details of which were covered in the earlier literature review. The overall rating for SAP $^{\circledR}{ }^{\circledR}$ S ERP is 0.20 (i.e. the software achieved $20 \%$ of the possible maximum against best practice forecasting principles) this compares with an average of 0.60 for dedicated business-forecasting programs. Although 0.60 was the average for dedicated business-forecasting programs, the SAS ETS (Econometrics and Time Series) offering (classified as a forecasting module of a statistical package) scored highest with 0.77 in the Tashman and Hoover review.

| SAP ${ }^{\circledR}$ ERP Forecasting Principles Review | SAP ${ }^{\text {® }}$ ERP Rating |
| :---: | :---: |
| Data Preparation | 0.20 |
| Examining whether series is forecastable | O |
| Cleaning the data (errors, missing values, outliers) | +, outlier correction |
| Adjusting for seasonality and trading days | O |
| Transforming the data | O |
| Plotting cleansed, transformed and deseasonalised data | +, limited plotting with SAP business graphics |
| Method Selection | 0.17 |
| Matching forecasting method to the data | + , Pegels based guidance in documentation only |
| Selecting methods based on comparison of track records | O |
| Discouraging needless complexity | O |
| Considering out-of-sample performance in method selection | +, basic MAE |
| Combining forecasts - formal procedure | O |
| Including dynamic terms in causal model | 0 |
| Method Implementation | 0.21 |
| Selecting fit vs. test period | O |
| Choosing best-fit criterion | O |
| Adjusting for expected events | +, limited event management |
| Weighting the most relevant data more heavily | O |
| Allowing user to integrate judgment | +, limited event management |
| Overriding statistical forecasts | + , manual input and/or override of forecasts |
| Integrating forecasts of explanatory variables into causal model | O |
| Method Evaluation | 0.1 |
| Testing validity of model assumptions | O |
| Distinguishing in-sample from out-of-sample forecast accuracy | O |
| Providing multiple measures of accuracy | + , not all visible to user (MAE visible, but not Theil's U statistic) |


| Providing error measures that adjust for scale and outliers | O |
| :---: | :---: |
| Measuring errors by forecast horizon | 0 |
| Assessment of Uncertainty | 0 |
| Providing objective prediction intervals | 0 |
| Developing empirical prediction intervals from forecast errors | 0 |
| Specifying sources of uncertainty | 0 |
| Combining prediction intervals from alternative methods | 0 |
| Forecast Presentation | 0.17 |
| Transparency in theoretical assumptions made | 0 |
| Explaining methodology | 0 |
| Illustrating how forecasts were generated | 0 |
| Graphically presenting point and interval forecasts | +, point forecasts only |
| Providing forecasts in exportable formats | +, Microsoft Excel download |
| Forecast Report | 0 |
| Forecasting a Product Hierarchy | 0.43 |
| Automatic Method Selection | ++ , based on tests for seasonality, trend, and resulting multiple measures of ex-post accuracy |
| Multiple procedures for reconciliation | ++ , range of hierarchical reconciliation |
| Adjustments for special events | +, limited event management |
| Procedures for intermittent demands | 0 |
| Identify problem forecasts for manual review | O |
| Automatic reconciliation of judgmental overrides | + range of hierarchical reconciliation |
| Facilitate comparison of forecasting and reconciling approaches | 0 |
| Ratings Legend: - Undermined, o Ignored, + Partially implemented, ++ Effectively Implemented | Overall Weighted Average for All Principles $=0.20$ |

Table 7. SAP ERP Forecasting Principles Review

In summary, SAP $^{\circledR}$, ERP system fails in many areas of decision support including the provision of correlograms, multiple forecast comparisons, a structured event management process, and visible historical error measures which could account for the high level of ERP users (approximately 45\%, in 2001) who perform demand forecasting in stand alone applications (Vega, 2001).

### 2.7 SAP ${ }^{\circledR}$ Demand Forecasting Research

Limited published research in the area of the $S A P^{\circledR}$ demand forecasting has been reported. Bahl and Boykin (2000) review the manufacturing resource planning functionality of $S A P^{\circledR}$ and conclude that $S^{\circledR}{ }^{\circledR}$ ERP contains all the features and options to configure a "sophisticated implementation of MRPII" and that the software is built upon best practice. Although the article explains the primary SAP ${ }^{\circledR}$ MRPII processes and configuration, it is an elementary description that does not describe or critique $\mathrm{SAP}^{\circledR}{ }^{\circledR} \mathrm{s}$ demand forecasting functionality.

Portougal (2005) describes some issues surrounding the implementation of SAP ${ }^{\circledR}$ for production planning at EA Cakes Limited. However, in the EA implementation the sales forecast is derived as follows: "sales staff compare actual sales with long-term forecasts and using judgment make necessary adjustments". Portougal (2005) does identify the manual nature of the EA Cakes forecasting approach as a problem, but does not provide any indication of alternatives.

Catt and Barbour (2005) describe the forecasting functionality of the $\mathrm{SAP}^{\circledR}$ offering, along with the underlying forecasting methods. They survey the literature in an attempt to identify which model might best meet the needs of the market concluding that $S A P^{\circledR,} \mathrm{S}$ available forecast models are fit for purpose.

SAP ${ }^{\circledR}$ also offers an advanced planning and scheduling (APS) application as part of the company's SCM (Supply Chain Management) suite. The SAP ${ }^{\circledR}$ application is known as the Advanced Planner and Optimiser (APO) and contains demand forecasting functionality that is superior to that of the SAP® ERP offering. Improvements over the SAP® ERP forecasting functionality include a more flexible (easily user customisable) planning table, the addition of Croston's (1972) method for forecasting products with intermittent demand, trend dampening, inclusion of causal forecasting in the form of multiple linear regression, composite forecasting that allows various weightings to
combine different forecasts, life cycle planning, and collaborative demand planning based on CPFR principles. A full description of APO functionality is presented in Bansal (2003). Seeger (2006) reviews SAP's APO offering against a variation of the Tashman and Hoover software principles criteria (2001) and concludes a rating of 0.44 (cw SAP ERP of 0.20). Seeger's rating still compares poorly with the average Tashman and Hoover rating of 0.60 for dedicated business-forecasting programs.

A further SAP ${ }^{\circledR}$ offering, SAP ${ }^{\circledR}$ Strategic Enterprise Management (SEM) contains a business planning and simulation component (SEM-BPS) incorporating linear regression and trend dampening in addition to the basic $S A P ®$ ERP functionality (See Table 6. SAP® Forecast Models and Parameters (Adapted from $\operatorname{SAP} ®$, 2006).

Chandra, Ulgen, Tsui and Kampfner (2000) conducted research on the development of non-linear demand forecasting algorithms for the SAP ${ }^{\circledR}$ APO environment. However, like the Bansal paper, this research did not address the forecasting functionality of the widely adopted $S A P^{\circledR} E R P$ system.

### 2.8 Conclusion of Literature Review

The review of the literature has identified the role of demand forecasting in the context of information and communication technology (ICT) enabled supply chain management (SCM). Further, it has concluded that SAP ${ }^{\circledR}$, ERP demand forecasting functionality appears to be adequately grounded in previous theoretical and empirical research. This statement is made in light of $S A P^{\circledR}$, use of exponential smoothing methods and the application of a variant of Pegels' classification for the selection of methods. The SAP® ERP offering was found to have some serious limitations including; lack of tools for time series feature identification (correlograms), no ability to perform forecast comparisons, no structured (qualitative or quantitative) event management process, and no standard reporting of historical error measures including the use of commercially oriented forecast error assessment.

The paucity of literature relating to $\mathrm{SAP}^{\circledR \text {, }}$ demand forecasting functionality appears to present a significant gap, particularly given the large number of users of this dominant ERP package. The gap raises a number of important questions regarding the professional application of demand forecasting with SAP ${ }^{\circledR 3}$ s ERP system, namely;

1. Do the $S A P^{\circledR}$ default forecast model smoothing parameters provide the "Best-fit" forecast for the company?
2. Does the combination of event management (causal factors) with time series techniques provide a "Better Fit" than the time series techniques alone?
3. Which of the nine available SAP ${ }^{\circledR}$ time series (univariate) forecasting models provides the "Best-fit" forecast for the company?
4. Are the forecast error measures utilised by $S A P ~^{\circledR}$ representative of the commercial impact of the forecasts?

The next Chapter will present the methodology used to answer the research questions.

Enterprise resource planning (ERP) systems such as SAP are widely adopted and typically contain sales forecasting functionality. The sales forecasting accuracy of ERP systems can have a critical impact on business profitability and empirical research into the effectiveness of ERP offerings should be considered a valuable endeavour.

The review of supply chain management and sales forecasting literature revealed no specific research on demand forecasting using any of SAP $^{\circledR}$, enterprise resource planning offerings, apart from the work of Catt and Barbour (2005). Given the current number of $S A P^{\circledR}$ users, combined with the significant growth of $S A P^{\circledR}$, a valuable opportunity exists to evaluate such systems in this important context. A further gap revealed the need to evaluate forecast model performance in a commercial context, i.e. costs relating to forecast error. However, commonly adopted measures of forecast accuracy, such as mean absolute error (MAE) and mean absolute percentage error (MAPE), do not provide explicit costs associated with forecast errors.

The following sections address the need for commercial forecast evaluation.

In an effort to improve on Mentzer and Moon's (2005) method I propose an extension based on margin weighted contribution as follows:

### 3.1 Margin Weighted Mean Absolute Percentage Error

$M W-M A P E=\sum_{t=1}^{n} M A P E_{p}\left(M_{p} / G M_{T}\right)$
where MAPE $_{p}=$ MAPE for Product p

$$
\begin{aligned}
& M_{p}=\text { Margin contribution for Product } \mathrm{p} \\
& G M_{T}=\text { Gross Margin (margin for all products) }
\end{aligned}
$$

An example follows:

| Product | Revenue (Units $\times$ Price) | Margin Contribution <br> $($ Revenue less Cost) | MAPE | Revenue Weighting | Margin Weighting |
| :---: | :---: | :---: | :---: | :---: | :---: |
| A | $100 \times \$ 5=\$ 500.00$ | $100 \times(\$ 5.00-\$ 2.50)=\$ 250.00$ | $12.00 \%$ | A. $0.12 \times(500 / 3,050)=0.020$ | A. $0.12 \times(250 / 1165)=0.026$ |
| B | $50 \times \$ 15=\$ 750.00$ | $50 \times(\$ 15.00-\$ 7.50)=\$ 375.00$ | $9.00 \%$ | B. $0.09 \times(750 / 3,050)=0.022$ | B. |
| C | $10 \times \$ 180=\$ 1,800.00$ | $10 \times(\$ 180.00-\$ 126.00)=\$ 540.00$ | $18.00 \%$ | C. $0.18 \times(1,800 / 3,050)=0.106$ | C. |
|  | Total Revenue | Gross Margin | Average MAPE | Revenue Weighted MAPE $(\mathrm{A}+\mathrm{B}+\mathrm{C})$ | Margin Weighted MAPE $(\mathrm{A}+\mathrm{B}+\mathrm{C})$ |
|  | $\$ 3,050.00$ | $\$ 1,165.00$ | $\mathbf{1 3 . 0 0 \%}$ | $\mathbf{1 4 . 8 0 \%})$ | $\mathbf{1 3 . 8 0 \%}$ |
|  |  |  |  |  |  |

Table 8. Margin Weighted MAPE Example

The example shown in Table 8 demonstrates the higher MAPE weighting applied based on product margin. A comparison of the three measures reveals that the average MAPE measure (13.00\%) has overstated the accuracy of the forecast by not considering financial impact. The Aggregate MAPE (14.80\%) has applied a disproportionately heavy weighting to Product C based on revenue thereby understating the financial impact and the Margin Weighted MAPE (13.80\%) has provided the most representative weighting based on product margin contribution. The differences in the relative percentages could of course differ based on product revenue and cost. However, the principle of weighting the MAPE based on margin contribution is a valuable step forward for commercial decision-making as margin weighting is more indicative of product profitability than revenue weighting.

### 3.2 Inventory Cost

Inventory costs are the costs associated with procuring or producing inventory and the cost of carrying inventory. The costs of procuring/producing inventory are known as unit variable costs (denoted by the symbol $v$ ) and include the price of the item plus freight for purchased items or the production costs for produced items and any other costs associated with making the item available for sale (Silver et al., 1998). The costs incurred by carrying inventory are less clear than those of procuring/producing it. They include storage, insurance, investment, obsolescence, damage, deterioration, and the opportunity cost of the funds tied up in inventory. Silver et al. (1998, p. 45) use the following formula for inventory carrying cost:

Inventory Carrying Cost:

Carrying costs per year $=\bar{I} v r$
Where $\bar{I}=$ average inventory in units
$v=$ unit variable cost
$r=$ carrying charge, the cost in dollars of carrying one dollar of inventory for one month.

### 3.3 Safety Stock Calculation

The calculation of safety stock takes two general forms, as described by Zinn and Marmorstein (1990); the first is calculated based on the variance of demand (the demand system), the second based on the variance of demand forecast errors (the forecast system). Zinn and Marmorstein's simulation of the two methods demonstrated a mean percentage reduction of $14.6 \%$ using the forecast system over the demand system for the same level of service. On the basis of the Zinn and Marmorstein research I will focus on the calculation of safety stock using the forecast system as follows:

Safety Stock Calculation:

$$
\begin{equation*}
S S=k \sigma \sqrt{R+L} \tag{21}
\end{equation*}
$$

where $S S=$ safety stock in units
$k=$ safety factor from a table of normal distribution probabilities (Table 9)
$\sigma \sqrt{R+L}=$ standard deviation of forecast errors in units over the critical protection period (review period $(R)$ and the replenishment lead time (L)), in months.

The safety stock calculation assumes independent demand, i.e. no autocorrelation.

| $k$ | Service <br> Level ( $\mathbf{P}_{\mathbf{1}}$ ) | $k$ | Service <br> Level ( $\mathbf{P}_{\mathbf{1}}$ ) |
| :---: | :---: | :---: | :---: |
| 4.0 | $99.997 \%$ | 1.9 | $97.128 \%$ |
| 3.9 | $99.995 \%$ | 1.8 | $96.407 \%$ |
| 3.8 | $99.993 \%$ | 1.7 | $95.544 \%$ |
| 3.7 | $99.989 \%$ | 1.6 | $94.520 \%$ |
| 3.6 | $99.984 \%$ | 1.5 | $93.319 \%$ |
| 3.5 | $99.977 \%$ | 1.4 | $91.924 \%$ |
| 3.4 | $99.966 \%$ | 1.3 | $90.320 \%$ |
| 3.3 | $99.952 \%$ | 1.2 | $88.493 \%$ |
| 3.2 | $99.931 \%$ | 1.1 | $86.434 \%$ |
| 3.1 | $99.903 \%$ | 1.0 | $84.135 \%$ |
| 3.0 | $99.865 \%$ | 0.9 | $81.594 \%$ |
| 2.9 | $99.813 \%$ | 0.8 | $78.815 \%$ |


| 2.8 | $99.744 \%$ | 0.7 | $75.804 \%$ |
| :--- | :--- | :--- | :--- |
| 2.7 | $99.653 \%$ | 0.6 | $72.575 \%$ |
| 2.6 | $99.534 \%$ | 0.5 | $69.147 \%$ |
| 2.5 | $99.379 \%$ | 0.4 | $65.543 \%$ |
| 2.4 | $99.180 \%$ | 0.3 | $61.791 \%$ |
| 2.3 | $98.928 \%$ | 0.2 | $57.926 \%$ |
| 2.2 | $98.610 \%$ | 0.1 | $53.983 \%$ |
| 2.1 | $98.214 \%$ | 0.0 | $50.000 \%$ |
| 2.0 | $97.725 \%$ |  |  |

Table 9. Normal Distribution $\mathrm{N}(0,1)$

The standard deviation of forecast errors is calculated as follows:
$\sigma=\sqrt{\pi / 2} \times$ MAE or an approximation $\sigma \approx 1.25 \times$ MAE
where MAE is the mean absolute forecast error

Having calculated the required safety stock to meet a given service level we can then determine the costs associated with the forecast error. Determining the costs associated with competing forecasting models makes the commercial value of each model explicit. To achieve this aim I have modified Silver, Pyke and Peterson's (1998, p. 263) formula for a specified fractional charge ( $B_{2}$ ) as follows:

### 3.4 Cost of Forecast Error

$C F E=\left(S S v r+\frac{B_{5} M_{p} \sigma \sqrt{R+L} G_{u}(k)}{R}\right) P$
where $C F E=$ annual cost of forecast error in dollars
$S S=$ safety stock in units
$v=$ unit cost, in \$/unit
$r=$ inventory carrying charge, in $\$ / \$ /$ month (cost in dollars of carrying one dollar of inventory for one month).
$B_{5}=$ fractional charge of margin per unit short
$M_{p}=$ product margin in dollars
$G_{u}(k)=$ standard unit normal loss function (unit normal distribution)
$P=$ period multiplier to convert from months to year

The cost of forecast error formula considers both costs of inventory (SSvr) and the costs associated with lost sales $\left(\frac{B_{5} M_{p} \sigma \sqrt{R+L} G_{u}(k)}{R}\right)$. The formula provides a comprehensive approach to evaluating forecast error costs and the trade offs between desired service level and inventory holding. It is important to note that the formula utilises product margin to ascertain the cost of lost sales, as opposed to Silver, Pyke and Peterson's use of unit cost. My rationale is that lost margin better reflects the true costs of poor service.

An example of the Cost of Forecast Error (CFE) follows using a constant model ( $1^{\text {st }}$ order exponential smoothing), alpha 0.2 applied to a product with a MAE of 4.31 units per month.

Monthly Mean Absolute Error (MAE) $=4.31$ units/month
Unit cost in \$/unit = \$31.33
Product margin in \$/unit = \$125.79
Leadtime + review period $=4$ months
Inventory holding cost, $r=2.5 \%$ of unit cost per month
Cost of lost sales in \$/unit = 50\% of unit margin
Service level factor, $k=1.645$ ( $P_{1}=95 \%$ )
Period multiplier to convert from monthly to annual value $=12$

Step 1: Estimate safety stock in units (service level factor $\times 1.25 \times$ MAE $\times$ the square root of the leadtime + review period)

$$
\begin{equation*}
\text { Safety Stock }(S S)=1.645 \times 1.25 \times 4.31 \times \sqrt{4}=17.72 \tag{24}
\end{equation*}
$$

Step 2: Multiply safety stock by monthly inventory carrying charge (safety stock x unit cost x monthly inventory holding cost)

$$
\begin{equation*}
17.72 \times \$ 31.33 \times 2.5 \%=\$ 13.88 \tag{25}
\end{equation*}
$$

Step 3: Estimate lost sales in units (standard deviation of forecast errors over review period and leadtime $x$ standard unit normal loss function of the service level). NB. Excel ${ }^{\circledR}$ notation shown.

$$
\begin{align*}
& 1.25 \times 4.31 \times \operatorname{SQRT}(4) \times(1 / \operatorname{SQRT}(2 * \mathrm{PI}()) \star \operatorname{EXP}(-\operatorname{POWER}(1.645,2) / 2)) \\
& -(1.645 *(1-\operatorname{NORMSDIST}(1.645))=\mathbf{0 . 2 2 4 6} \tag{26}
\end{align*}
$$

Note: Normsdist is the Excel ${ }^{\circledR}$ spreadsheet function for the following equation:

$$
f(k)=\frac{1}{\sqrt{2 \pi}} e^{-\frac{k^{2}}{2}}
$$

Step 4: Estimate lost sales margin due to unavailable product (percentage charge per unit short x product margin in dollars x standard unit normal loss function)

$$
\begin{equation*}
(50 \% \times \$ 125.79) \times 0.2246=\$ 14.13 \text { per month } \tag{27}
\end{equation*}
$$

Step 5: Add safety stock holding cost and lost sales margin and multiply by 12 to annualise to arrive at the cost of forecast error (CFE).

$$
\begin{equation*}
(\$ 13.88+\$ 14.13) \times 12=\$ 336.12 \text { per annum } \tag{28}
\end{equation*}
$$

In the above the annual CFE equals $1.23 \%$ of annual revenue for the sample SKU (\$336.12/\$27,339.00).

A further example and explanation of the Cost of Forecast Error (Catt, 2007) is presented in appendix F: Assessing the Cost of Forecast Error, Foresight: The International Journal of Applied Forecasting - Summer 2007, Issue 7.

The MW-MAPE and CFE help address the important need to evaluate forecast model performance in a commercial context. The next section will detail the research questions and hypotheses.

### 3.5 Research Questions and Hypotheses

Enterprise resource planning systems are complex integrated tools, with SAP ${ }^{\circledR}$ ERP requiring the configuration of 10,000+ data tables in a full system implementation and containing in excess of 16,000 standard transactions. Evaluating such tools in their entirety would be a substantial task requiring a team of researchers. However, as a central indicator of the likely outcome of the application of the $\mathrm{SAP}^{\circledR}$ logistics module to the company, the available demand forecasting models are evaluated. The specific research aim is to evaluate and identify the $\mathrm{SAP}^{\circledR}$ forecasting model / technique that provides the "best-fit" for the company's product portfolio. In order to achieve the specific research aim the following research questions and hypotheses have been developed:

1. Do the $S A P^{\circledR}$ default forecast model smoothing parameters provide the "Best-fit" forecast for the company?
$\mathrm{H} 1_{0}$ : There is no statistically significant difference between the $\mathrm{SAP}^{\circledR}$ default smoothing parameters and fitted smoothing parameters, for any of the applicable forecasting models, as measured by the means of Mean Absolute Deviation (MAE).
$H 1_{A}$ : Fitted smoothing parameters produce a statistically significant better forecast than the $\mathrm{SAP}^{\circledR}$ default parameters based on Mean Absolute Deviation (MAE), for any of the applicable forecasting models.
$\mathrm{H} 2_{0}$ : There is no statistically significant difference between the $\mathrm{SAP}^{\circledR}$ default smoothing parameters and fitted smoothing parameters, for any of the applicable forecasting models, as measured by the means of Cost of Forecast Error (CFE).
$\mathrm{H} 2_{\mathrm{A}}$ : Fitted smoothing parameters produce a statistically significant better forecast than the SAP ${ }^{\circledR}$ default parameters based on the Cost of Forecast Error
(CFE), for any of the applicable forecasting models.
2. Does the combination of event management (causal factors) with time series techniques provide a "Better Fit" than the time series techniques alone?
$\mathrm{H} 1_{0}$ : There is no statistically significant difference between event management combined with time series techniques and time series techniques alone, for any of the applicable forecasting models, as measured by the means of Mean Absolute Deviation (MAE).
$\mathrm{H} 1_{\mathrm{A}}$ : The combination of event management with time series techniques produce a statistically significant better forecast based on Mean Absolute Deviation (MAE), for any of the applicable forecasting models.
$\mathrm{H} 2_{0}$ : There is no statistically significant difference between event management combined with time series techniques and time series techniques alone, for any of the applicable forecasting models, as measured by the means of Cost of Forecast Error (CFE).
$\mathrm{H} 2_{A}$ : The combination of event management with time series techniques produce a statistically significant better forecast based on the Cost of Forecast Error (CFE), for any of the applicable forecasting models.

The causal factors in question 2 take the form of promotions. The adjustment of forecasts for expected future events is considered a strong research need in forecasting (Armstrong, 2001).
3. Which of the ten available SAP $^{\circledR}$ forecasting models provides the "Best-fit" forecast for the company?
$\mathrm{H}_{1}$ : There is no statistically significant difference between any of the ten available models, as measured by the means of Mean Absolute Deviation (MAE). $\mathrm{H}_{\mathrm{A}}$ : There is a statistically significant difference between the ten available models, based on Mean Absolute Deviation (MAE).
$\mathrm{H}_{2}$ : There is no statistically significant difference between any of the ten available models, as measured by the means of Cost of Forecast Error (CFE).
$\mathrm{H} 2_{\mathrm{A}}$ : There is a statistically significant deference between the ten available models, based on the Cost of Forecast Error (CFE).
4. Are the forecast error measures utilised by $S A P^{\circledR}$ representative of the commercial impact of the forecasts?
$\mathrm{H}_{1}$ : SAP ${ }^{\circledR}$, s error measures adequately reflect the commercial impact of forecast error.
$\mathrm{H}_{\mathrm{A}}$ : $\mathrm{SAP}^{\circledR}$, error measures do not adequately reflect the commercial impact of forecast error.

### 3.6 Research Method

Primary domains of forecasting research include model development and testing, model performance and application, and model implementation and management (Moon, Mentzer, \& Smith, 2003). Model development and testing is primarily concerned with the development and testing of forecasting algorithms/techniques. Model performance and application is usually situational in nature and attempts to identify the situations where certain models are more appropriate. Model implementation and management is concerned with organisational practices and processes that contribute to forecast effectiveness. The proposed research falls within the model performance and application domain (Moon et al., 2003), with the focus of the research being the effectiveness of the SAP ${ }^{\circledR}$ ERP tool in applying sales demand forecasting. Forecasting research areas and associated questions and methods are shown in Figure 14 (Forecasting Research Methods). Each of these research areas and associated questions employ techniques suited to the particular question being researched. However, each technique should be considered in light of its respective strengths and weaknesses.

| Research Areas | Questions | Method | Method Strengths and Weaknesses |
| :---: | :---: | :---: | :---: |
| Model Development and Testing | Is this new model better than earlier models? | Laboratory Experiment | Greater internal validity, but lower external validity - better controlled, but less generalisable (Neuman, 2000) |
| Model <br> Performance and Application | Is this model, or combination of models, "considered" superior in this particular situation? | Field <br> Experiment <br> Case <br> Study <br> Survey <br> Simulation | Lower internal validity, but higher external validity - replication can be difficult (Neuman, 2000) <br> Captures local situation in great detail, but can be difficult to generalise (Cockburn, 2003) <br> Opportunity to study many variables, but limited in ability to determine causes (Cockburn, 2003) <br> Greater internal validity, but lower external validity - better controlled, but less generalisable (Cockburn, 2003) |
| Model <br> Implementation <br> and <br> Management | Which organisational forecasting practices produce superior results? | Survey <br> Case <br> Study | Opportunity to study many variables, but limited in ability to determine causes (Cockburn, 2003) <br> Captures local situation in great detail, but can be difficult to generalise (Cockburn, 2003) |
| Internal Validity - Validity determined by whether an experimental treatment was the sole cause of changes in a dependent variable. External Validity - The ability of an experiment to generalise the results to the external environment (Zikmund, 1997). |  |  |  |

Figure 14. Forecasting Research Methods

The research is in the context of a New Zealand medium-sized enterprise (the company) operating an enterprise resource planning system, i.e. the research takes the form of a single case study. Yin (2003) states "In general, case studies are the preferred strategy when "how" or "why" questions are being posed, when the investigator has little control
over events, and when the focus is on a contemporary as opposed to historical phenomena". It is notable that the "company" was the first small to medium sized enterprise (SME) in the New Zealand market with a turnover of less than NZ\$100 million to implement $S A P^{\circledR}$, s enterprise resource planning system (SAP ${ }^{\circledR}$ ERP). Given the significant marketing push by SAP to capture the SME ERP market (SAP, 2007); a valuable opportunity existed to evaluate such systems in this important new context.

Apart from the contextual importance of the "company" as an early SAP ERP small-medium enterprise site, the adoption of a case study approach was also motivated by the case study providing access to data such as product costs and margins, as well as sales data. The access to a rich data set, encompassing product level financial data, not just sales data, was a critical requirement in evaluating the cost of forecast error.

In summary, the proposed research method is a positivist-quantitative case study, based on Neuman's (2000) criteria, described next. The research will test hypotheses regarding forecasting techniques; measures have been systematically developed prior to the study (error measures); data are numerical (historical sales, forecasts, and error measures); procedures are standard and replication is facilitated; analysis will use statistics, charts, and tables relating to the hypothesis.

Having explained the case study methodology, the next Chapter will explain the approach to data collection.

The data collection section describes the forecasting models applied, the data sampling approach, and the method used to adjust the baseline forecasts with event management.

Seven of the nine available forecast models in $S A P ~^{\circledR}$ were each run using both default $\mathrm{SAP}^{\circledR}$ smoothing parameters and fitted smoothing parameters (14 model combinations). The fitted models applied the same fitted smoothing value to all SKUs in the respective data sets, not individually fitted parameters for each SKU. The two ARRSES variants (Constant model with smoothing factor adaptation (1st-order exponential smoothing) and the trend model (2nd-order exponential smoothing model with parameter optimization) were also run, but due to the automatic nature of these models did not allow a fitted comparison to be made. An individual SKU best-fit model (model 17) and $\mathrm{SAP}^{\circledR,}$ s automatic model selection method (model 18) were also run along with a Naïve1 forecast (model 19) as a benchmark for comparative purposes. All 19 models/combinations were also event management adjusted bringing the total to 38 , as detailed in Table 10.

| Profile | Forecast Model | Parameters |
| :---: | :--- | :--- |
| 1 | Constant model <br> (1st-order exponential smoothing) | Alpha 0.2 (SAP ${ }^{\circledR}$ default) |
| 2 | Constant model - Fitted <br> (1st-order exponential smoothing) | Fitted Alpha |
| 3 | Constant model with smoothing factor <br> adaptation (1st-order exponential <br> smoothing) | N/A - Automatic |
| 4 | Moving average model | 24 historical values (SAP ${ }^{\circledR}$ <br> default) |


| 5 | Moving average model - Fitted | Fitted number of historical values |
| :---: | :---: | :---: |
| 6 | Weighted moving average model | Weighting: 0.4, 0.3, 0.2, 0.1 (SAP ${ }^{\circledR}$ default) |
| 7 | Weighted moving average model - Fitted | Fitted weighting |
| 8 | Trend model (1st-order exponential smoothing) | Alpha 0.2, Beta 0.1 (SAP ${ }^{\circledR}$ defaults) |
| 9 | Trend model - Fitted (1st-order exponential smoothing) | Fitted Alpha and Beta |
| 10 | Trend model (2nd-order exponential smoothing model) | Alpha 0.2 (SAP ${ }^{\circledR}$ default) |
| 11 | Trend model - Fitted (2nd-order exponential smoothing model) | Fitted Alpha |
| 12 | Trend model (2nd-order exponential smoothing model with parameter optimization) | N/A -Automatic |
| 13 | Seasonal model (Winters' method) | Alpha 0.2, Gamma 0.3 (SAP ${ }^{\circledR}$ defaults) 12 periods per season |
| 14 | Seasonal model (Winters' method) Fitted | Fitted Alpha and Gamma 12 periods per season |
| 15 16 | Seasonal trend model (1st-order exponential smoothing model) <br> Seasonal trend model - Fitted (1st-order exponential smoothing model) | Alpha 0.2, Beta 0.1, Gamma 0.3 (SAP ${ }^{\circledR}$ defaults) <br> 12 periods per season <br> Fitted Alpha, Beta, and Gamma 12 periods per season |
| 17 | Individual SKU (combination of best-fit methods) | Best Historical Fit |
| 18 | SAP ${ }^{\circledR}$ Automatic Model Selection (with automatic smoothing factor adjustment to minimise mean absolute deviation) | N/A - Automatic |
| 19 | Naïve1 | N/A |
| 20-38 | Profiles 1 to 19 adjusted for planned promotions (Event management). | Event Management: <br> Percentage adjustment determined by average historical sales increase during promotional periods over sales during non-promotional periods. |

Table 10. Forecast Models and Smoothing Parameters

The Individual SKU (model 17, combination of best-fit methods) was derived from choosing the forecasting model, at SKU level, with the lowest historical MAE over the fitting/initialization period.

### 4.1 Sampling

The forecast model/parameter combinations were applied to a stratified random sample of 50 stock keeping units (SKUs) and their associated historical monthly sales data. The time series consists of 10 SKUs with 60 months of historical sales data each and 40 SKUs with 24 months of historical sales data each, thereby providing a total historical data set of 1,560 data points. This ratio of $20 \%$ of 60 month SKUs and $80 \%$ of 24 month SKUs reflects the actual mix of active SKU history at total company level. A systematic random sample was obtained by ranking all products with 24 months of sales data by annual revenue and selecting every $\mathrm{k}^{\text {th }}$ product to obtain a representative sample of 40 SKUs. The same sampling procedure was employed to obtain the 10 SKUs with 60 months of history each. The total sample equates to approximately $7 \%$ of active SKUs, $1.4 \%$ of these with 60 months of history and $5.6 \%$ of these with 24 months of history. The choice of 24 month and 60 month data sets was made on the basis of evaluating relatively noisy (high random error component) short lifecycle, trend/fashion oriented products (Table 12. 24 Month History SKUs) and less noisy, longer lifecycle products (Table 13. 60 Month History SKUs). A combined data set description of the time series features is provided in Table 11 which is an adaptation of Adya et al. (2000) time series features for rule based forecasting. An additional feature category (Commercial Attributes) and three further features have been included to help aid contextualisation of the data sets (gross margin, cost of lost sales and inventory carrying charge).

| Time Series Features |  |  |
| :---: | :---: | :---: |
| Feature Categories | Features | Features Description |
| Causal forces | Unknown | The net directional effect of the principal factors acting on the series. Growth exerts an upward force. Decay exerts a downward force. Supporting forces push in direction of historical trend. Opposing forces work against the trend. Regressing forces work towards a mean. When uncertain, forces should be unknown. |
| Functional form | Refer to Appendix BSales History Linear Regression and Autocorrelation (ACF) graphs to assess instability criteria | Multiplicative or Additive - Expected pattern of the trend of the series. |
| Cycles expected | Cycles expected | Regular movement of the series about the basic trend. |
| Forecast horizon | 24 Month Data Set (12 month hold-out) <br> 60 Month Data Set (24 month hold-out) | Horizon for which forecasts are being made. |
| Subject to events | Subject to events: |  |
| Start-up series |  | Series provides data for a start-up. |
| Related to other series |  |  |
| Types of data | Positive values only | Only positive values in time series |
|  | No | Bounded values such as percentages and asymptotes |
|  | No Missing observations | No missing observations in the series |
| Level | Not Biased | Level is not biased by any other events. |
| Trend | Refer to Appendix B Sales History Linear Regression and Autocorrelation (ACF) graphs to assess instability criteria | Trend Direction - Direction of trend after fitting linear regression to past data. |
| Length of series | 24 Month Data Set 60 Month Data Set | Number of observations in the series. |
|  | Monthly | Time interval represented between the observations. |
| Seasonality | Refer to Appendix B Sales History Linear Regression and Autocorrelation (ACF) graphs to assess instability criteria | Autocorrelation - Whether seasonality is present in the series. |


| Uncertainty | Refer to Appendix B Sales History Linear Regression and Autocorrelation (ACF) graphs to assess instability criteria | Coeff. of variation about trend $>0.2$ Standard deviation divided by the mean for the trend adjusted data. |
| :---: | :---: | :---: |
|  |  | Basic and recent trends not in same direction |
| Instability | Refer to Appendix B Sales History Linear Regression and Autocorrelation (ACF) graphs to assess instability criteria | Irrelevant early data - Early portion of the series results from a substantially different underlying process. |
|  |  | Suspicious pattern - Series that show a substantial change in recent pattern. |
|  |  | Unstable recent trend - Series that show marked changes in recent trend pattern. |
|  |  | Outliers present - Isolated observation near a 2 std. deviation band of linear regress. |
|  |  | Recent run not long - The last six period-to-period movements are not in same direction. |
|  |  | Near a previous extreme - A last observation that is $90 \%$ more than the highest or $110 \%$ lower than lowest observation. |
|  |  | Changing basic trend - Underlying trend that is changing over the long run. |
|  |  | Level discontinuities - Changes in the level of the series (steps) |
|  |  | Last observation unusual - Last observation deviates substantially from previous data. |
| Commercial Attributes | Gross margin $=68.4 \%$ average across both data sets | Product gross margin percentage to provide indicative SKU value |
|  | Cost of lost sales $=50 \%$ for all SKUs in both data sets | Cost of lost sales (fractional charge of margin per unit short) in \% of unit margin per annum to provide relative importance of service level versus inventory carrying costs |
|  | Inventory carrying charge = 30\% per annum for all SKUs in both data sets | Inventory carrying charge in percentage of unit cost per annum to provide relative importance of service level versus inventory carrying costs |

Table 11. Case Study Time Series Features (Adapted from Adya et al., 2000)

Summary Statistics:
24 Month History SKUs

| Stock Keeping Unit | Observations (monthly data points) | Minimum Unit Sales | Maximum <br> Unit Sales | Mean Unit Sales | Standard deviation of Sales | Coefficient of Variation \% |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| SKU-24-001 | 24 | 4 | 23 | 13.86 | 5.48 | 39.5\% |
| SKU-24-002 | 24 | 3 | 21 | 10.13 | 4.30 | 42.5\% |
| SKU-24-003 | 24 | 71 | 366 | 176.00 | 76.40 | 43.4\% |
| SKU-24-004 | 24 | 74 | 295 | 158.25 | 64.96 | 41.0\% |
| SKU-24-005 | 24 | 42 | 127 | 76.88 | 29.01 | 37.7\% |
| SKU-24-006 | 24 | 662 | 1456 | 1022.20 | 216.66 | 21.2\% |
| SKU-24-007 | 24 | 13 | 79 | 35.35 | 15.29 | 43.3\% |
| SKU-24-008 | 24 | 20 | 95 | 45.04 | 21.86 | 48.5\% |
| SKU-24-009 | 24 | 9 | 32 | 18.27 | 6.69 | 36.6\% |
| SKU-24-010 | 24 | 17 | 91 | 47.75 | 22.50 | 47.1\% |
| SKU-24-011 | 24 | 12 | 77 | 33.97 | 15.89 | 46.8\% |
| SKU-24-012 | 24 | 20 | 75 | 39.54 | 13.82 | 34.9\% |
| SKU-24-013 | 24 | 11 | 31 | 18.97 | 5.28 | 27.8\% |
| SKU-24-014 | 24 | 19 | 141 | 64.24 | 32.01 | 49.8\% |
| SKU-24-015 | 24 | 12 | 137 | 48.71 | 31.51 | 64.7\% |
| SKU-24-016 | 24 | 31 | 145 | 77.58 | 26.33 | 33.9\% |
| SKU-24-017 | 24 | 16 | 51 | 30.39 | 10.61 | 34.9\% |
| SKU-24-018 | 24 | 40 | 166 | 103.72 | 34.99 | 33.7\% |
| SKU-24-019 | 24 | 18 | 81 | 35.40 | 12.53 | 35.4\% |
| SKU-24-020 | 24 | 7 | 46 | 19.61 | 9.25 | 47.2\% |
| SKU-24-021 | 24 | 7 | 75 | 29.46 | 16.33 | 55.4\% |
| SKU-24-022 | 24 | 35 | 157 | 65.13 | 25.77 | 39.6\% |
| SKU-24-023 | 24 | 26 | 107 | 54.54 | 19.28 | 35.3\% |
| SKU-24-024 | 24 | 10 | 194 | 72.04 | 43.00 | 59.7\% |
| SKU-24-025 | 24 | 10 | 98 | 42.50 | 21.64 | 50.9\% |
| SKU-24-026 | 24 | 36 | 130 | 66.66 | 22.80 | 34.2\% |
| SKU-24-027 | 24 | 24 | 123 | 61.90 | 22.87 | 36.9\% |
| SKU-24-028 | 24 | 22 | 114 | 47.45 | 21.65 | 45.6\% |
| SKU-24-029 | 24 | 3 | 57 | 17.16 | 12.81 | 74.7\% |
| SKU-24-030 | 24 | 12 | 97 | 35.50 | 22.30 | 62.8\% |
| SKU-24-031 | 24 | 15 | 68 | 35.31 | 14.69 | 41.6\% |
| SKU-24-032 | 24 | 8 | 38 | 18.66 | 7.71 | 41.3\% |
| SKU-24-033 | 24 | 6 | 26 | 12.18 | 4.77 | 39.2\% |
| SKU-24-034 | 24 | 23 | 79 | 46.60 | 16.16 | 34.7\% |
| SKU-24-035 | 24 | 10 | 28 | 17.42 | 5.49 | 31.5\% |
| SKU-24-036 | 24 | 10 | 41 | 23.93 | 8.81 | 36.8\% |
| SKU-24-037 | 24 | 11 | 42 | 23.95 | 8.63 | 36.0\% |
| SKU-24-038 | 24 | 116 | 837 | 536.08 | 236.55 | 44.1\% |
| SKU-24-039 | 24 | 261 | 1158 | 604.51 | 237.42 | 39.3\% |
| SKU-24-040 | 24 | 242 | 1579 | 750.58 | 357.35 | 47.6\% |
| Averages |  |  |  | 115.94 | 44.54 | 42.4\% |

Table 12. 24 Month History SKUs

Summary Statistics:
60 Month History SKUs

| Stock Keeping <br> Unit | Observations <br> (monthly data <br> points) | Minimum <br> Unit Sales | Maximum <br> Unit Sales | Mean <br> Unit <br> Sales | Standard <br> deviation <br> of Sales | Coefficient of <br> Variation \% |
| :--- | ---: | ---: | ---: | ---: | ---: | ---: |
| SKU-60-001 | 60 | 23 | 62 | 42.30 | 8.68 | $20.5 \%$ |
| SKU-60-002 | 60 | 213 | 624 | 429.36 | 102.76 | $23.9 \%$ |
| SKU-60-003 | 60 | 29 | 97 | 63.29 | 15.77 | $24.9 \%$ |
| SKU-60-004 | 60 | 137 | 825 | 373.92 | 141.34 | $37.8 \%$ |
| SKU-60-005 | 60 | 51 | 287 | 174.46 | 59.69 | $34.2 \%$ |
| SKU-60-006 | 60 | 112 | 268 | 200.27 | 37.60 | $18.8 \%$ |
| SKU-60-007 | 60 | 266 | 675 | 422.43 | 94.70 | $22.4 \%$ |
| SKU-60-008 | 60 | 67 | 248 | 158.70 | 38.40 | $24.2 \%$ |
| SKU-60-009 | 60 | 80 | 260 | 178.00 | 38.71 | $21.7 \%$ |
| SKU-60-010 | 60 | 31 | 129 | 71.37 | 20.53 | $28.8 \%$ |
| Averages |  |  |  |  | 211.41 | 55.82 |

Table 13. 60 Month History SKUs

The naming convention used to identify SKUs, yet maintain commercial confidentiality is as follows: SKU-24-010 = Stock Keeping Unit -24 month data set product number 10. (Refer to Appendix A - Data Set Statistics).

The historical sales data are an aggregation of point of sale data from each of the company's 22 stores. Point of sale data are more representative of true customer demand, than is warehouse replenishment to stores which is distorted by lot sizing and store merchandising requirements (H. Lee, Padmanabhan, \& Whang, 1997). However, point of sale data still does not account for lost sales, e.g. due to stock outs. Given that the determination of demand, not sales is the true aim of sales forecasting it can be said that the use of historical sales for forecasting is actually a surrogate for actual demand. In the case study retail setting all sales were transacted in the same period (month) as recorded inventory movements, i.e. no delayed fulfillment took place.

The historical sales data and forecast values populate an $\mathrm{SAP}^{\circledR}$ planning table (S914). In the case of the 60 month series (10 SKUs), the first 34 months of sales history was used to initialize/fit the forecast methods and the final 24 months to evaluate the
accuracy (best-fit) of each forecast model/parameter combination. For the 24 month series (40 SKUs), the first 10 months of sales history was used to initialise/fit the forecast methods and the final 12 months used to evaluate the accuracy (best-fit) of each forecast model/parameter combination. The 12 month evaluation period is referred to as "holdout" data. Note: Given that the forecasts are 3-step ahead (to reflect the company's procurement lead time) and run on the first day of new month, the fitting period ends 2 months prior to the first forecast/holdout period hence the missing 2 month period described above.

The identification of optimal smoothing parameters was performed in Microsoft ${ }^{\circledR}$ Excel $^{\circledR}$ by reproducing each of the exponential smoothing methods and then using Solver (Generalized Reduced Gradient (GRG2) algorithm) to minimize the mean absolute error (MAE) over the respective initialisation/fitting periods for all products in the given data set ( 24 month and 60 month). The resulting optimized parameter models were then evaluated along with the $\mathrm{SAP}^{\circledR}$ default parameters so as to provide an independent and objective evaluation of $S A P^{\circledR,}$ s default smoothing parameter selections. The grouped fitting approach was adopted based on the work of Robb and Silver (2002) to mitigate potential over-fitting with shortening product lifecycles.

The forecast values were then run at fixed periods of three months, being the company's planning horizon (lead-time) to order and procure product from China. Following each three month forecast run the next month of historical sales data was successively applied to the forecast models and a further fixed period of three months was forecast, thereby providing a single new monthly forecast value three months ahead (3-step ahead forecast). This iterative process was performed 24 times so as to provide two years of forecast sales for the 60 month sample and 12 times for the 24 month sample. This methodology is referred to as a rolling-origin evaluation (Tashman, 2000).

### 4.2 Event Management Adjustment

The event management adjustment of the baseline forecast is based on the average historical percentage increase of sales during promotional periods versus nonpromotional periods and is therefore a strictly quantitative approach to the adjustment of the baseline statistical forecasts. As SAP ${ }^{\circledR}$, $\operatorname{ERP}$ functionality does not incorporate regression analysis or intervention analysis, the percentage change is calculated from simple sales analysis. Historical promotional periods for the company show an average unit sales increase of $15 \%$ and three months of the year show an average decrease of around $20 \%$ of average monthly sales.

These changes in demand only apply to certain SKUs, i.e. SKUs that are actively promoted. SKUs that show historical sensitivity to promotional activity, which sometimes change from year to year, are adjusted using the $\mathrm{SAP}^{\circledR}$ event management transaction (MC64) by 115\% (15\% increase) and known "slow months" are adjusted to 80\% (20\% decrease). This method of adjusting for periods of both promotional activity and known slow periods is simplistic and it should be noted that the average percentages were arrived at from company total unit sales and are not solely based on the systematic sample used in this case study.

Having detailed the data collection, the next section presents the results of the study.

### 5.0 RESULTS

The results section commences by detailing the methods used to assess "best-fit" then presents the results of the case study in a series of tables with explanations.

Methodologically, in order to assess which forecast model/parameter combination provides the best-fit, all 12 models were evaluated ( 38 model/parameter and event management adjusted variants in total). "Best-fit" was considered against the following five criteria, with CFE as the primary measure (See Appendix D - Summary Forecast Error Measures, for the tables that contain the detail of the five forecast error measure criteria):

1. Average, across all products for each model, mean absolute error (MAE) for overall magnitude of error (a standard error measure, i.e. in the base unit of measure, in this case unit forecast versus unit sales).

$$
\begin{equation*}
M A E=\frac{1}{n} \sum_{t=1}^{n}\left|e_{t}\right| \tag{29}
\end{equation*}
$$

2. Average, across all products for each model, mean absolute percentage error (MAPE) for relative overall fit (a relative error measure).

$$
\begin{equation*}
M A P E=\frac{1}{n} \sum_{t=1}^{n}\left|P E_{t}\right| \tag{30}
\end{equation*}
$$

where $P E_{t}=\left(\frac{Y_{t}-F_{t}}{Y_{t}}\right) \times 100$

The choice of forecast accuracy measures is based on the widespread use of these measures in forecasting competitions (particularly the M-Series competitions), along with their ease of calculation, understanding and interpretation (Makridakis, 1993a). However, the overall fit, weighted by both revenue (revenue weighted mean absolute percentage error (RW-MAPE)) and margin (product margin contribution, margin weighted mean absolute percentage error (MW-MAPE)) and cost of forecast error (CFE) were also applied.
3. Total, across all products for each model, revenue weighted mean absolute percentage error (RW-MAPE) for relative overall fit with consideration of product revenue (financial impact).

$$
\begin{equation*}
R W-M A P E=\sum_{t=1}^{n} \operatorname{MAPE}_{p}\left(D_{p} / D_{T}\right) \tag{31}
\end{equation*}
$$

where $M A P E_{P}=$ MAPE for Product p
$D_{p}=$ Dollar demand for Product p
$D_{T}=$ Total dollar demand for all products
4. Total, across all products for each model, margin weighted mean absolute percentage error (MW-MAPE) for relative overall fit with consideration of product margin contribution (financial impact).
$M W-M A P E=\sum_{t=1}^{n} M A P E_{p}\left(M_{p} / G M_{T}\right)$
where MAPE $_{p}=$ MAPE for Product $p$
$M_{p}=$ Margin contribution for Product p
$G M_{T}=$ Gross Margin (margin for all products)
5. Total, across all products for each model, Cost of Forecast Error (CFE), an absolute cost derived from MAE. To determine the financial impact of the relative forecast errors associated with each model a forecast error formula based on safety stock is estimated as follows:

$$
\begin{equation*}
S S=k \sigma \sqrt{R+L} \tag{33}
\end{equation*}
$$

where $S S=$ safety stock in units
$k=$ safety factor from a table of normal distribution probabilities
(Table 5)
$\sigma \sqrt{R+L}=$ standard deviation of forecast errors in units over the critical protection period (review period $(R)$ and the replenishment lead time $(\mathrm{L})$ ), in months.

The standard deviation of forecast errors is calculated as follows:

$$
\begin{align*}
& \sigma=\sqrt{\pi / 2} \times \text { MAE or an approximation } \sigma \approx 1.25 \times \text { MAE }  \tag{34}\\
& \text { where MAE is the mean absolute forecast error }
\end{align*}
$$

The safety stock calculation (SS ) along with the standard deviation of forecast errors over the replenishment lead time $(\sigma \sqrt{R+L})$ is then used to establish the total forecast error cost as follows:

$$
\begin{equation*}
C F E=\left(S S v r+\frac{B_{5} M_{p} \sigma \sqrt{R+L} G_{u}(k)}{R}\right) P \tag{35}
\end{equation*}
$$

where $C F E=$ annual cost of forecast error in dollars
$S S=$ safety stock in units
$v=$ unit cost, in \$/unit
$r=$ inventory carrying charge, in $\$ / \$ /$ month
$B_{5}=$ fractional charge of margin per unit short
$M_{p}=$ product margin in dollars
$G_{u}(k)=$ standard unit normal loss function (unit normal distribution)
$P=$ period multiplier to convert from months to year

For the purposes of this case study $B_{5}$ is set at $50 \%$ and $r$ is $2.5 \%$ per month ( $30 \%$ per annum). The setting of $B_{5}$ at $50 \%$ is justified through Corsten and Gruen's (2004) study showing that unavailable products typically result in a loss to the retailer of $40 \%$ of sales (due to out-of-stock products) plus an additional 10\% estimate that reflects the loss of goodwill and the resulting ongoing loss of custom. The $10 \%$ component could of course well be a serious understatement. The setting of $r$ at $2.5 \%$ per month (30\% per annum) is considered a reasonable, and possibly conservative, estimate that includes handling and storage costs, cost of capital and opportunity cost, and the obsolescence that is a large factor in the company's relatively short lifecycle products. The company management arbitrarily set the safety factor ( $k$ ) at 1.645 which equates to a $\mathrm{P}_{1}$ service level of $95 \%$ and it is therefore used for this case study. The replenishment lead time (L), including the review period $(R)$ of one month, is set at 4 months. Lead time variability also has a very high impact on costs associated with maintaining a high service level. However, as the aim of this case study is to assess forecast variability then $R+L$ is considered constant at 4 months. For additional work on the impact of lead time variability on safety stock see Chopra, Reinhardt, and Dada (2004). Finally, so as to annualize all costs, the term $P$ is set at 12 (months). Refer to section 3.4 (Cost of Forecast Error), equations $23-28$ for a worked example of the Cost of Forecast Error (CFE) measure.

The results are presented as follows:

Summary tables showing forecast models/profile parameters, and associated accuracy measures (MAE, MAPE, RW-MAPE, MW-MAPE, and Cost of Forecast Error), namely:
(a) SAP ${ }^{\circledR}$ Default versus Fitted Smoothing Parameters (Table 14).
(b) Baseline Forecasts versus Event Management (EM) Adjusted Forecasts (Table 15 \& Table 16).
(c) Best-fitting Model (Table 17 and Table 18).

Tables for each SKU and forecast model combination with mean MAE, MAPE, RWMAPE, MW-MAPE, and CFE for the total hold-out period are shown in Appendix D Summary Forecast Error Measures. Tables 8, 9, 10, 11, and 12 are all derived from the tables shown in Appendix D.

### 5.1 SAP ${ }^{\circledR}$ Default versus Fitted Smoothing Parameters

Table 14 compares the default $S A P^{\circledR}$ smoothing parameters with historically fitted smoothing parameters (or period/weighting parameters in the case of the two moving average models). Table 14 shows sixteen tabular columns in two sections. The upper section represents the 24 month models and the lower section represents the 60 month models. The first column specifies the relevant forecast model. Columns two through eleven contain the following forecast error measures in column order: default MAE, default MAPE, default revenue weighted MAPE, default margin weighted MAPE, default cost of forecast error, fitted MAE, fitted MAPE, fitted revenue weighted MAPE, fitted margin weighted MAPE, fitted cost of forecast error. The final five columns (columns twelve to sixteen) represent the forecast error measure differences between the $\mathrm{SAP}^{\circledR}$ default and fitted smoothing parameters as follows: MAE, MAPE, revenue weighted MAPE, margin weighted MAPE, cost of forecast error. Statistically significant differences between forecasts using the $S A P^{\circledR}$ default and fitted smoothing parameters are indicated with an asterisk beside the significant forecast error measure.

It is important to note that fitted models that produced the same smoothing/weighting values as the default have been excluded. In the case of the 24 month models all seasonal and seasonal/trend models were excluded as insufficient history was available to fit these models. Models that automatically adapt the smoothing constants, i.e. the constant model (1st order exponential smoothing) with automatic alpha adaptation and the trend model (2nd order exponential smoothing) with automatic alpha adaptation were also excluded as no comparison can be made.

The 24 month MAE differences range from a 3.76 unit reduction in forecast error to a 0.70 unit increase, MAPE from a $6.87 \%$ reduction to a $3.24 \%$ increase. Revenue weighted MAPE from a $7.01 \%$ decrease to a $2.34 \%$ increase, margin weighted MAPE
from a $7.10 \%$ decrease to a $2.54 \%$ increase, and cost of forecast error from a $\$ 3,001$ decrease to a $\$ 1,014$ increase.

The 60 month MAE differences range from a 13.94 unit reduction in forecast error to a 8.67 unit increase, MAPE from a $8.29 \%$ reduction to a $4.54 \%$ increase. Revenue weighted MAPE from a $9.34 \%$ decrease to a $5.74 \%$ increase, margin weighted MAPE from a $9.14 \%$ decrease to a $5.53 \%$ increase, and cost of forecast error from a \$1,046 decrease to a \$471 increase.

## Default versus Fitted Smoothing Parameters

| Baseline Forecasts $\mathbf{2 4}$ Month | Default MAE | Default <br> MAPE | Default Weighted MAPE |  | Default Cost of Forecast Error |  | Fitted <br> MAE | Fitted MAPE |  | Comparison - Default versus Fitted |  |  |  |  |  |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  |  |  |  |  |  |  |  |  |  |  | ted Cost Forecast Error | MAE | MAPE | Reveue Weighted MAPE | Margin Weighted MAPE |  | ost of ecast Error |
| Constant model (1st order exponential smoothing) | 39.33 | 43.33\% | 39.32\% | 39.38\% | \$ | 22,750 |  | 39.14 | 46.57\% | 41.66\% | 41.92\% | \$ | 23,763 | -0.19 | 3.24\% | 2.34\% | 2.54\% | \$ | 1,014 * |
| Moving Average Model | 41.91 | 42.67\% | 39.00\% | 39.18\% | \$ | 23,347 | 40.11 | 42.95\% | 39.41\% | 39.28\% | \$ | 22,580 | -1.80 | 0.28\% | 0.41\% | 0.10\% | \$ | (767) |
| Trend model (1st order exponential smoothing) | 38.54 | 47.01\% | 42.45\% | 42.51\% | \$ | 23,112 | 39.24 | 47.79\% | 42.29\% | 42.53\% | \$ | 24,000 | 0.70 | 0.78\% | -0.16\% | 0.02\% | \$ | 888 |
| Trend model (2nd order exponential smoothing) | 41.98 | 51.45\% | 46.82\% | 47.02\% | \$ | 25,581 | 38.22 | 44.58\% | 39.81\% | 39.91\% | \$ | 22,580 | -3.76 * | -6.87\% | -7.01\% | -7.10\% | \$ | $(3,001)$ * |
| Mean | 40.44 | 46.11\% | 41.90\% | 42.02\% | \$ | 23,698 | 39.18 | 45.47\% | 40.79\% | 40.91\% | \$ | 23,231 | -1.26 | -0.64\% | -1.11\% | -1.11\% | \$ | (467) |
|  |  |  |  |  |  |  |  |  | Percentag | ge showing | imp | rovement | 75.00\% | 25.00\% | 50.00\% | 25.00\% |  | .00\% |


| Baseline Forecasts 60 Month | Default MAE | Default <br> MAPE | Default <br> Reveue Weighted MAPE | Default <br> Margin Weighted <br> MAPE | Default Cost of Forecast Error |  | Fitted MAE | Fitted MAPE | Fitted <br> Reveue Weighted <br> MAPE |  | Fitted Cost of Forecast Error |  | Comparison - Default versus Fitted |  |  |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  |  |  |  |  |  |  | MAE |  |  |  |  |  | MAPE | Reveue Weighted MAPE | Margin Weighted MAPE |  | ost of recast Error |
| Constant model (1st order exponential smoothing) | 36.55 | 24.45\% | 23.01\% | 23.13\% | \$ | 3,181 |  | 34.81 | 23.03\% | 21.29\% | 21.49\% | \$ | 3,046 | -1.74 | -1.42\% | -1.72\% | -1.65\% | \$ | (135) |
| Moving Average Model | 49.87 | 31.53\% | 30.79\% | 30.79\% | \$ | 4,210 | 35.93 | 23.24\% | 21.45\% | 21.65\% | \$ | 3,164 | -13.94 * | -8.29\% | -9.34\% | -9.14\% | \$ | $(1,046)$ * |
| Weighted Moving Average Model | 35.42 | 23.30\% | 21.40\% | 21.63\% | \$ | 3,105 | 35.05 | 22.98\% | 21.22\% | 21.43\% | \$ | 3,091 | -0.37 | -0.32\% | -0.18\% | -0.20\% | \$ | (15) |
| Trend model (1st order exponential smoothing) | 35.65 | 21.51\% | 20.70\% | 20.78\% | \$ | 3,095 | 34.82 | 22.21\% | 20.54\% | 20.82\% | \$ | 3,000 | -0.83 | 0.70\% | -0.16\% | 0.04\% | \$ | (96) |
| Trend model (2nd order exponential smoothing) | 39.18 | 24.04\% | 22.24\% | 22.48\% | \$ | 3,442 | 47.85 | 28.58\% | 27.98\% | 28.01\% | \$ | 3,913 | 8.67 | 4.54\% | 5.74\% | 5.53\% | \$ | 471 |
| Seasonal model (Winters' method) | 40.14 | 25.52\% | 23.68\% | 23.91\% | \$ | 3,448 | 38.27 | 25.17\% | 22.88\% | 23.18\% | \$ | 3,349 | -1.86 | -0.35\% | -0.80\% | -0.73\% | \$ | (99) |
| Seasonal Trend Model (Holt-Winters' method) | 39.83 | 24.35\% | 22.73\% | 22.93\% | \$ | 3,428 | 39.17 | 25.26\% | 22.54\% | 22.98\% | \$ | 3,419 | -0.66 | 0.92\% | -0.19\% | 0.06\% | \$ | (9) |
| Mean | 39.52 | 24.96\% | 23.51\% | 23.66\% | \$ | 3,416 | 37.99 | 24.35\% | 22.56\% | 22.79\% | \$ | 3,283 | -1.53 | -0.60\% | -0.95\% | -0.87\% | \$ | (133) |
|  |  |  |  |  |  |  |  |  | Percentage showing improvement $85.71 \%$ |  |  |  |  | 57.14\% | 85.71\% | 57.14\% |  | 5.71\% |

Table 14. SAP ${ }^{\circledR}$ Default versus Fitted Smoothing Parameters
Fitted model comparisons that are superior to the $S A P ~^{\circledR}$ default models are shown with a negative sign, or bracketed in the case of cost of forecast error, i.e. lower forecast error values being favourable

### 5.2 Baseline Forecasts versus Event Management Adjusted Forecasts

The results of the baseline forecasts versus event management adjusted forecasts are shown in Table 15 and Table 16. Table 15 and Table 16 each show sixteen tabular columns. The first column specifies the forecast model. Columns two through eleven contain the following forecast error measures in column order: baseline MAE, baseline MAPE, baseline revenue weighted MAPE, baseline margin weighted MAPE, baseline cost of forecast error, event management adjusted MAE, event management adjusted MAPE, event management adjusted revenue weighted MAPE, event management adjusted margin weighted MAPE, and event management adjusted cost of forecast error. The final five columns (columns twelve to sixteen) represent the forecast error measure differences between the baseline and event management adjusted forecasts as follows: MAE, MAPE, revenue weighted MAPE, margin weighted MAPE, and cost of forecast error. Statistically significant differences between forecasts using the baseline and event management adjusted forecasts are indicated with an asterisk beside the significant forecast error measure.

The 24 month MAE differences range from a 0.98 unit reduction in forecast error to a 3.97 unit increase, MAPE from a $1.08 \%$ reduction to a $0.69 \%$ increase. Revenue weighted MAPE from a $1.23 \%$ decrease to a $1.17 \%$ increase, margin weighted MAPE from a $1.28 \%$ decrease to a $1.21 \%$ increase, and cost of forecast error from a $\$ 605$ decrease to a $\$ 1,224$ increase.

The 60 month MAE differences range from a 1.69 unit reduction in forecast error to a 1.49 unit increase, MAPE from a $1.36 \%$ reduction to a $0.16 \%$ increase. Revenue weighted MAPE from a $0.92 \%$ decrease to a $0.05 \%$ increase, margin weighted MAPE from a $0.92 \%$ decrease to a $0.04 \%$ increase, and cost of forecast error from a $\$ 128$ decrease to a $\$ 128$ increase.

| Forecasts 24 Month | Baseline | MAPE | Reveue Weighted MAPE | Margin Weighted MAPE | Cost of Error |  | Event Management Adjusted |  |  |  | Cost of <br> Forecast Error |  | Comparis | BaselineMAPE | versus EMReveueWeightedMAPE | Margin Weighted MAPE | Cost ofForecast Error |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  |  |  |  |  |  |  | MAE | MAPE | Reveue Weighted MAPE | Margin Weighted MAPE |  |  |  |  |  |  |  |  |
| Constant model (1st order exponential smoothing) Alpha 0.2 (SAP defaut) | 39.33 | 43.33\% | 39.32\% | 39.38\% | \$ | 22,750 | 38.68 | 42.79\% | 38.47\% | 38.48\% | \$ | 22,256 | -0.65 | -0.54\% | -0.85\% | -0.90\% | \$ | (493) |
| Constant model (1st order exponential smoothing) Alpha Fitted | 39.14 | 46.57\% | 41.66\% | 41.92\% | \$ | 23,763 | 38.27 | 45.94\% | 40.73\% | 40.90\% | \$ | 23,226 | -0.87 | -0.63\% | -0.93\% | -1.02\% | \$ | (537) |
| Constant model (1st order exponential smoothing) Automatic Alpha Adaptation | 39.68 | 49.16\% | 43.11\% | 43.61\% | \$ | 24,889 | 39.43 | 49.06\% | 42.59\% | 43.01\% | \$ | 24,599 | -0.25 | -0.10\% | -0.51\% | -0.60\% | \$ | (290) |
| Moving Average Model 24 Historical Values (SAP Defaut) | 41.91 | 42.67\% | 39.00\% | 39.18\% | \$ | 23,347 | 41.65 | 42.23\% | 38.43\% | 38.56\% | \$ | 22,968 | -0.26 | -0.45\% | -0.57\% | -0.61\% | \$ | (379) |
| Moving Average Model Historical Values Fitted | 40.11 | 42.95\% | 39.41\% | 39.28\% | \$ | 22,580 | 39.31 | 42.39\% | 38.41\% | 38.23\% | \$ | 22,032 | -0.80 | -0.57\% | -1.00\% | -1.05\% | \$ | (548) |
| Weighted Moving Average Model Weighting Group 1 (SAP defaut) | 39.04 | 46.56\% | 41.75\% | 41.97\% | \$ | 23,753 | 38.17 | 45.73\% | 40.69\% | 40.83\% | \$ | 23,148 | -0.87 | -0.83\% | -1.06\% | -1.14\% | \$ | (605) |
| Weighted Moving Average Model Weighting Group Fitted | 39.04 | 46.56\% | 41.75\% | 41.97\% | \$ | 23,753 | 38.17 | 45.73\% | 40.69\% | 40.83\% | \$ | 23,148 | -0.87 | -0.83\% | -1.06\% | -1.14\% | \$ | (605) |
| Trend model (1st order exponential smoothing) Alpha 0.2 , Beta 0.1 (SAP defaut) | 38.54 | 47.01\% | 42.45\% | 42.51\% | \$ | 23,112 | 37.94 | 45.92\% | 41.25\% | 41.23\% | \$ | 22,579 | -0.60 | -1.08\% | -1.20\% | -1.28\% | \$ | (533) |
| Trend model (1st order exponential smoothing) Alpha, Beta Fitted | 39.24 | 47.79\% | 42.29\% | 42.53\% | \$ | 24,000 | 38.46 | 46.85\% | 41.17\% | 41.36\% | \$ | 23,516 | -0.77 | -0.94\% | -1.13\% | -1.17\% | \$ | (484) |
| Trend model (2nd order exponential smoothing) Alpha 0.2 (SAP defaut) | 41.98 | 51.45\% | 46.82\% | 47.02\% | \$ | 25,581 | 41.18 | 50.53\% | 45.59\% | 45.70\% | \$ | 25,009 | -0.80 | -0.92\% | -1.23\% | -1.32\% | \$ | (572) |
| Trend model (2nd order exponential smoothing) Alpha Fitted | 38.22 | 44.58\% | 39.81\% | 39.91\% | \$ | 22,580 | 37.43 | 43.88\% | 38.75\% | 38.78\% | \$ | 22,024 | -0.79 | -0.70\% | -1.06\% | -1.13\% | \$ | (556) |
| Trend model (2nd order exponential smoothing) Automatic Alpha Adaptation | 51.76 | 67.49\% | 57.10\% | 57.75\% | \$ | 32,939 | 51.37 | 67.64\% | 56.65\% | 57.27\% | \$ | 32,630 | -0.39 | 0.16\% | -0.46\% | -0.49\% | \$ | (310) |
| Seasonal model (Winters' method) Alpha 0.2, Gamma 0.3 (SAP defaut) | 57.54 | 72.13\% | 68.97\% | 69.38\% | \$ | 34,615 | 60.47 | 72.60\% | 69.81\% | 70.24\% | \$ | 35,458 | 2.93 | 0.48\% | 0.84\% | 0.86\% | \$ | 843 |
| Seasonal model (Winters' method) Alpha, Gamma Fitted | 57.54 | 72.13\% | 68.97\% | 69.38\% | \$ | 34,615 | 60.47 | 72.60\% | 69.81\% | 70.24\% | \$ | 35,458 | 2.93 | 0.48\% | 0.84\% | 0.86\% | \$ | 843 |
| Seasonal Trend Model (Holt-Winters' method) Alpha 0.2, Beta 0.1, Gamma 0.3 (SAP defal | 66.95 | 83.04\% | 80.00\% | 80.22\% | \$ | 39,723 | 70.93 | 83.72\% | 81.17\% | 81.43\% | \$ | 40,947 | 3.97 | 0.69\% | 1.17\% | 1.21\% |  | 1,224 |
| Seasonal Trend Model (Holt-Winters' method) Alpha, Beta, Gamma Fitted | 66.95 | 83.04\% | 80.00\% | 80.22\% | \$ | 39,723 | 70.93 | 83.72\% | 81.17\% | 81.43\% | \$ | 40,947 | 3.97 | 0.69\% | 1.17\% | 1.21\% | \$ | 1,224 |
| Individual SKU Best Historical Fit | 38.23 | 45.21\% | 40.91\% | 41.05\% | \$ | 23,341 | 40.81 | 44.88\% | 41.43\% | 41.66\% | \$ | 24,023 | 2.58 | -0.33\% | 0.52\% | 0.61\% |  | 682 |
| SAP Automatic Model Selection SAP Procedure 2 | 37.67 | 45.34\% | 40.07\% | 40.33\% | \$ | 22,798 | 36.69 | 44.70\% | 39.02\% | 39.22\% | \$ | 22,224 | -0.98 | -0.64\% | -1.05\% | -1.11\% | \$ | (574) |
| Naive 1 | 44.16 | 55.64\% | 48.18\% | 48.77\% | \$ | 27,859 | 43.91 | 55.57\% | 47.58\% | 48.09\% | \$ | 27,522 | -0.26 | -0.07\% | -0.59\% | -0.67\% |  | (337) |
| Mean | 45.11 | 54.35\% | 49.56\% | 49.81\% | \$ | 27,143 | 45.49 | 54.03\% | 49.13\% | 49.34\% | \$ | 27,038 | 0.38 | -0.32\% | -0.43\% | -0.47\% | \$ | (106) |
| * statistically significant at the 0.05 level |  |  |  |  |  |  |  |  | Percen | age showing | im | rovement | 73.68\% | 73.68\% | 73.68\% | 73.68\% |  | 73.68\% |

Table 15. Baseline versus Event Management Adjusted - 24 Month
Event management adjusted models that are superior to the baseline models are shown with a negative sign, or bracketed in the case of cost of forecast error, i.e. lower forecast error values being favourable.

## Baseline versus Event Management Adjusted

| Forecasts 60 Month | Baseline |  | Reveue Weighted MAPE | Margin Weighted MAPE | Event Management Adjusted |  |  |  |  |  |  |  | ompariso | Baseline | versus Em |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | MAE | MAPE |  |  | Cost of <br> Forecast <br> Error |  | MAE | MAPE | Reveue Weighted MAPE | Margin Weighted MAPE | Cost of <br> Forecast Error |  | MAE | MAPE | Reveue Weighted MAPE | Margin Weighted MAPE |  | ost of recast |
| Constant model (1st order exponential smoothing) Alpha 0.2 (SAP default) | 36.55 | 24.45\% | 23.01\% | 23.13\% | \$ | 3,181 | 35.09 | 23.14\% | 22.09\% | 22.21\% | \$ | 3,069 | -1.46 | -1.31\% | -0.92\% | -0.92\% | \$ | (112) |
| Constant model (1st order exponential smoothing) Alpha Fitted | 34.81 | 23.03\% | 21.29\% | 21.49\% | \$ | 3,046 | 33.29 | 21.81\% | 20.42\% | 20.62\% | \$ | 2,931 | -1.52 | -1.21\% | -0.87\% | -0.87\% |  | (115) |
| Constant model (1st order exponential smoothing) Automatic Alpha Adaptation | 36.99 | 24.30\% | 22.01\% | 22.27\% | \$ | 3,180 | 35.98 | 23.47\% | 21.40\% | 21.66\% | \$ | 3,106 | -1.01 | -0.83\% | -0.60\% | -0.61\% |  | (74) |
| Moving Average Model 24 Historical Values (SAP Defaut) | 49.87 | 31.53\% | 30.79\% | 30.79\% | \$ | 4,210 | 49.48 | 30.55\% | 30.13\% | 30.13\% | \$ | 4,173 | -0.38 | -0.98\% | -0.66\% | -0.66\% | \$ | (37) |
| Moving Average Model Historical Values Fitted | 35.93 | 23.24\% | 21.45\% | 21.65\% | \$ | 3,164 | 34.25 | 22.01\% | 20.61\% | 20.82\% | \$ | 3,035 | -1.68 | -1.23\% | -0.83\% | -0.83\% |  | (128) |
| Weighted Moving Average Model Weighting Group 1 (SAP defaut) | 35.42 | 23.30\% | 21.40\% | 21.63\% | \$ | 3,105 | 33.73 | 22.11\% | 20.52\% | 20.74\% | \$ | 2,982 | -1.69 | -1.19\% | -0.88\% | -0.89\% | \$ | (124) |
| Weighted Moving Average Model Weighting Group Fitted | 35.05 | 22.98\% | 21.22\% | 21.43\% | \$ | 3,091 | 33.61 | 21.88\% | 20.45\% | 20.65\% | \$ | 2,981 | -1.44 | -1.10\% | -0.78\% | -0.78\% | \$ | (110) |
| Trend model (1st order exponential smoothing) Alpha 0.2 , Beta 0.1 (SAP default) | 35.65 | 21.51\% | 20.70\% | 20.78\% | \$ | 3,095 | 34.05 | 20.78\% | 20.08\% | 20.14\% | \$ | 2,995 | -1.60 | -0.73\% | -0.62\% | -0.64\% |  | (100) |
| Trend model (1st order exponential smoothing) Alpha, Beta Fitted | 34.82 | 22.21\% | 20.54\% | 20.82\% | \$ | 3,000 | 33.92 | 21.64\% | 20.05\% | 20.32\% | \$ | 2,941 | -0.89 | -0.57\% | -0.48\% | -0.50\% |  | (58) |
| Trend model (2nd order exponential smoothing) Alpha 0.2 (SAP defaut) | 39.18 | 24.04\% | 22.24\% | 22.48\% | \$ | 3,442 | 37.56 | 23.10\% | 21.57\% | 21.80\% | \$ | 3,321 | -1.63 | -0.94\% | -0.67\% | -0.68\% | \$ | (121) |
| Trend model (2nd order exponential smoothing) Alpha Fitted | 47.85 | 28.58\% | 27.98\% | 28.01\% | \$ | 3,913 | 46.44 | 27.57\% | 27.18\% | 27.19\% | \$ | 3,813 | -1.41 | -1.01\% | -0.81\% | -0.82\% | \$ | (101) |
| Trend model (2nd order exponential smoothing) Automatic Alpha Adaptation | 42.79 | 27.03\% | 25.72\% | 25.88\% | \$ | 3,843 | 41.68 | 26.28\% | 25.15\% | 25.30\% | \$ | 3,761 | -1.11 | -0.75\% | -0.57\% | -0.58\% | \$ | (83) |
| Seasonal model (Winters' method) Alpha 0.2, Gamma 0.3 (SAP defaut) | 40.14 | 25.52\% | 23.68\% | 23.91\% | \$ | 3,448 | 39.99 | 25.36\% | 23.55\% | 23.78\% | \$ | 3,436 | -0.15 | -0.16\% | -0.13\% | -0.13\% |  | (12) |
| Seasonal model (Winters' method) Alpha, Gamma Fitted | 38.27 | 25.17\% | 22.88\% | 23.18\% | \$ | 3,349 | 38.31 | 25.20\% | 22.86\% | 23.16\% | \$ | 3,356 | 0.04 | 0.03\% | -0.02\% | -0.02\% |  | 6 |
| Seasonal Trend Model (Holt-Winters' method) Alpha 0.2, Beta 0.1, Gamma 0.3 (SAP defaı | 39.83 | 24.35\% | 22.73\% | 22.93\% | \$ | 3,428 | 39.84 | 24.45\% | 22.76\% | 22.95\% | \$ | 3,430 | 0.01 | 0.10\% | 0.03\% | 0.03\% |  | 2 |
| Seasonal Trend Model (Holt-Winters' method) Alpha, Beta, Gamma Fitted | 39.17 | 25.26\% | 22.54\% | 22.98\% | \$ | 3,419 | 39.17 | 25.42\% | 22.59\% | 23.02\% | \$ | 3,423 | 0.00 | 0.16\% | 0.05\% | 0.04\% |  | 3 |
| Individual SKU Best Historical Fit | 35.40 | 24.83\% | 22.63\% | 22.77\% | \$ | 3,220 | 36.89 | 23.46\% | 22.55\% | 22.50\% | \$ | 3,349 | 1.49 | -1.36\% | -0.07\% | -0.27\% | \$ | 128 |
| SAP Automatic Model Selection SAP Procedure 2 | 37.12 | 28.53\% | 27.45\% | 27.24\% | \$ | 3,259 | 36.13 | 27.49\% | 26.63\% | 26.41\% | \$ | 3,192 | -1.00 | -1.04\% | -0.82\% | -0.83\% |  | (67) |
| Naive 1 | 39.25 | 25.02\% | 23.47\% | 23.63\% | \$ | 3,493 | 39.00 | 24.72\% | 23.26\% | 23.43\% | \$ | 3,468 | -0.25 | -0.30\% | -0.21\% | -0.20\% | \$ | (25) |
| Mean | 38.64 | 24.99\% | 23.35\% | 23.53\% | \$ | 3,362 | 37.81 | 24.23\% | 22.83\% | 22.99\% | \$ | 3,303 | -0.83 | -0.76\% | -0.52\% | -0.54\% | \$ | (59) |
| * statistically significant at the 0.05 level |  |  |  |  |  |  |  |  | Percent | age showing | im | ovement | 78.95\% | 84.21\% | 89.47\% | 89.47\% |  | 78.95\% |

Table 16. Baseline versus Event Management Adjusted - 60 Month
Event management adjusted models that are superior to the baseline models are shown with a negative sign, or bracketed in the case of cost of forecast error, i.e. lower forecast error values being favourable.

### 5.3 Best-fitting Model

To determine "best-fit" all 38 models and parameter combinations were ranked based on relative MAE, MAPE, RW-MAPE, MW-MAPE, and cost of forecast error performance.

Table 17 (24 month models) and Table 18 (60 month models) each show eleven tabular columns. The first column specifies the forecast model. Columns two through six contain the following forecast error measures for each forecast model in column order: MAE, MAPE, revenue weighted MAPE, margin weighted MAPE, and cost of forecast error. The final five columns (columns seven to eleven) show the relative rankings of the forecast models for MAE, MAPE, revenue weighted MAPE, margin weighted MAPE, and cost of forecast error. The actual rankings for 24 month models, shown in Table 17, and for 60 month models in Table 18 is based solely on cost of forecast error (CFE). However, rankings for all measures are shown.

The 24 month best-fitting models (Table 11) show a MAE range of 36.69 units to 70.93 units, MAPE of $42.23 \%$ to $83.72 \%$, revenue weighted MAPE of $38.41 \%$ to $81.17 \%$, margin weighted MAPE of $38.23 \%$ to $81.43 \%$, and cost of forecast error ranging from $\$ 22,024$ to $\$ 40,947$.

The 60 month best-fitting models (Table 12) show a MAE range of 33.29 units to 49.87 units, MAPE of $20.78 \%$ to $31.53 \%$, revenue weighted MAPE of $20.05 \%$ to $30.79 \%$, margin weighted MAPE of $20.14 \%$ to $30.79 \%$, and cost of forecast error ranging from \$2,931 to \$4,210.

## Best Fitting Model

| 24 Month Models | MAE | MAPE | Reveue Weighted MAPE | Margin Weighted MAPE | $\begin{gathered} \text { Cost of } \\ \text { Forecast Error } \end{gathered}$ |  | Rank MAE | Rank MAPE | Rank RWMAPE | Rank MWMAPE | Rank Cost |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| 1 Trend model (2nd order exponential smoothing) Alpha Fitted Event Management | 37.43 | 43.88\% | 38.75\% | 38.78\% | \$ | 22,024 | 2 | 7 | 4 | 4 | 1 |
| 2 Moving Average Model Historical Values Fitted Event Management | 39.31 | 42.39\% | 38.41\% | 38.23\% | \$ | 22,032 | 17 | 2 | 1 | 1 | 2 |
| 3 SAP Automatic Model Selection SAP Procedure 2 Event Management | 36.69 | 44.70\% | 39.02\% | 39.22\% | \$ | 22,224 | 1 | 9 | 6 | 6 | 3 |
| 4 Constant model (1st order exponential smoothing) Alpha 0.2 (SAP defaut) Event Management | 38.68 | 42.79\% | 38.47\% | 38.48\% | \$ | 22,256 | 12 | 4 | 3 | 2 | 4 |
| 5 Trend model (1st order exponential smoothing) Alpha 0.2, Beta 0.1 (SAP defaut) Event Management | 37.94 | 45.92\% | 41.25\% | 41.23\% | \$ | 22,579 | 4 | 15 | 16 | 15 | 5 |
| 6 Moving Average Model Historical Values Fitted Baseline | 40.11 | 42.95\% | 39.41\% | 39.28\% | \$ | 22,580 | 21 | 5 | 8 | 7 | 6 |
| 7 Trend model (2nd order exponential smoothing) Alpha Fitted Baseline | 38.22 | 44.58\% | 39.81\% | 39.91\% | \$ | 22,580 | 7 | 8 | 9 | 9 | 7 |
| 8 Constant model (1st order exponential smoothing) Alpha 0.2 (SAP default) Baseline | 39.33 | 43.33\% | 39.32\% | 39.38\% | \$ | 22,750 | 18 | 6 | 7 | 8 | 8 |
| 9 SAP Automatic Model Selection SAP Procedure 2 Baseline | 37.67 | 45.34\% | 40.07\% | 40.33\% | \$ | 22,798 | 3 | 12 | 10 | 10 | 9 |
| 10 Moving Average Model 24 Historical Values (SAP Defautt) Event Management | 41.65 | 42.23\% | 38.43\% | 38.56\% | \$ | 22,968 | 24 | 1 | 2 | 3 | 10 |
| 11 Trend model (1st order exponential smoothing) Alpha 0.2, Beta 0.1 (SAP default) Baseline | 38.54 | 47.01\% | 42.45\% | 42.51\% | \$ | 23,112 | 11 | 21 | 22 | 21 | 11 |
| 12 Weighted Moving Average Model Weighting Group 1 (SAP default) Event Management | 38.17 | 45.73\% | 40.69\% | 40.83\% | \$ | 23,148 | 5 | 13 | 11 | 11 | 12 |
| 13 Weighted Moving Average Model Weighting Group Fitted Event Management | 38.17 | 45.73\% | 40.69\% | 40.83\% | \$ | 23,148 | 5 | 13 | 11 | 11 | 12 |
| 14 Constant model (1st order exponential smoothing) Alpha Fitted Event Management | 38.27 | 45.94\% | 40.73\% | 40.90\% | \$ | 23,226 | 9 | 16 | 13 | 13 | 14 |
| 15 Individual SKU Best Historical Fit Baseline | 38.23 | 45.21\% | 40.91\% | 41.05\% | \$ | 23,341 | 8 | 11 | 14 | 14 | 15 |
| 16 Moving Average Model 24 Historical Values (SAP Default) Baseline | 41.91 | 42.67\% | 39.00\% | 39.18\% | \$ | 23,347 | 25 | 3 | 5 | 5 | 16 |
| 17 Trend model (1st order exponential smoothing) Alpha, Beta Fitted Event Management | 38.46 | 46.85\% | 41.17\% | 41.36\% | \$ | 23,516 | 10 | 20 | 15 | 16 | 17 |
| 18 Weighted Moving Average Model Weighting Group 1 (SAP defaut) Baseline | 39.04 | 46.56\% | 41.75\% | 41.97\% | \$ | 23,753 | 13 | 17 | 19 | 19 | 18 |
| 19 Weighted Moving Average Model Weighting Group Fitted Baseline | 39.04 | 46.56\% | 41.75\% | 41.97\% | \$ | 23,753 | 13 | 17 | 19 | 19 | 18 |
| 20 Constant model (1st order exponential smoothing) Alpha Fitted Baseline | 39.14 | 46.57\% | 41.66\% | 41.92\% | \$ | 23,763 | 15 | 19 | 18 | 18 | 20 |
| 21 Trend model (1st order exponential smoothing) Alpha, Beta Fitted Baseline | 39.24 | 47.79\% | 42.29\% | 42.53\% | \$ | 24,000 | 16 | 22 | 21 | 22 | 21 |
| 22 Individual SKU Best Historical Fit Event Management | 40.81 | 44.88\% | 41.43\% | 41.66\% | \$ | 24,023 | 22 | 10 | 17 | 17 | 22 |
| 23 Constant model (1st order exponential smoothing) Automatic Alpha Adaptation Event Management | 39.43 | 49.06\% | 42.59\% | 43.01\% | \$ | 24,599 | 19 | 23 | 23 | 23 | 23 |
| 24 Constant model (1st order exponential smoothing) Automatic Alpha Adaptation Baseline | 39.68 | 49.16\% | 43.11\% | 43.61\% | \$ | 24,889 | 20 | 24 | 24 | 24 | 24 |
| 25 Trend model (2nd order exponential smoothing) Alpha 0.2 (SAP default) Event Management | 41.18 | 50.53\% | 45.59\% | 45.70\% | \$ | 25,009 | 23 | 25 | 25 | 25 | 25 |
| 26 Trend model (2nd order exponential smoothing) Alpha 0.2 (SAP defaut) Baseline | 41.98 | 51.45\% | 46.82\% | 47.02\% | \$ | 25,581 | 26 | 26 | 26 | 26 | 26 |
| 27 Naïve 1 Event Management | 43.91 | 55.57\% | 47.58\% | 48.09\% | \$ | 27,522 | 27 | 27 | 27 | 27 | 27 |
| 28 Naïve 1 Baseline | 44.16 | 55.64\% | 48.18\% | 48.77\% | \$ | 27,859 | 28 | 28 | 28 | 28 | 28 |
| 29 Trend model (2nd order exponential smoothing) Automatic Alpha Adaptation Event Management | 51.37 | 67.64\% | 56.65\% | 57.27\% | \$ | 32,630 | 29 | 30 | 29 | 29 | 29 |
| 30 Trend model (2nd order exponential smoothing) Automatic Alpha Adaptation Baseline | 51.76 | 67.49\% | 57.10\% | 57.75\% | \$ | 32,939 | 30 | 29 | 30 | 30 | 30 |
| 31 Seasonal model (Winters' method) Alpha 0.2, Gamma 0.3 (SAP defaut) Baseline | 57.54 | 72.13\% | 68.97\% | 69.38\% | \$ | 34,615 | 31 | 31 | 31 | 31 | 31 |
| 32 Seasonal model (Winters' method) Alpha, Gamma Fitted Baseline | 57.54 | 72.13\% | 68.97\% | 69.38\% | \$ | 34,615 | 31 | 31 | 31 | 31 | 31 |
| 33 Seasonal model (Winters' method) Alpha 0.2, Gamma 0.3 (SAP default) Event Management | 60.47 | 72.60\% | 69.81\% | 70.24\% | \$ | 35,458 | 33 | 33 | 33 | 33 | 33 |
| 34 Seasonal model (Winters' method) Alpha, Gamma Fitted Event Management | 60.47 | 72.60\% | 69.81\% | 70.24\% | \$ | 35,458 | 33 | 33 | 33 | 33 | 33 |
| 35 Seasonal Trend Model (Holt-Winters' method) Alpha 0.2, Beta 0.1, Gamma 0.3 (SAP default) Baseline | 66.95 | 83.04\% | 80.00\% | 80.22\% | \$ | 39,723 | 35 | 35 | 35 | 35 | 35 |
| 36 Seasonal Trend Model (Holt-Winters' method) Alpha, Beta, Gamma Fitted Baseline | 66.95 | 83.04\% | 80.00\% | 80.22\% | \$ | 39,723 | 35 | 35 | 35 | 35 | 35 |
| 37 Seasonal Trend Model (Holt-Winters' method) Alpha 0.2, Beta 0.1, Gamma 0.3 (SAP defaut) Event Management | 70.93 | 83.72\% | 81.17\% | 81.43\% | \$ | 40,947 | 37 | 37 | 37 | 37 | 37 |
| 38 Seasonal Trend Model (Holt-Winters' method) Alpha, Beta, Gamma Fitted Event Management | 70.93 | 83.72\% | 81.17\% | 81.43\% | \$ | 40,947 | 37 | 37 | 37 | 37 | 37 |

Table 17. Best-fitting Model - 24 Month

Best Fitting Model

| 60 Month Models | MAE | MAPE | Reveue Weighted MAPE | Margin Weighted MAPE | Cost of Forecast Error |  | \|Rank MAE | Rank MAPE | Rank RWMAPE | Rank MWMAPE | Rank Cost |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| 1 Constant model (1st order exponential smoothing) Alpha Fitted Event Management | 33.29 | 21.81\% | 20.42\% | 20.62\% | \$ | 2,931 | 1 | 4 | 3 | 3 | 1 |
| 2 Trend model (1st order exponential smoothing) Alpha, Beta Fitted Event Management | 33.92 | 21.64\% | 20.05\% | 20.32\% | \$ | 2,941 | 4 | 3 | 1 | 2 |  |
| 3 Weighted Moving Average Model Weighting Group Fitted Event Management | 33.61 | 21.88\% | 20.45\% | 20.65\% | \$ | 2,981 | 2 | 5 | 4 | 4 | 3 |
| 4 Weighted Moving Average Model Weighting Group 1 (SAP defaut) Event Management | 33.73 | 22.11\% | 20.52\% | 20.74\% | \$ | 2,982 | 3 | 7 | 5 | 5 | 4 |
| 5 Trend model (1st order exponential smoothing) Alpha 0.2, Beta 0.1 (SAP defaut) Event Management | 34.05 | 20.78\% | 20.08\% | 20.14\% | \$ | 2,995 | 5 | 1 | 2 | 1 | 5 |
| 6 Trend model (1st order exponential smoothing) Alpha, Beta Fitted Baseline | 34.82 | 22.21\% | 20.54\% | 20.82\% | \$ | 3,000 | 8 | 8 | 6 | 8 | 6 |
| 7 Moving Average Model Historical Values Fitted Event Management | 34.25 | 22.01\% | 20.61\% | 20.82\% | \$ | 3,035 | 6 | 6 | 7 | 7 | 7 |
| 8 Constant model (1st order exponential smoothing) Alpha Fitted Baseline | 34.81 | 23.03\% | 21.29\% | 21.49\% | \$ | 3,046 | 7 | 10 | 10 | 10 | 8 |
| 9 Constant model (1st order exponential smoothing) Alpha 0.2 (SAP default) Event Management | 35.09 | 23.14\% | 22.09\% | 22.21\% | \$ | 3,069 | 10 | 12 | 16 | 15 | 9 |
| 10 Weighted Moving Average Model Weighting Group Fitted Baseline | 35.05 | 22.98\% | 21.22\% | 21.43\% | \$ | 3,091 | 9 | 9 | 9 | 9 | 10 |
| 11 Trend model (1st order exponential smoothing) Alpha 0.2, Beta 0.1 (SAP defaut) Baseline | 35.65 | 21.51\% | 20.70\% | 20.78\% | \$ | 3,095 | 13 | 2 | 8 | 6 | 11 |
| 12 Weighted Moving Average Model Weighting Group 1 (SAP default) Baseline | 35.42 | 23.30\% | 21.40\% | 21.63\% | \$ | 3,105 | 12 | 14 | 11 | 11 | 12 |
| 13 Constant model (1st order exponential smoothing) Automatic Alpha Adaptation Event Management | 35.98 | 23.47\% | 21.40\% | 21.66\% | \$ | 3,106 | 15 | 16 | 12 | 13 | 13 |
| 14 Moving Average Model Historical Values Fitted Baseline | 35.93 | 23.24\% | 21.45\% | 21.65\% | \$ | 3,164 | 14 | 13 | 13 | 12 | 14 |
| 15 Constant model (1st order exponential smoothing) Automatic Alpha Adaptation Baseline | 36.99 | 24.30\% | 22.01\% | 22.27\% | \$ | 3,180 | 19 | 18 | 15 | 16 | 15 |
| 16 Constant model (1st order exponential smoothing) Alpha 0.2 (SAP default) Baseline | 36.55 | 24.45\% | 23.01\% | 23.13\% | \$ | 3,181 | 17 | 21 | 26 | 24 | 16 |
| 17 SAP Automatic Model Selection SAP Procedure 2 Event Management | 36.13 | 27.49\% | 26.63\% | 26.41\% | \$ | 3,192 | 16 | 33 | 33 | 33 | 17 |
| 18 Individual SKU Best Historical Fit Baseline | 35.40 | 24.83\% | 22.63\% | 22.77\% | \$ | 3,220 | 11 | 23 | 21 | 19 | 18 |
| 19 SAP Automatic Model Selection SAP Procedure 2 Baseline | 37.12 | 28.53\% | 27.45\% | 27.24\% | \$ | 3,259 | 20 | 35 | 35 | 35 | 19 |
| 20 Trend model (2nd order exponential smoothing) Alpha 0.2 (SAP defaut) Event Management | 37.56 | 23.10\% | 21.57\% | 21.80\% | \$ | 3,321 | 21 | 11 | 14 | 14 | 20 |
| 21 Individual SKU Best Historical Fit Event Management | 36.89 | 23.46\% | 22.55\% | 22.50\% | \$ | 3,349 | 18 | 15 | 19 | 18 | 21 |
| 22 Seasonal model (Winters' method) Alpha, Gamma Fitted Baseline | 38.27 | 25.17\% | 22.88\% | 23.18\% | \$ | 3,349 | 22 | 25 | 25 | 26 | 22 |
| 23 Seasonal model (Winters' method) Alpha, Gamma Fitted Event Management | 38.31 | 25.20\% | 22.86\% | 23.16\% | \$ | 3,356 | 23 | 26 | 24 | 25 | 23 |
| 24 Seasonal Trend Model (Holt-Winters' method) Alpha, Beta, Gamma Fitted Baseline | 39.17 | 25.26\% | 22.54\% | 22.98\% | \$ | 3,419 | 25 | 27 | 18 | 22 | 24 |
| 25 Seasonal Trend Model (Holt-Winters' method) Alpha, Beta, Gamma Fitted Event Management | 39.17 | 25.42\% | 22.59\% | 23.02\% | \$ | 3,423 | 26 | 29 | 20 | 23 | 25 |
| 26 Seasonal Trend Model (Holt-Winters' method) Alpha 0.2, Beta 0.1, Gamma 0.3 (SAP defaut) Baseline | 39.83 | 24.35\% | 22.73\% | 22.93\% | \$ | 3,428 | 29 | 19 | 22 | 20 | 26 |
| 27 Seasonal Trend Model (Holt-Winters' method) Alpha 0.2, Beta 0.1, Gamma 0.3 (SAP defaut) Event Management | 39.84 | 24.45\% | 22.76\% | 22.95\% | \$ | 3,430 | 30 | 20 | 23 | 21 | 27 |
| 28 Seasonal model (Winters' method) Alpha 0.2, Gamma 0.3 (SAP default) Event Management | 39.99 | 25.36\% | 23.55\% | 23.78\% | \$ | 3,436 | 31 | 28 | 29 | 29 | 28 |
| 29 Trend model (2nd order exponential smoothing) Alpha 0.2 (SAP defaut) Baseline | 39.18 | 24.04\% | 22.24\% | 22.48\% | \$ | 3,442 | 27 | 17 | 17 | 17 | 29 |
| 30 Seasonal model (Winters' method) Alpha 0.2, Gamma 0.3 (SAP default) Baseline | 40.14 | 25.52\% | 23.68\% | 23.91\% | \$ | 3,448 | 32 | 30 | 30 | 30 | 30 |
| 31 Naïve 1 Event Management | 39.00 | 24.72\% | 23.26\% | 23.43\% | \$ | 3,468 | 24 | 22 | 27 | 27 | 31 |
| 32 Naïve 1 Baseline | 39.25 | 25.02\% | 23.47\% | 23.63\% | \$ | 3,493 | 28 | 24 | 28 | 28 | 32 |
| 33 Trend model (2nd order exponential smoothing) Automatic Alpha Adaptation Event Management | 41.68 | 26.28\% | 25.15\% | 25.30\% | \$ | 3,761 | 33 | 31 | 31 | 31 | 33 |
| 34 Trend model (2nd order exponential smoothing) Alpha Fitted Event Management | 46.44 | 27.57\% | 27.18\% | 27.19\% | \$ | 3,813 | 35 | 34 | 34 | 34 | 34 |
| 35 Trend model (2nd order exponential smoothing) Automatic Alpha Adaptation Baseline | 42.79 | 27.03\% | 25.72\% | 25.88\% | \$ | 3,843 | 34 | 32 | 32 | 32 | 35 |
| 36 Trend model (2nd order exponential smoothing) Alpha Fitted Baseline | 47.85 | 28.58\% | 27.98\% | 28.01\% | \$ | 3,913 | 36 | 36 | 36 | 36 | 36 |
| 37 Moving Average Model 24 Historical Values (SAP Default) Event Management | 49.48 | 30.55\% | 30.13\% | 30.13\% | \$ | 4,173 | 37 | 37 | 37 | 37 | 37 |
| 38 Moving Average Model 24 Historical Values (SAP Defaut) Baseline | 49.87 | 31.53\% | 30.79\% | 30.79\% | \$ | 4,210 | 38 | 38 | 38 | 38 | 38 |

Table 18. Best-fitting Model - 60 Month

The next Chapter analyses both the financial impact and statistical significance of the results in relation to the research questions.

### 6.0 ANALYSIS

This Chapter analyses the results of the case study in relation to the research questions presented in Chapter 3.0 (Methodology). The primary objective of this case study is to identify and evaluate the $S A P^{\circledR}$ sales forecasting method that provides the "best-fit" for the company's sales forecasting requirements, taking into consideration the impact of fitting, event management adjustment, and the commercial importance of forecast errors.

As stated in the introduction, the research approach detailed in the preceding sections can serve as a template for businesses wishing to evaluate their ERP based forecasting systems and gain higher levels of customer service while minimising inventory holding cost. However, the results and analysis are case specific.

To reiterate from Chapter 4.0 (Data Collection), the time series consist of 10 SKUs with 60 months of historical sales data each and 40 SKUs with 24 months of historical sales data each, equating to approximately 7\% of active SKUs held by the company. To arrive at a total company cost of forecast error the cost of each model has therefore been multiplied by 14.285 to extrapolate the $7 \%$ sample to $100 \%$. The average total inventory holding cost to the company is approximately $\$ 4,000,000$ New Zealand dollars with sales of $\$ 24,000,000$.

Tests for statistical significance are applied as follows:
(a) Default versus fitted smoothing parameters: Matched t-test applied to MAE and CFE (Table 19 and Table 20)
(b) Baseline forecasts versus event management adjusted forecasts: Matched t-test applied to MAE and CFE (Table 21 and Table 22)
(c) Best-fitting Method: ANOVA (repeated measures) applied to MAE and CFE (Table 23 and Table 24)
(d) Coefficient of determination $\left(r^{2}\right)$ applied to ranked forecast error measures (Table 25 and Table 26)

Significant results for Tables 13, 14, 15, and 16 are shown against a Bonferroni adjustment, i.e. $\mathrm{p}<0.05$ is divided by the total number of applicable tests. The Bonferroni adjustment ensures multiple tests remain statistically significant by reducing the $p$ value (Moore \& McCabe, 1993).

### 6.1 SAP ${ }^{\circledR}$ Default versus Fitted Smoothing Parameters

In the case of the 24 month models (Table 14. $\mathrm{SAP} ®^{\circledR}$ Default versus Fitted Smoothing Parameters) historical fitting outperformed the SAP ${ }^{\circledR}$ default in $75.00 \%$ of cases ( 3 out of the 4 models) based on MAE, $25.00 \%$ of cases for MAPE, $50.00 \%$ of cases for RW-MAPE, $25.00 \%$ of cases for MW-MAPE, and $50.00 \%$ of cases for Cost of Forecast Error. The overall average improvement across all products was -1.26 (units) for MAE, $-0.64 \%$ for MAPE, $-1.11 \%$ for RW-MAPE, $-1.11 \%$ for MW-MAPE, and a cost of forecast error reduction of $\$ 467$.

The mean fitted improvement for all applicable 24 month models based on total cost of forecast error was $2.01 \%$ (average total cost of forecast error of $\$ 23,698$ for SAP ${ }^{\circledR}$ default versus $\$ 23,231$ for fitted models) and for MAE was $3.22 \%$.

For the 60 month models (Table 14. SAP® Default versus Fitted Smoothing Parameters) historical fitting outperformed the SAP ${ }^{\circledR}$ default in $85.71 \%$ of cases (6 out of the 7 models) based on MAE, $57.14 \%$ of cases for MAPE, $85.71 \%$ of cases for RWMAPE, $57.14 \%$ of cases for MW-MAPE, and $85.71 \%$ of cases for Cost of Forecast Error. The overall average improvement across all products was -1.53 (units) for MAE, $-0.60 \%$ for MAPE, $-0.95 \%$ for RW-MAPE, $-0.87 \%$ for MW-MAPE, and a cost of forecast error reduction of \$133.

The mean fitted improvement for all 60 month models based on total cost of forecast error was $4.04 \%$ (average cost of forecast error of $\$ 3,416$ for $S A P^{\circledR}$ default versus $\$ 3283$ for fitted models) and for MAE was also 4.04\%.

The matched t-test was used to determine the statistical significance of the applicable models by comparing the SKU level MAE and CFE differences between default smoothing parameters and fitted smoothing parameters. Significant results are shown against a Bonferroni adjustment, i.e. significant at the $\mathrm{p}<0.0125$ for Table 13 and significant at the $\mathrm{p}<0.007142857$ for Table 14. The Bonferroni adjustment ensures multiple tests remain statistically significant by reducing the $p$ value.

| Default versus Fitted Matched t-test for 24 Month Models |  |  |  |  |
| :--- | :---: | :---: | :---: | :---: |
| Siginifcant at the 0.0125 level (equivalent to p<0.05 for a single t-test) | Mean Absolute Error | Cost of Forecast Error |  |  |
| Constant model (1st order exponential smoothing) | p value | Significant | p value | Significant |
| Moving Average Model | 0.346 | No | 0.007 | Yes |
| Trend model (1st order exponential smoothing) | 0.139 | No | 0.074 | No |
| Trend model (2nd order exponential smoothing) | 0.312 | No | 0.015 | No |

Table 19. SAP ${ }^{\circledR}$ Default versus Fitted Smoothing Parameters Matched t-test 24 Month Models

The matched t-test of default versus fitted smoothing parameters for 24 month models (Table 19) was found to be statistically significant for one model based on MAE (trend model $2^{\text {nd }}$ order exponential smoothing). Two of the four models (constant model $1^{\text {st }}$ order and trend model $2^{\text {nd }}$ order) were found to be significant based on cost of forecast error.

| Default versus Fitted Matched t-test for $\mathbf{6 0}$ Month Models | Mean Absolute Error |  | Cost of Forecast Error |
| :--- | :---: | :---: | :---: |
| Siginifcant at the 0.007142857 level (equivalent to p<0.05 for a single t-test) | p value | Significant | p value |
| Significant |  |  |  |
| Constant model (1st order exponential smoothing) | 0.012 | No | 0.018 |
| Moving Average Model | No |  |  |
| Weighted Moving Average Model | 0.001 | Yes | 0.001 |
| Trend model (1st order exponential smoothing) | 0.147 | No | 0.358 |
| Trend model (2nd order exponential smoothing) | 0.325 | No | 0.238 |
| Seasonal model (Winters' method) | No |  |  |
| Seasonal Trend Model (Holt-Winters' method) | No |  |  |

Table 20. SAP ${ }^{\circledR}$ Default versus Fitted Smoothing Parameters Matched t-test 60 Month Models

The matched t-test of default versus fitted smoothing parameters for 60 month models (Table 20) was found to be statistically significant for the moving average model based on both MAE and CFE.

### 6.2 Baseline Forecasts versus Event Management Adjusted Forecasts

In the case of the 24 month models (Table 15), event management adjustment outperformed baseline forecasts in $73.68 \%$ of cases (14 out of the 19 models) based on MAE, MAPE, RW-MAPE, MW-MAPE, and cost of forecast error. The overall average comparisons were +0.38 (units) for MAE (an unfavorable result for event management), $-0.32 \%$ for MAPE, $-0.43 \%$ for RW-MAPE, $-0.47 \%$ for MW-MAPE, and a cost of forecast error reduction of $\$ 106$ across all models.

The mean event management adjusted improvement for all 24 month models based on total cost of forecast error was $0.39 \%$ (average cost of forecast error of $\$ 27,143$ for baseline forecasts versus $\$ 27,038$ for event management adjusted forecasts) and for MAE was -0.84\% (unfavorable).

For the 60 month models (Table 10) event management adjustment outperformed the baseline forecasts in $78.95 \%$ of cases (15 of the 19 models) based on MAE, 84.21\% of cases for MAPE, 89.47\% of cases for RW-MAPE, 89.47\% of cases for MW-MAPE, and $78.95 \%$ of cases for cost of forecast error. The overall average improvements were -0.83 (units) for MAE, $-0.76 \%$ for MAPE, $-0.52 \%$ for RW-MAPE, $0.54 \%$ for MW-MAPE, and a cost of forecast error reduction of $\$ 59$ across all models. The mean event management adjusted improvement for all 60 month models based on total cost of forecast error was $1.79 \%$ (average cost of forecast error of $\$ 3,363$ for baseline forecasts versus $\$ 3,303$ for event management adjusted forecasts) and for MAE was 2.18\%.

The matched t-test was used to determine the statistical significance of the applicable models by comparing the SKU level MAE and CFE differences between baseline and event management adjusted forecasts for adjusted SKUs only (18 SKUs (45\%) of the 24 month data set and 3 SKUs (30\%) of the 60 month data set). Significant results are shown against a Bonferroni adjustment, i.e. significant at the $\mathrm{p}<0.002631579$
for both Table 15 and Table 16. The Bonferroni adjustment ensures multiple tests remain statistically significant by reducing the $p$ value.

| Baseline versus Event Management Adjusted Matched T-Test | Mean Absolute Error |  | Cost of Forecast Error |  |
| :---: | :---: | :---: | :---: | :---: |
| Siginifcant at the 0.002631579 level (equivalent to $\mathrm{p}<0.05$ for a single t-test) | $p$ value | Significant | p value | Significant |
| Constant model (1st order exponential smoothing) Alpha 0.2 (SAP default) | 0.266 | No | 0.102 | No |
| Constant model (1st order exponential smoothing) Alpha Fitted | 0.190 | No | 0.074 | No |
| Constant model (1st order exponential smoothing) Automatic Alpha Adaptation | 0.427 | No | 0.265 | No |
| Moving Average Model 24 Historical Values (SAP Default) | 0.382 | No | 0.157 | No |
| Moving Average Model Historical Values Fitted | 0.295 | No | 0.138 | No |
| Weighted Moving Average Model Weighting Group 1 (SAP default) | 0.204 | No | 0.060 | No |
| Weighted Moving Average Model Weighting Group Fitted | 0.204 | No | 0.060 | No |
| Trend model (1st order exponential smoothing) Alpha 0.2, Beta 0.1 (SAP default) | 0.347 | No | 0.140 | No |
| Trend model (1st order exponential smoothing) Alpha, Beta Fitted | 0.284 | No | 0.119 | No |
| Trend model (2nd order exponential smoothing) Alpha 0.2 (SAP default) | 0.311 | No | 0.135 | No |
| Trend model (2nd order exponential smoothing) Alpha Fitted | 0.277 | No | 0.115 | No |
| Trend model (2nd order exponential smoothing) Automatic Alpha Adaptation | 0.342 | No | 0.187 | No |
| Seasonal model (Winters' method) Alpha 0.2, Gamma 0.3 (SAP default) | 0.037 | No | 0.062 | No |
| Seasonal model (Winters' method) Alpha, Gamma Fitted | 0.037 | No | 0.062 | No |
| Seasonal Trend Model (Holt-Winters' method) Alpha 0.2, Beta 0.1, Gamma 0.3 (SAP default) | 0.056 | No | 0.052 | No |
| Seasonal Trend Model (Holt-Winters' method) Alpha, Beta, Gamma Fitted | 0.056 | No | 0.052 | No |
| Individual SKU Best Historical Fit | 0.150 | No | 0.189 | No |
| SAP Automatic Model Selection SAP Procedure 2 | 0.212 | No | 0.079 | No |
| Naïve 1 | 0.406 | No | 0.187 | No |

Table 21. Baseline versus Event Management Adjusted Matched t-test 24 Month Models
In relation to 24 month models the matched t-test of baseline forecasts versus event management adjusted forecasts (Table 21) was not found to be statistically significant.

| 60 Month Models |  |  |  |  |
| :---: | :---: | :---: | :---: | :---: |
| Baseline versus Event Management Adjusted Matched T-Test | Mean Absolute Error |  | Cost of Forecast Error |  |
| Siginifcant at the $\mathbf{0 . 0 0 2 6 3 1 5 7 9}$ level (equivalent to $\mathrm{p}<0.05$ for a single t-test) | $p$ value | Significant | $p$ value | Significant |
| Constant model (1st order exponential smoothing) Alpha 0.2 (SAP default) | 0.077 | No | 0.025 | No |
| Constant model (1st order exponential smoothing) Alpha Fitted | 0.082 | No | 0.030 | No |
| Constant model (1st order exponential smoothing) Automatic Alpha Adaptation | 0.105 | No | 0.051 | No |
| Moving Average Model 24 Historical Values (SAP Default) | 0.049 | No | 0.089 | No |
| Moving Average Model Historical Values Fitted | 0.081 | No | 0.028 | No |
| Weighted Moving Average Model Weighting Group 1 (SAP default) | 0.102 | No | 0.049 | No |
| Weighted Moving Average Model Weighting Group Fitted | 0.078 | No | 0.026 | No |
| Trend model (1st order exponential smoothing) Alpha 0.2, Beta 0.1 (SAP default) | 0.195 | No | 0.179 | No |
| Trend model (1st order exponential smoothing) Alpha, Beta Fitted | 0.165 | No | 0.134 | No |
| Trend model (2nd order exponential smoothing) Alpha 0.2 (SAP default) | 0.087 | No | 0.041 | No |
| Trend model (2nd order exponential smoothing) Alpha Fitted | 0.115 | No | 0.067 | No |
| Trend model (2nd order exponential smoothing) Automatic Alpha Adaptation | 0.088 | No | 0.055 | No |
| Seasonal model (Winters' method) Alpha 0.2, Gamma 0.3 (SAP default) | 0.294 | No | 0.317 | No |
| Seasonal model (Winters' method) Alpha, Gamma Fitted | 0.431 | No | 0.389 | No |
| Seasonal Trend Model (Holt-Winters' method) Alpha 0.2, Beta 0.1, Gamma 0.3 (SAP default) | 0.480 | No | 0.433 | No |
| Seasonal Trend Model (Holt-Winters' method) Alpha, Beta, Gamma Fitted | 0.497 | No | 0.449 | No |
| Individual SKU Best Historical Fit | 0.160 | No | 0.123 | No |
| SAP Automatic Model Selection SAP Procedure 2 | 0.138 | No | 0.110 | No |
| Weighted Moving Average Model Weighting Group 1 (SAP default) | 0.216 | No | 0.193 | No |

Table 22. Baseline versus Event Management Adjusted Matched t-test 24 Month Models
For the 60 month models the matched $t$-test of baseline forecast versus event management adjusted (Table 22) was not found to be statistically significant.

### 6.3 Best-fitting Model

For the 24 month models (Table 17) the least cost of forecast error model at $\$ 22,024$ was the trend model (2 ${ }^{\text {nd }}$ order exponential smoothing) with alpha fitted and event management. The second best performer was the moving average historical values fitted and event management. It is notable that although the moving average produced the second least cost forecast it ranked $17^{\text {th }}$ out of 38 based on MAE. The moving average model was subject to large deviations on five SKUs due to notable trends and inherent lag, which resulted in the poor MAE rating. Although due to the relative margin contributions of the high trend SKUs the model was not negatively impacted on a cost basis. See Appendix B - Sales History Linear Regression and Autocorrelation (ACF) graphs, specifically SKU-24-010, SKU-24-018, SKU-24-030, SKU-24-039, and SKU-24-040).

The worst performing 24 month models, based on a forecast error cost of $\$ 40,947$, were the seasonal trend (Holt-Winter's method) with alpha 0.2, beta 0.1, and gamma 0.3 (SAP ${ }^{\circledR}$ defaults) combined with event management and the seasonal trend (Holt-Winter's method) with alpha, beta, and gamma fitted combined with event management. The same two seasonal trend models also ranked last at 37 equal against all other performance measures. Twenty six of the thirty eight 24 month models outperformed the two naïve model variants (ranked 27 and 28 ) based on cost. The cost of forecast error range from the best performing model to the worst was \$22,024 (trend model (2 $2^{\text {nd }}$ order exponential smoothing) with alpha fitted and event management) to $\$ 40,947$ (both seasonal trend models (Holt-Winter's method) with event management). This range equates to the best performing model operating at $53.7 \%$ of the cost of the worst performing models.

For the 60 month models (Table 18) the best performing model, based on cost of forecast error of $\$ 2,931$ was the constant model ( $1^{\text {st }}$ order exponential smoothing), with
alpha fitted and event management. The worst performing 60 month model was the moving average model with 24 historical values (SAP ${ }^{\circledR}$ default) baseline with a cost of forecast error of $\$ 4,210$. Thirty of the thirty eight 60 month models outperformed the two naïve benchmark model variants (ranked 31 and 32) based on cost. The cost of forecast error range from the best performing model to the worst was $\$ 2,931$ (constant model ( $1^{\text {st }}$ order exponential smoothing) alpha fitted and event management) to \$4,210 (moving average model 24 historical values (SAP ${ }^{\circledR}$ default) baseline). This range equates to the best performing model operating at $69.6 \%$ of the cost of the worst performing model.

Note: Differences between the rankings based on the five performance measures are explored in section 7.4 (Forecast Error Measures).

Appendix C (Model Fitting Parameters) provides smoothing/weighting parameters and details of the $\mathrm{SAP}^{\circledR}$ automatic model selection parameters. It can be seen from Appendix C that the $\mathrm{SAP}^{\circledR}$ automatic model selection - $\mathrm{SAP}^{\circledR}$ procedure 2 has indeed selected varying models and smoothing parameter combinations based on tests of trend, seasonality, and MAE in the historical sales data set.

Extrapolated forecast error cost curves are shown in Figure 15 (24 Month), Figure 16 ( 60 Month) and Figure 17 (combined 24 month and 60 month data set). Only the best performing model from each category is shown, i.e. constant, trend, seasonal, seasonal trend, individual SKU best historical fit, SAP ${ }^{\circledR}$ automatic model selection, and the naïve1 as the benchmark model. It is important to note that the cost curves have been extrapolated to reflect the total costs associated with forecast error over the company's entire product portfolio. To recapitulate, the time series consists of 10 SKUs with 60 months of historical sales data each and 40 SKUs with 24 months of historical sales data each, equating to approximately $7 \%$ of active SKUs. To arrive at a total
company cost of forecast error the cost of each model has therefore been multiplied by
14.285 to extrapolate the $7 \%$ sample to $100 \%$.


Figure 15. Extrapolated Forecast Error Cost Curves - 24 Month Models


Figure 16. Extrapolated Forecast Error Cost Curves - 60 Month Models


Figure 17. Combined Extrapolated Forecast Error Cost Curves

The 24 month cost curves show the trend model (2nd order exponential smoothing) alpha fitted and EM as the least cost at $\$ 287,922$, followed by moving average model historical values fitted and EM at $\$ 288,860$ (+0.32\% higher than the least cost model), SAP ${ }^{\circledR}$ automatic model selection SAP $^{\circledR}$ procedure and EM at $\$ 289,598$ (+0.58\%), individual sku best historical fit baseline at $\$ 304,146$ ( $+5.33 \%$ ), naïve1 baseline at $\$ 360,474$ (+20.13\%), seasonal model (Winters' method) alpha 0.2, gamma 0.3 (SAP ${ }^{\circledR}$ default) baseline at $\$ 450,786(+36.13 \%)$, and finally the seasonal trend model (Holt-Winters' method) alpha 0.2 , beta 0.1 , gamma 0.3 (SAP ${ }^{\circledR}$ default) baseline at $\$ 518,407$ ( $+44.46 \%$ ) being the most costly model.

The 60 month cost curves show the constant model (1st order exponential smoothing) alpha fitted and EM at $\$ 41,391$, followed by trend model (1st order exponential smoothing) alpha, beta fitted and EM at \$41,520 (+0.31\% higher than the least cost model), SAP $^{\circledR}$ automatic model selection SAP $^{\circledR}$ procedure 2 and EM at \$45,182 (+8.38\%), individual sku best historical fit baseline at $\$ 45,511$ (+9.05\%), seasonal model (Winters' method) alpha, gamma fitted baseline at \$47,278 (+12.45\%), seasonal trend model (Holt-Winters' method) alpha 0.2 , beta 0.1 , gamma 0.3 (SAP ${ }^{\circledR}$ default) baseline at $\$ 48,220$ (+14.16\%), and naïve1 baseline at $\$ 49,352$ (+16.13\%) being the most costly model using the 60 month data set.

The combined (Figure 17. Combined Extrapolated Forecast Error Cost Curves) cost curves show the moving average model historical values fitted and EM at $\$ 332,532$, SAP ${ }^{\circledR}$ automatic model selection SAP $^{\circledR}$ procedure 2 and EM at $\$ 335,736$ (+0.95\%), trend model (2nd order exponential smoothing) alpha fitted and EM at $\$ 342,932$ (+3.03\%), individual sku best historical fit and EM at $\$ 360,803$ (+7.83\%), naïve1 baseline at \$410,782 (+19.04\%), seasonal model (Winters' method) alpha, gamma fitted baseline at $\$ 498,939$ (+33.35\%), and the seasonal trend model (Holt-Winters' method) alpha 0.2, beta 0.1, gamma 0.3 (SAP ${ }^{\circledR}$ default) baseline at $\$ 567,478$ ( $+41.40 \%$ ). The cost curves
also demonstrate that the lowest cost is achieved by a service level of approximately $98 \%(k \approx 2.0)$ as opposed to the $95 \%$ service level ( $k \approx 1.6$ ) used in determining the costs of forecast error in Table 17 and Table 18. The difference in service level also accounts for the slight change in model ranking by cost of forecast error, i.e. cost curve results versus best-fit tables (Table 17 and Table 18). The high service level reflects the high margins (average SKU margin of 68.4\%) associated with the case study's data set and as such is not to be taken as a generalisable finding.

| Repeated Measures ANOVA | MAE 24 Month |  |  |
| :---: | :---: | :---: | :---: |
| $P$ value | $\mathrm{P}<0.0001$ |  |  |
| $P$ value summary | *** |  |  |
| Are means signif. different? ( $P$ < 0.05) | Yes |  |  |
| Number of groups | 38 |  |  |
| F | 6.683 |  |  |
| R squared | 0.1463 |  |  |
| Was the pairing significantly effective? |  |  |  |
| R squared | 0.8776 |  |  |
| F | 310.8 |  |  |
| $P$ value | $\mathrm{P}<0.0001$ |  |  |
| $P$ value summary | *** |  |  |
| Is there significant matching? ( $\mathrm{P}<0.05$ ) | Yes |  |  |
| ANOVA Table | SS df |  | MS |
| Treatment (between columns) | 164800 | 37 | 4454 |
| Individual (between rows) | 8078000 | 39 | 207100 |
| Residual (random) | 961600 | 1443 | 666.4 |
| Total | 9205000 | 1519 |  |
| Repeated Measures ANOVA | CFE 24 Month |  |  |
| $P$ value | $\mathrm{P}<0.0001$ |  |  |
| $P$ value summary | *** |  |  |
| Are means signif. different? ( $\mathrm{P}<0.05$ ) | Yes |  |  |
| Number of groups | 38 |  |  |
| F | 13.61 |  |  |
| R squared | 0.2587 |  |  |
| Was the pairing significantly effective? |  |  |  |
| R squared | 0.7655 |  |  |
| F | 163 |  |  |
| $P$ value | $\mathrm{P}<0.0001$ |  |  |
| $P$ value summary | *** |  |  |
| Is there significant matching? ( $\mathrm{P}<0.05$ ) | Yes |  |  |
| ANOVA Table | SS df |  | MS |
| Treatment (between columns) | 35210000 | 37 | 951600 |
| Individual (between rows) | 4.44E+08 | 39 | 11400000 |
| Residual (random) | $1.01 \mathrm{E}+08$ | 1443 | 69920 |
| Total | 5.81E+08 | 1519 |  |

Table 23. Repeated Measures ANOVA for 24 Month Models

| Repeated Measures ANOVA | MAE 60 Month |  |  |
| :---: | :---: | :---: | :---: |
| $P$ value | $\mathrm{P}<0.0001$ |  |  |
| $P$ value summary | *** |  |  |
| Are means signif. different? $(P<0.05)$ | Yes |  |  |
| Number of groups | 38 |  |  |
| F | 2.573 |  |  |
| R squared | 0.2224 |  |  |
| Was the pairing significantly effective? |  |  |  |
| R squared | 0.8713 |  |  |
| F | 322 |  |  |
| $P$ value | $\mathrm{P}<0.0001$ |  |  |
| $P$ value summary | *** |  |  |
| Is there significant matching? ( $\mathrm{P}<0.05$ ) | Yes |  |  |
| ANOVA Table | SS df |  | MS |
| Treatment (between columns) | 6773 | 37 | 183.1 |
| Individual (between rows) | 206100 | 9 | 22900 |
| Residual (random) | 23690 | 333 | 71.14 |
| Total | 236600 | 379 |  |
| Repeated Measures ANOVA | CFE 60 Month |  |  |
| $P$ value | $\mathrm{P}<0.0001$ |  |  |
| $P$ value summary | *** |  |  |
| Are means signif. different? ( $\mathrm{P}<0.05$ ) | Yes |  |  |
| Number of groups | 38 |  |  |
| F | 3.775 |  |  |
| R squared | 0.2955 |  |  |
| Was the pairing significantly effective? |  |  |  |
| R squared | 0.9496 |  |  |
| F | 989.9 |  |  |
| P value | $\mathrm{P}<0.0001$ |  |  |
| $P$ value summary | *** |  |  |
| Is there significant matching? ( $\mathrm{P}<0.05$ ) | Yes |  |  |
| ANOVA Table | SS df |  | MS |
| Treatment (between columns) | 395900 | 37 | 10700 |
| Individual (between rows) | 25250000 | 9 | 2806000 |
| Residual (random) | 943800 | 333 | 2834 |
| Total | 26590000 | 379 |  |

Table 24. Repeated Measures ANOVA for 60 Month Models

An analysis of variance (ANOVA) was performed at SKU level across all models for MAE and forecast error cost and found to be highly significant ( $p<0.0001$ ) for both the 24 month and 60 month series (Table 23 and Table 24).

### 6.4 Forecast Error Measures

Table 25 (24 month data set) and Table 26 ( 60 month data set) detail the goodness of fit statistics for ranked MAE, MAPE, RW-MAPE, and MW-MAPE against cost of forecast error. Corresponding charts are shown in Figure 18 (24 month data set) and Figure 19 (60 month data set).

In the case of the 24 month data set the $\mathrm{r}^{2}$ of the ranked MAE is the lowest correlation at 0.7578 . However, for the 60 month data set the $r^{2}$ of the ranked MAE is found to have the highest correlation at 0.9623 . Although, as can be seen in Figure 18 (24 month data set) and Figure 19 (60 month data set) a high degree of deviation from the ranked cost line applies to all error measures. In the case of the three MAPE variants (MAPE, RW-MAPE, and MW-MAPE) MW-MAPE has the highest $r^{2}$ for both the 24 month data set $\left(r^{2}=0.9321\right)$ and the 60 month data set $\left(r^{2}=0.9173\right)$ demonstrating a higher correlation with CFE than MAPE and RW-MAPE.

| 24 Month Models | Rank MAE | Rank MAPE | Rank RW-MAPE | Rank MW-MAPE |
| :---: | :---: | :---: | :---: | :---: |
| Goodness of Fit |  |  |  |  |
| $\mathrm{r}^{2}$ | 0.7578 | 0.9089 | 0.9196 | 0.9321 |
| Sy.x | 5.492 | 3.361 | 3.156 | 2.9 |
| Is slope significantly non-zero? |  |  |  |  |
| F | 112.6 | 359.3 | 411.8 | 494.4 |
| DFn, DFd | 1.000, 36.00 | 1.000, 36.00 | 1.000, 36.00 | 1.000, 36.00 |
| $P$ value | < 0.0001 | < 0.0001 | < 0.0001 | < 0.0001 |
| Deviation from zero? | Significant | Significant | Significant | Significant |
| Data |  |  |  |  |
| Number of $X$ values | 38 | 38 | 38 | 38 |
| Maximum number of $Y$ replicates | 1 | 1 | 1 | 1 |
| Total number of values | 38 | 38 | 38 | 38 |
| Number of missing values | 0 | 0 | 0 | 0 |

Table 25. Error Measure Correlation (24 Month)

| 60 Month Models | Rank MAE | Rank MAPE | Rank RW-MAPE | Rank MW-MAPE |
| :---: | :---: | :---: | :---: | :---: |
| Goodness of Fit |  |  |  |  |
| $\mathrm{r}^{2}$ | 0.9623 | 0.8886 | 0.9131 | 0.9173 |
| Sy.x | 2.188 | 3.76 | 3.321 | 3.24 |
| Is slope significantly non-zero? |  |  |  |  |
| F | 918.5 | 287.2 | 378.4 | 399.4 |
| DFn, DFd | 1.000, 36.00 | 1.000, 36.00 | 1.000, 36.00 | 1.000, 36.00 |
| $P$ value | < 0.0001 | < 0.0001 | < 0.0001 | < 0.0001 |
| Deviation from zero? | Significant | Significant | Significant | Significant |
| Data |  |  |  |  |
| Number of $X$ values | 38 | 38 | 38 | 38 |
| Maximum number of $Y$ replicates | 1 | 1 | 1 | 1 |
| Total number of values | 38 | 38 | 38 | 38 |
| Number of missing values | 0 | 0 | 0 | 0 |

Table 26. Error Measure Correlation (60 Month)


Figure 18. Correlation of Ranked Measures (24 Month)


Figure 19. Correlation of Ranked Measures (60 Month)


Figure 20. Mean Absolute Error versus Cost of Forecast Error

Figure 20 provides a clear example of the deviations of MAE versus Cost of Forecast Error (CFE). This example uses the constant model ( $1^{\text {st }}$ order exponential smoothing) fitted with event management adjustment, applied to all 24 month SKUs.

The analysis found the fitting of forecast smoothing parameters using historical data and the differences between forecasting models (best-fit) to be statistically significant. The analysis also supports the evaluation of sales forecasts with cost of forecast error (CFE) as a more commercially useful measure than the widely adopted mean absolute error (MAE) and mean absolute percentage error (MAPE) measures. Event management adjustment of baseline statistical forecasts was not found to be statistically significant. The next Chapter discusses the analysis and draws conclusions.

### 7.0 DISCUSSION AND CONCLUSIONS

This Chapter discusses the results and analysis relating them to prior work and ERP forecasting practice and then makes conclusions regarding each of the four research questions. The conclusions should be viewed as case specific and reflect the particular time series characteristics, costs, and margins of the company in question.

### 7.1 SAP ${ }^{\circledR}$ Default versus Fitted Smoothing Parameters

The first research question concerned the performance of the $S A P^{\circledR}$ default smoothing parameters compared with fitted smoothing parameters. Based on the matched t-test the difference between default and fitted smoothing parameters was statistically significant based on both MAE and CFE (applying a Bonferroni adjustment). In addition to statistical significance, there was an average cost of forecast error reduction of $\$ 467$ for the 24 month models and an average cost of forecast error reduction of $\$ 133$ for the 60 month models.

Both the 24 month and 60 month data set were relatively noisy (containing a high degree of random error) with a coefficient of variation of $42.4 \%$ for the 24 month data set and $25.7 \%$ for the 60 month data set (See Appendix A - Data Set Statistics). This relatively high level of variation could well be responsible for the varying performance of default versus fitted models.

In reviewing the model fitting parameters (Appendix C), in the majority of cases (73\%), across both the 24 month and 60 month data sets, the fitted models used a higher smoothing parameter (more responsive to recent history) than the $\mathrm{SAP}^{\circledR}$ default. The higher smoothing parameters are likely due to the models responding to trend in the data set (Silver, Pyke and Peterson, 1998, p. 107) (refer to Appendix B).

Such relatively high smoothing parameters have been reported in the literature with other studies (Chatfield, 1978; Makridakis et al., 1982) also showing relatively high fitted parameters, i.e. $>0.3$. Gardner (1985) states that there is no evidence to support a restricted range of smoothing parameters and that parameters should be estimated from the data. The $S A P^{\circledR}$ default smoothing parameters provide a relatively high degree of smoothing, i.e. low parameters values, and with the exception of the automatic alpha adaptation models and $\mathrm{SAP}^{\circledR}$ automatic model selection procedure, are arbitrary in nature.

The individual SKU best historical fit method was ranked 15 out of 38 for the 24 month models (Table 11) and 18 out of 38 for the 60 month models (Table12), indicating that such a method may have been subject to over-fitting (Narayan Pant \& Starbuck, 1990). The individual SKU best historical fit method was based on the best historical fit at SKU level as opposed to fit based on the entire data set for the other fitted models. With shortening product life-cycles, the fitting of model parameters over entire groups is suggested by Robb and Silver (2002) to mitigate such potential over-fitting. Also, Fildes et al. (1998) recommend that parameters be re-optimized each time forecasts are made.

The overall conclusion, with respect to research question one, is that the SAP ${ }^{\circledR}$ default parameters perform relatively well, but statistically significant gains were achieved from fitting models to the particular historical data sets used in this case study. In terms of effect size, i.e. commercial impact based on cost of forecast error, the mean improvement of fitting models was $2.01 \%$ for the 24 month data set and $4.04 \%$ for the 60 month data set. The potential benefit of fitting model parameters, extrapolated to total company inventory, represents $0.27 \%$ of total inventory value $(\$ 4,000,000)$, or $\$ 10,929$. (Average extrapolated baseline cost of forecast error is $\$ 451,606$ multiplied by the weighted average fitting improvement $2.42 \%$ ( $2.01 \%$ improvement for 24 month data set ( $80 \%$ of sample) and $4.04 \%$ improvement for 60 month data set ( $20 \%$ of data)).

In consideration of both the statistical significance and effect size (dollar improvement), based on this particular data set, it is suggested that smoothing parameters should be fitted to the case study historical data set to provide statistically significant gains in forecast accuracy.

| Research Question 1: Do the SAP ${ }^{\circledR}$ default forecast model smoothing parameters provide the "Best-fit" forecast for The Company? | Findings |
| :---: | :---: |
| $\mathrm{H} 1_{0}$ : There is no statistically significant difference between the SAP ${ }^{\circledR}$ default smoothing parameters and fitted smoothing parameters, for any of the applicable forecasting models, as measured by the means of Mean Absolute Deviation (MAE). <br> $\mathrm{H} 1_{\mathrm{A}}$ : Fitted smoothing parameters produce a statistically significant better forecast than the SAP ${ }^{\circledR}$ default parameters based on Mean Absolute Deviation (MAE), for any of the applicable forecasting models. | Null Hypothesis <br> Rejected |
| $\mathrm{H}_{0}$ : There is no statistically significant difference between the SAP ${ }^{\circledR}$ default smoothing parameters and fitted smoothing parameters, for any of the applicable forecasting models, as measured by the means of Cost of Forecast Error (CFE). <br> $\mathrm{H} 2_{\mathrm{A}}$ : Fitted smoothing parameters produce a statistically significant better forecast than the $\mathrm{SAP}^{\circledR}$ default parameters based on the Cost of Forecast Error (CFE), for any of the applicable forecasting models. | Null Hypothesis <br> Rejected |

### 7.2 Baseline Forecasts versus Event Management Adjusted Forecasts

The second research question concerned the performance of baseline (unadjusted) forecasts compared with event management adjusted forecasts.

Based on the matched t-test the difference between baseline and event management adjusted forecasts was not statistically significant for either MAE or CFE (based on a Bonferroni adjustment). Although event management adjustment was not statistically significant, there was an average cost of forecast error reduction of $\$ 106$ for the 24 month data set and an average cost of forecast error reduction of $\$ 59$ for the 60 month data set.

In the case of the 24 month data set models all seasonal model variants performed better without event management adjustment, probably due to such models inherently identifying and extrapolating the historical promotional periods without the need for adjustment. Both the 24 month and 60 month data sets used in the case study had promotional periods that took place during the same month each year during the historical (fitting) period. However, one major promotion was changed in the holdout negating any seasonal extrapolation based on previous years. The changing of promotional dates (periods) therefore presents a problem for seasonal exponential smoothing models that have identified and extrapolated such events from earlier periods.

The exclusion of the seasonal models produces a very different result for the average cost of forecast error, with the reduction increasing from $\$ 106$ to $\$ 410$. The same exclusion of the seasonal models sees the mean event management adjusted improvement for all 24 month models based on total cost of forecast error improve to a 2.03\% reduction (average cost of forecast error of $\$ 24,550$ for baseline forecasts versus $\$ 24,063$ for event management adjusted forecasts) and for MAE to a $1.63 \%$ reduction. Notably, a similar, yet less pronounced, result exists for 3 of the 4 seasonal models
applied to the 60 month data set. The exclusion of the 60 month seasonal models sees the total cost of forecast error improve to a $2.29 \%$ reduction (average cost of forecast error of $\$ 3,350$ for baseline forecasts versus $\$ 3,274$ for event management adjusted forecasts) and for MAE to a $2.78 \%$ reduction.

The potential benefit of applying event management (excluding all seasonal models), extrapolated to total company inventory, represents a $0.23 \%$ of total inventory value ( $\$ 4,000,000$ ), or $\$ 9,393$ (Average extrapolated baseline cost of forecast error is $\$ 451,606$ multiplied by the weighted average event management improvement 2.08\% (2.03\% improvement for 24 month data set ( $80 \%$ of sample data) and $2.29 \%$ improvement for 60 month data set (20\% of sample data)).

Assumptions: All SKUs subject to promotional activity, 24 month average improvement plus 60 month average improvement multiplied by 14.285 (7\% sample data set extrapolated to $100 \%$ stock holding).

Based on the results, seasonal models should be used cautiously for the case study data sets that are subject to large promotional impacts if the planned (future) promotional periods differ from that of the past, i.e. changes in month of occurrence or the anticipated effects of future promotions differ from that of historical events.

Irrespective of the lack of statistical significance, the event management adjusted models performed relatively well against most forecast error measures. For the 24 month data set, event management adjusted models take the top 5 positions based on cost of forecast error (Table 17) and for the 60 month models also take the top 5 positions (Table 18). The overall improvements achieved by the event management adjustment of
baseline statistical forecasts are reported in the literature in this area (Armstrong, 2001; Goodwin, 2005; Nikolopoulos et al., 2005).

In conclusion, with respect to research question two, the application of event management should be used cautiously when using seasonal models as historical events could be extrapolated and compounded by further event management adjustment. Although not statistically significant, the event management adjustment of constant and trend models yields notable improvements against all forecast error measures and should be seriously considered by the case company, contingent on the degree and impact of anticipated promotional activities.

| Research Question 2: Does the combination of event management (causal factors) with time series techniques provide a "Better Fit" than the time series techniques alone? | Findings |
| :---: | :---: |
| $\mathrm{H} 1_{0}$ : There is no statistically significant difference between event management combined with time series techniques and time series techniques alone, for any of the applicable forecasting models, as measured by the means of Mean Absolute Deviation (MAE). <br> $\mathrm{H}_{\mathrm{A}}$ : The combination of event management with time series techniques produce a statistically significant better forecast based on Mean Absolute Deviation (MAE), for any of the applicable forecasting models. | Null Hypothesis <br> Supported |
| $\mathrm{H}_{2}$ : There is no statistically significant difference between event management combined with time series techniques and time series techniques alone, for any of the applicable forecasting | Null Hypothesis <br> Supported |


|  | models, as measured by the means of Cost of Forecast Error <br>  <br> (CFE). <br> $\mathrm{H} 2_{A}$ : <br> The combination of event management with time series <br>  <br> techniques produce a statistically significant better forecast |
| :--- | :--- | :--- |
|  |  |
|  | based on the Cost of Forecast Error (CFE), for any of the |
| applicable forecasting models. |  |

For the benefit of practitioners unfamiliar with the concept of statistical significance it is worth noting that the second finding (research question 2) is not considered statistically significant based on the differences in the means of the baseline and event management adjusted forecasts. However, the lack of statistical significance should not detract from the potential economic benefits of applying such approaches - as statistical significance essentially attempts to determine if results could have been produced by chance. Such tests do not provide an indication of the importance of the treatment (e.g. use of a different forecasting model) and as such the statistical term "significance" should not be confused with importance or effect size (economic benefit in the case of this study). For a more detailed treatment of statistical significance testing see Armstrong (2005) "Significance Tests Harm Progress in Forecasting" who argues that significance testing should be abandoned in favour of the use of effect size and confidence intervals so as to not inadvertently discard useful findings.

### 7.3 Best-fitting Model

The third research question concerned identifying the forecast model with the best overall fit. Based on ANOVA the difference between models was highly statistically significant ( $\mathrm{p}<0.0001$ ).

For the 24 month data set (Table 17) the top performing model, based on lowest forecast error cost, was the trend model (2nd order exponential smoothing) with alpha fitted and event management adjustment. The second best performer was the moving average historical values fitted and event management. It is notable that although the moving average produced the second least cost forecast it ranked $17^{\text {th }}$ out of 38 based on MAE. As already stated in Chapter 7.0, the moving average model was subject to large deviations on five SKUs due to notable trends and inherent lag which resulted in the poor MAE rating.

The seasonal models for the 24 month data set all performed poorly and were all less accurate than the two Naive1 models. The poor performance of the seasonal models was anticipated, as applying seasonal techniques to a time series of only 24 months is inappropriate, primarily due to insufficient history to initialize the model ( Armstrong, 2001; Gardner, 1985; Gardner \& Dannenbring, 1980; Pegels, 1969)

The seasonal models performed poorly when they were event management adjusted, likely due to the models wrongly identifying historical promotions and forecasting them accordingly. The difficulty being that when the promotional periods do not occur in the same months as the previous year(s) then a very costly error resulted.

The automatic alpha adaptation models all appeared in the bottom half of the 24 month models. The poor performance of the automatic alpha adaptation models is indicative of the highly noisy data set with a coefficient of variation of $42.4 \%$ (refer Appendix A) which compares to a reported coefficient of variation for electrical goods of $27.26 \%$ (Wacker \& Lummus, 2002). There is also a reported propensity of automatic
alpha adaptation models to overreact and produce poor forecasts (Taylor, 2004). The automatic alpha adaptation models all performed poorly relative to their fixed smoothing parameter equivalents.

For the 60 month data set (Table 18) the top performing model, based on lowest cost of forecast error, was the constant model ( $1^{\text {st }}$ order exponential smoothing) with alpha fitted and event management adjustment. Seven of the top ten 60 month models were constant models with trend models accounting for the remaining three. This mix of constant and trend models appears to reflect the characteristics of the 60 month data set well, as can be seen from the linear regression (trend) charts in Appendix B.

Unlike the 24 month seasonal models, the 60 month seasonal models all performed better than the two Naïve1 models. The improved performance reflects the more appropriate length of the time series and the level of autocorrelation in the data. The autocorrelation charts for the 60 month data set (shown in Appendix B) are testimony to the higher level of seasonality identifiable than in the 24 month data set (also shown in Appendix B). Two of the four automatic alpha adaptation models appeared in the top half of the 60 month models likely reflecting the less noisy characteristics of the data set (coefficient of variation of $25.7 \%$ ). However, like the 24 month models, the automatic alpha adaptation models all performed poorly relative to their fixed smoothing parameter equivalents.

Figure 17 shows the total extrapolated (company level) forecast error costs ranging from $\$ 332,532$ for the moving average model historical values fitted event management to $\$ 567,478$ for the seasonal trend model (Holt-Winters' method) alpha, beta, gamma fitted baseline.

Notably, the theory based (Pegels, 1969) SAP ${ }^{\circledR}$ automatic model selection SAP ${ }^{\circledR}$ procedure 2 with event management performed well at $\$ 335,736$, just $0.95 \%$ more costly than the moving average. The "best-fit" results lend support to the concept of selecting
methods based on the underlying time series characteristics of the data, i.e. level, trend, and seasonality. Such an approach has been strongly advocated in the literature (Armstrong, 2001; Fildes \& Beard, 1992; Gardner, 1985; Gardner \& Dannenbring, 1980; Pegels, 1969).

In conclusion, the results have demonstrated a highly statistically significant difference $(p<0.0001)$ between forecasting models along with substantial differences in costs associated with model accuracy. Naive1 was chosen as a benchmark model with the majority of $\mathrm{SAP}^{\circledR}$ forecasting techniques performing well in relation to the benchmark. The exception being inappropriately applied techniques, namely seasonal and seasonaltrend models using a short data set ( 24 month). The selection of models based on time series characteristics is generally supported by the forecasting literature and advocated in $\mathrm{SAP}^{\circledR>}$ s literature. It is also embedded in the $\mathrm{SAP}^{\circledR}$ automatic selection procedure which performed extremely well for the combined and extrapolated cost curves. Based on this case study data set an indicative range of forecast error costs is between $8.31 \%$ $(\$ 332,532)$ and $14.19 \%(\$ 567,478)$ of total inventory value $(\$ 4,000,000)$ therefore providing a potential saving of $5.87 \%$ ( 234,946 ), being the difference between the best and worst models.

| Research Question 3: Which of the ten available SAP ${ }^{\circledR}$ forecasting models provides the "Best-fit" forecast for the company? | Findings |
| :---: | :---: |
| $\mathrm{H} 1_{0}$ : There is no statistically significant difference between any of the ten available models, as measured by the means of Mean Absolute Deviation (MAE). <br> $\mathrm{H} 1_{A}$ : There is a statistically significant difference between the ten available models, based on Mean Absolute Deviation (MAE). | Null Hypothesis <br> Rejected |
| $\mathrm{H} 2_{0}$ : There is no statistically significant difference between any of the ten available models, as measured by the means of Cost of Forecast Error (CFE). <br> $\mathrm{H} 2_{\mathrm{A}}$ : There is a statistically significant deference between the ten available models, based on the Cost of Forecast Error (CFE). | Null Hypothesis Rejected |

### 7.4 Forecast Error Measures

The fourth and final research question concerned the effectiveness of $S A P^{\circledR}$, primary forecast error measure, mean absolute error, in relation to the commercial impact of the forecast error.

The strongest evidence to support the use of a forecast error cost measure, as opposed to a traditional forecast error measure, is the ranking of MAE versus CFE shown in Table 17 (Best-fitting Model - 24 Month). Table 17 ranks the moving average model historical values fitted and event management at $17^{\text {th }}$ place based on MAE but 2nd place based on CFE. Clearly, a management decision to discount this method based on its MAE performance would have resulted in additional and unnecessary cost to maintain the same level of customer service. A similar pattern emerges for the constant model ( $1^{\text {st }}$ order exponential smoothing) alpha 0.2 (SAP ${ }^{\circledR}$ default) and event management which ranked in $12^{\text {th }}$ place based on MAE and $4^{\text {th }}$ place based on CFE and the moving average model historical values fitted baseline which ranked $21^{\text {st }}$ based on MAE and $6^{\text {th }}$ based on CFE.

As for Table 12 (Best-fitting Model - 60 Month), similar inconsistencies exist, yet they are less pronounced. For example, the trend model ( $1^{\text {st }}$ order exponential smoothing), alpha, beta fitted and event management ranked $4^{\text {th }}$ place based on MAE and $2^{\text {nd }}$ based on CFE.

The low criterion validity of MAE in relation to the CFE has also been reported by Mahmoud and Pegels (1989) stating that "the cost of forecasting error does not appear to be related to any of the other accuracy measures used at the forecast phase". The other forecast accuracy measures used by Mahmoud and Pegels were; MSE, MPE, MAPE, and Theil's U-statistic. The overall ranking of the error measures for the combined 24 month and 60 month data sets was MW-MAPE most highly correlated with CFE at $r^{2}=0.9247$, RW-MAPE $r^{2}=0.9163$, MAPE $r^{2}=0.8987$, and the lowest correlation
being MAE $r^{2}=0.8600$.
To recapitulate, Flores, Olson and Pearce (1993) state "the statistical criteria may not be the most suitable because statistical measures of forecast accuracy are not designed to capture the economic implications associated with managing an inventory system". Roberts and Whybark (1974) consider forecast cost implications as "probably the most essential measure" of forecast model performance.

Armstrong (2001) proposes a forecasting principle that the analysis should be tailored to the decision which supports the conclusion of this case study, being the use of a direct cost of forecasting measure to aid commercial decision making. Irrespective of the correlation (goodness of fit) between MAE and CFE a practitioner obviously cannot gain an appreciation of the relative commercial impact of competing forecast models based purely on MAE alone.

In conclusion, $\mathrm{SAP}^{\circledR}$ s use of mean absolute error is not representative or indicative of the commercial impact of forecast errors.

| Research Question 4: Are the forecast error measures utilised by SAP ${ }^{\circledR}$ representative of the commercial impact of the forecasts? | Findings |
| :---: | :---: |
| $\mathrm{H} 1_{0}$ : $\mathrm{SAP}^{\circledR}{ }^{\circledR}$ s error measures adequately reflect the commercial impact of forecast error. <br> $\mathrm{H} 1_{\mathrm{A}}$ : $\mathrm{SAP}^{\circledR}{ }^{\circledR}$ s error measures do not adequately reflect the commercial impact of forecast error. | Null Hypothesis Rejected |

### 7.5 Return on Investment via Improvements in Sales Forecasting

It has been estimated that the cost of an $\mathrm{SAP}^{\circledR}$ implementation project can be as high 2-3\% of company revenue (Escalle, Cotteleer, \& Austin, 1999). In the particular case of the company that supplied the data for this study the costs of implementing SAP ${ }^{\circledR}$ (licence and implementation consulting costs) was approximately $3.2 \%$ of annual revenue. As stated in section 4.1, enterprise resource planning systems are complex integrated tools, and evaluating such tools in their entirety would be a substantial task requiring a team of researchers. However, as a central indicator of the likely outcome of the application of the $\mathrm{SAP}^{\circledR}$ logistics module to the company, the available demand forecasting models are evaluated.

A common approach to assessing investment decisions is to calculate the net present value (NPV) of the proposed project. NPV is defined by Mills and Robertson (1999) as "the sum of the cash flows discounted at the cost of capital minus the capital outlay". In order to make such a financial assessment the potential forecasting improvements detailed in section 7.3 (Best-fitting Model) have been used. Based on this data set the range of forecast error costs is between \$332,532 (moving average model historical values fitted and EM) and \$567,478 (seasonal trend model (Holt-Winters' method) alpha 0.2, beta 0.1, gamma 0.3 (SAP ${ }^{\circledR}$ default) baseline). This represents an annual cost reduction of $\$ 234,946$ (a best case improvement scenario being the difference between the best and worst models). A second NPV scenario is the improvement between the moving average model historical values fitted and EM $(\$ 332,532)$ and the Naïve1 forecast $(\$ 410,782)$, being an annual cost of forecast error reduction of $\$ 78,250$. The two NPV scenarios are shown in Table 27 and Figure 21 below:

| Year | Worst to Best Discounted Cash Flows |  | Cash Flow |  | Discount | Present Value |  | Naïve1DiscountedCash Flows |  | Cash Flow |  | Discount | Present Value |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| 0 | \$ | $(750,000)$ |  |  |  |  | \$ | $(750,000)$ |  |  |  |  |  |
| 1 | \$ | $(536,413)$ | \$ | 234,946 |  | 0.909 | \$ | 213,587 | \$ | $(678,864)$ | \$ | 78,250 | 0.909 | \$ | 71,136 |
| 2 | \$ | $(342,243)$ | \$ | 234,946 | 0.826 | \$ | 194,170 | \$ | $(614,194)$ | \$ | 78,250 | 0.826 | \$ | 64,670 |
| 3 | \$ | $(165,725)$ | \$ | 234,946 | 0.751 | \$ | 176,518 | \$ | $(555,404)$ | \$ | 78,250 | 0.751 | \$ | 58,790 |
| 4 | \$ | $(5,253)$ | \$ | 234,946 | 0.683 | \$ | 160,471 | \$ | $(501,958)$ | \$ | 78,250 | 0.683 | \$ | 53,446 |
| 5 | \$ | 140,629 | \$ | 234,946 | 0.621 | \$ | 145,883 | \$ | $(453,370)$ | \$ | 78,250 | 0.621 | \$ | 48,587 |
| 6 | \$ | 273,250 | \$ | 234,946 | 0.564 | \$ | 132,621 | \$ | $(409,200)$ | \$ | 78,250 | 0.564 | \$ | 44,170 |
| 7 | \$ | 393,815 | \$ | 234,946 | 0.513 | \$ | 120,564 | \$ | $(369,046)$ | \$ | 78,250 | 0.513 | \$ | 40,155 |
| 8 | \$ | 503,418 | \$ | 234,946 | 0.467 | \$ | 109,604 | \$ | $(332,541)$ | \$ | 78,250 | 0.467 | \$ | 36,504 |
| 9 | \$ | 603,058 | \$ | 234,946 | 0.424 | \$ | 99,640 | \$ | $(299,356)$ | \$ | 78,250 | 0.424 | \$ | 33,186 |
| 10 | \$ | 693,640 | \$ | 234,946 | 0.386 | \$ | 90,582 | \$ | $(269,187)$ | \$ | 78,250 | 0.386 | \$ | 30,169 |
|  |  |  |  |  | NPV | \$ | 693,640 |  |  |  |  | NPV | \$ | $(269,187)$ |

Table 27. Net Present Value of Forecasting Improvements


Figure 21. Discounted Cash Flow Chart

The NPV calculation shown in Table 27 is based on a year 0 implementation cost of $\$ 750,000$ (licenses and consulting). Discounted cash flows are shown in the "Discounted Cash Flow" columns and are a function of subtracting the cash flow (annual CFE reduction) discounted at 10\% per annum from the "Present Value" columns.

The NPV of the first scenario (moving average model historical values fitted and EM improvement cost reduction over the seasonal trend model (Holt-Winters' method) alpha 0.2, beta 0.1 , gamma 0.3 (SAP ${ }^{\circledR}$ default) baseline) is $\$ 693,640$. The NPV of the second scenario (moving average model historical values fitted and EM cost reduction over the Naïve1 forecast) is ( $\$ 269,187$ ). Based on NPV, the first scenario is clearly attractive with the entire costs of the $\mathrm{SAP}^{\circledR}$ implementation being met by the improvement in forecasting (CFE reduction) in year 5. The second scenario fails to provide a positive net present value and as such the forecasting gains alone do not justify the cost of implementing the ERP system.

The NPV analysis makes a number of critical assumptions as follows:

1. The only gains from the implementation of the $S A P^{\circledR}$ ERP system are achieved through a reduction in CFE.
2. The forecasting gains (relative CFE reduction) are constant over the 10 year horizon of the NPV calculation.
3. Ongoing system maintenance, upgrades, and enhancement are not included in the NPV calculation.

Arguably the most important of the three assumptions is that the only benefit from the adoption of $S A P ® E R P$ is a function of CFE reduction. However, Murphy and Simon (2002) report the following tangible and intangible benefits associated with ERP
adoption: Operational (cost reduction, cycle time reduction, productivity improvement, quality improvement), Managerial (better resource management, improved decision making and planning, performance improvement), Strategic (support for business growth, support business alliance, build business innovations, build cost leadership, generate product differentiation, build external linkages), IT Infrastructure (build business flexibility for current and future changes, IT costs reduction, increased IT infrastructure capability), Organisational (support organisational changes, facilitate business learning, empowerment, build common visions). It is therefore important to note that benefits other than CFE reductions should be expected with the adoption of ERP systems. However the CFE reductions alone could be achieved using spreadsheet software such as Microsoft ${ }^{\circledR}$ Excel ${ }^{\circledR}$ and are not conditional on implementing ERP software.

In summary, it is possible that an organisation that has applied a forecasting model which is highly inappropriate, relative to the organisation's sales patterns, could potentially justify the investment in an ERP system (or pay for the existing system) by the adoption of a more appropriate forecasting model. It is notable that the CFE gains achieved in this case study reflect the frequently long overseas procurement lead times in the New Zealand environment, the relatively high margin (average SKU margin of 68.4\%) and the relatively volatile short life-cycle fashion oriented products of the company. As such, it cannot be assumed that a comparable "Best Case" NPV can be obtained under other organisational settings.

The following Chapter presents the implications and recommendations based on the discussion and conclusions.

### 8.0 RECOMMENDATIONS AND DIRECTIONS FOR FURTHER RESEARCH

This Chapter presents the implications of the research findings and makes some consequential recommendations. Directions for further research are then suggested and are drawn to the attention of researchers and $\mathrm{SAP}^{\circledR}$ developers.

### 8.1 Implications of Findings

The implications of the findings are specific to the time series and economic characteristics of the case study data set. In relation to the fitting of smoothing parameters, the study found both a statistically significant and commercially compelling argument in favour of fitting model parameters to historical data.

The application of event management showed small benefits in relation to the total cost of inventory, although the performance of the majority of models did improve based on event management adjustment, which lends support to Armstrong's (2005) notion that significance testing should be ignored in favour of effect size. This assertion implies that a very simple approach to event management adjustment does yield consistent, albeit relatively minor benefits. Depending on the impact that promotional activity has on an organisation, a more sophisticated approach to event management could be considered. Unfortunately a serious limitation of SAP ${ }^{\circledR>}$ S ERP offering is the lack of structured methods for event management adjustment, i.e. there is no incorporation of structured judgmental and/or intervention analysis techniques. The lack of structured methods for event management adjustment of baseline statistical forecasts leaves the practitioner exposed to ad-hoc judgmental adjustments and/or having to perform quantitative analysis outside of $S A P^{\circledR}$, both of which are unsatisfactory approaches for such an important aspect of demand forecasting.

The identification of a "best-fit" model (moving average model with historical values fitted and event management across both 24 month and 60 month data sets) revealed a statistically significant and commercially compelling difference between models. The range of forecast error costs associated with different models represented a notable percentage of total inventory cost and should be viewed as an important finding.

The application of theory based approaches to model selection was demonstrated to be useful, i.e. selection based on time series characteristics such as level, trend, and seasonality (Refer to section 7.3 Best-fitting Model). Makridakis et al (1998, p. 23) state "the single most important thing to do when first exploring the data is to visualize through graphs".

The use of $S A P^{\circledR}$, automatic model selection strategy (procedure 2 ) is based on the identification of trend and/or seasonal characteristics and is an efficient and seemingly accurate approach to employ for practitioners who do not wish to analyse the data and select appropriate models themselves.

A serious limitation of SAP ${ }^{\circledR \text {, }}$ s offerings (ERP, APO DP (Demand Planning), and SEM-BPS) is the lack of standard autocorrelation graphics, e.g. autocorrelation function (ACF) charts. Along with trend, ACF charts (also known as correlograms) are a fundamental tool in identifying time series patterns to allow the appropriate selection of a forecasting model. Makridakis et al (1998, p. 40) describes the plot of the autocorrelation function as "a standard tool in exploring a time series before forecasting. It provides a useful check for seasonality, cycles, and other time series patterns". To mitigate the lack of ACF functionality, the practitioner can download historical sales data from either the SAP $^{\circledR}$ SOP or SD (sales and distribution) modules to Microsoft ${ }^{\circledR}$ Excel $^{\circledR}$ and perform a seasonal plot. A seasonal plot is a plot of the sales data against individual
months that makes identification of seasonality considerably easier than viewing the data as a time series plot (Figure 22 and Figure 23).


Figure 22. Time Series Plot of SKU-60-004


Figure 23. Seasonal Plot of SKU-60-004

Alternatively, Excel ${ }^{\circledR}$ add-ins to generate correlograms can be obtained from a number of vendors including Palisade (www.palisade.com) and Lumenaut (www.lumenaut.com).

Finally, the development and application of the Cost of Forecast Error (CFE) measure demonstrated that a total reliance on mean absolute error was incompatible
with commercial decision making and not likely to yield optimum forecasting model selection results. Given the lack of commercial forecast evaluation, in any of $\mathrm{SAP}^{\circledR 3} \mathrm{~s}$ offerings, practitioners can perform the required analysis using Microsoft ${ }^{\circledR}$ Excel ${ }^{\circledR}$, or a similar spreadsheet application. An alternative to using such third party applications is to leverage the integrated nature of the $S A P ~^{\circledR}$ offering and develop the necessary $A B A P$ (Advanced Business Application Programming) code to reference the applicable data tables and then calculate the cost of forecast error within the system.

Practitioners should note that the CFE measure developed and applied in this case study is highly margin sensitive and the case study data set SKU margins were high, thereby suggesting a very high service level should be maintained. Such high service levels will not be applicable to all companies and commercial forecast error analysis needs to be performed on a company-specific basis. Companies with relatively low margin products will find that lower service levels (less safety stock) will likely prove more economic as the potential lost margin from a lower service level will not be as great. This does not imply that the results will be worse, just that the emphasis of benefits (inventory versus service level) may differ.

The next section presents recommendations based on these findings.

### 8.2 Recommendations

The following recommendations are aimed at three audiences; practitioners, ERP vendors (primarily, but not exclusively $\mathrm{SAP}^{\circledR}$ ), and academics. The recommendations are methodological in nature and as such are not attempts to generalise the specific findings of the case study. Supporting seminal literature is referenced for each recommendation.

### 8.2.1 Practitioner Recommendations

Based on the specific findings of this case study combined with supporting literature, it is recommended that practitioners apply the following steps for product forecasting using SAP ${ }^{\circledR 3}$ s ERP application;

1. Identify Time Series Features: Identify the time series features of the data (level, trend, seasonality, and series length) to ensure that an appropriate forecasting method is selected Makridakis et al (1998, p. 23). Given the lack of trend and seasonality analysis tools in SAP® ERP (identified in section 3.8 - Conclusion of Literature Review) practitioners can download historical sales information from the SOP module (SAP ${ }^{\circledR}$ transaction MC94) as follows:
a. Choose Extras -> Microsoft ${ }^{\circledR}$ Excel ${ }^{\circledR}$
b. Enter the path name for the excel.exe file on the user's computer.
c. Choose Continue

The historical sales data are then downloaded to Excel ${ }^{\circledR}$ where it can be charted and trend lines (regression) applied to identify trend. Seasonal plots can also be produced to identify seasonality.
2. Select and Implement Forecasting Method(s): Apply forecasting models based on historical time series features (level/trend/seasonality) - refer to

Figure 24. $\mathrm{SAP®}$ Model Identification for Different Historical Patterns (Adapted from SAP®, 2006) and the length of the time series (Pegels, 1969) or employ $\mathrm{SAP}^{\circledR}$, s automatic selection procedure. As stated in the conclusion of Chapter 2.0 (Literature Review), SAP $^{\circledR 3}$ s demand forecasting functionality appears to be adequately grounded in previous theoretical and empirical research, namely the use of exponential smoothing models. Practitioners can also have a reasonable level of confidence that the relatively low (highly smoothed) SAP ${ }^{\circledR}$ default forecast smoothing parameters are appropriate for noisy data sets, but historical fitting is likely to yield some further gains in accuracy (Fildes et al., 1998). Consideration should also be given to the use of event management adjustment in the context of their own organisation's promotional activity (Goodwin \& Fildes 1999; Adya, Armstrong, Collopy, \& Kennedy, 2000; Goodwin, 2000). The possibility of utilising third party software, or robust external manual processes, to provide the necessary structure for adjustments to baseline forecasts should also be considered.


Figure 24. SAP ${ }^{\circledR}$ Model Identification for Different Historical Patterns (Adapted from $\mathrm{SAP}^{\circledR}$, 2006)
3. Evaluate Forecasts: Develop and apply a financial forecasting metric to be used in conjunction with SAP $^{\circledR 1}$ s forecasting error measures (Roberts \& Whybark, 1974; Gardner, 1990; Lee, Cooper, \& Adam 1993). Again, the downloading of necessary data to Excel ${ }^{\circledR}$ can facilitate the development of an appropriate financial metric, or the development of code using SAP ${ }^{\circledR 1}$ S ABAP (Advanced Business Application Programming). Refer to equations 23-28 (section 3.4 Cost of Forecast Error) for details of the cost of forecast error (CFE) measure developed for and applied in this case study. The use of forecast error cost curves is recommended as a useful approach to determining the best-fit forecast model and optimum service level values for the given data set.
4. Use and Monitor Forecasts: Use forecasts and monitor on an ongoing basis (Makridakis et al., 1998). The potential change of underlying time series features and subsequent forecast accuracy should be regularly monitored. As products, or product groups, enter different phases of their lifecycle then the selection and use of different forecasting models may be necessary to ensure maximum service level at least cost (Refer to section 7.3 Best-fitting Model).

### 8.2.2 ERP Vendor Recommendations

The four recommendations presented above are aimed at practitioners currently using $S A P^{\circledR}{ }^{\circledR}$ S ERP offering. However, $S^{\circledR}{ }^{\circledR}$ and/or other ERP vendors could substantially improve their offerings by incorporating seasonal plots and/or autocorrelation charts, linear regressions lines for trend analysis, event management based on structured judgmental forecasting and intervention analysis, along with the use of commercial forecast error measures such as CFE. The integrated nature of ERP offerings would facilitate the use of existing financial information for the calculation of such measures. SAP $^{\circledR}$ should also give consideration to adopting the more common forecasting notation, such as that used by Makridakis et al. (1998), to aid practitioner understanding. The incorporation of such improvements into $\mathrm{SAP}^{\circledR}$, offerings could help reduce the $45 \%$ of ERP users (Vega, 2001) that rely on stand-alone forecasting software.

### 8.2.3 Academic Recommendations

Based on this work, the primary recommendation is that academics adopt commercially oriented forecast error measures, e.g. CFE measure or more extensive simulation approaches, and present such outputs along with the more traditional measures such as MAE and MAPE. The use of commercial forecast error measures would assist in clarifying the relative value of competing forecasting models and aid practitioner decision making. Inherent in such a recommendation is the need for forecasting research data sets to be extended to include commercial characteristics such as cost and margin.

A further recommendation is that practitioners de-emphasize statistical significance testing in favour of effect sizing (Refer to section 2.5 Empirical Forecasting Studies).

### 8.3 Contributions to Knowledge

This study has made four specific contributions to knowledge as follows:

1. The empirical evaluation of $S A P^{\circledR}$,s forecasting models and methods with subsequent finding-based recommendations to assist practitioner decision making, supported by peer-reviewed literature. The study has bridged some of the gaps between previous forecasting research and practice, i.e. the recommended use of time series characteristics identification using autocorrelation charts and linear trends, fitting of forecast models to historical data, adoption of more structured approaches to event management, and the use of commercial forecast error measures (Refer to section 8.2 Recommendations). The limited generalisation of the case study findings has been methodological in nature, i.e. concerned with the replication of fundamental forecasting principles as opposed to the specific results of the forecast accuracy of the given case study data sets.
2. The development/enhancement of two commercially oriented forecast error measures; Cost of Forecast Error (CFE) and the margin weighted MAPE (MWMAPE) measure to provide practitioners and academics alike with forecast error measures more aligned with commercial decision making than the traditional non-financial measures such as MAE or MAPE (Refer to section 3.0 Methodology).
3. The provision of empirical data to support Armstrong's (2005) arguments for the use of effect sizing (e.g. forecast error measure reduction) over statistical significance testing (Refer to section 6.2 Baseline Forecasts versus Event Management Adjusted Forecasts).
4. An indication to business of the indicative value of adopting ERP systems through establishing the net present value (NPV) of the forecasting gains obtained in this study (Refer to section 7.5 Return on Investment via Improvements in Sales Forecasting).
5. The application of Tashman and Hoover's (2001) software assessment framework to SAP ${ }^{\circledR 3}$ s ERP forecasting functionality (Refer to Table 7. SAP ERP Forecasting Principles Review). The review provides succinct and objective guidance to practitioners regarding the limitations of $S A P^{\circledR,}$ s functionality in relation to some competing offerings. The review of the SAP ${ }^{\circledR}$ ERP system was conducted by the author who has nearly a decade of experience using and implementing various releases of $\mathrm{SAP}^{\circledR}$, s offering. This experience covers multiple industries and commercial environments ranging in size from $\$ 20 \mathrm{~m}$ to \$1.5bn NZD in annual sales turnover. The author also has a total of twenty years experience with a range of other ERP offerings.

### 8.4 Directions for Further Research

This study used the sales data (sales in units, product costs, and margins) provided by one New Zealand company and as such has provided only a single case study in relation to the large number of worldwide SAP $^{\circledR}$ users. Extensions to this study involving the specific quantification of time series features of a broader commercial data set could prove useful to the wider $S A P D^{\circledR}$ community. The application of a range of parameters to unit cost $(v)$, product margin $\left(M_{p}\right)$, cost of inventory holding $(r)$, leadtime (L) and cost of shortages ( $B_{5}$ ) could also prove valuable in that a generalisable plot of cost of forecast error (CFE) could be provided.

As detailed in Chapter 1.0 (Introduction) this case study was subject to specific limitations in an effort to make the process accessible to $\mathrm{SAP}^{\circledR}$ practitioners without the need for additional specialist tools such as statistical analysis software. Such limitations, by nature, excluded some potentially important areas of research. Valuable extensions to this study could include comparative research between SAP ${ }^{\circledR}$, $\operatorname{ERP}$ offering and the more sophisticated (and expensive) Demand Planning element of the Advanced Planner and Optimiser (APO), part of $\mathrm{SAP}^{\circledR \text {, }} \mathrm{s}$ supply chain management suite. As highlighted in Chapter 2.0 (Literature Review) APO includes additional forecasting functionality including; a dampening profile for trend methods, linear regression, seasonal linear regression, median method (determines the median of the basic and trend parameters, as well as the seasonal index if applicable), Croston's method (for products with intermittent demand), multiple linear regression, composite forecasting (combines forecasts from alternative forecasting methods (such as times series, casual, and/or judgmental). It would be useful for prospective $S A P ~^{\circledR}$ customers to be able to quantify the relative commercial costs and benefits between the SAP ${ }^{\circledR}$ ERP and APO offerings and/or stand-alone third party forecasting engines.

Further extensions outside of the current SAP $^{\circledR}$ offerings could include a comparison of SAP ${ }^{\circledR,}$ s ARRSES models and Taylor's (2004) smooth transition exponential smoothing (STES) automatic alpha adaptation method, along with the potential benefits of applying structured judgmental adjustment approaches to baseline forecasts.

In conclusion, SAP ${ }^{\circledR}$ is the dominant ERP provider and further empirical research into the functionality of $S A P^{\circledR,}$ s offerings and subsequent dissemination via practitioneroriented journals should be considered a valuable endeavour.

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## 10. APPENDICES

Appendix A - Data Sets

| 60 Month Data Set Fititing | $\stackrel{\text { ¢ }}{6}$ | ？ | 哭 | $\begin{aligned} & \hline \stackrel{\circ}{\circ} \mathrm{i} \\ & \hline \end{aligned}$ | $\begin{aligned} & 2 . \\ & \hline ⿳ 亠 丷 厂 彡 \\ & \hline \end{aligned}$ | 管 | － | $\begin{aligned} & \hline \stackrel{\circ}{\dot{\circ}} \\ & \hline \end{aligned}$ | 旁 | 家 | 旁 | 管 | 产 | $\begin{aligned} & \text { 륭 } \\ & \hline \end{aligned}$ | $\begin{array}{\|l\|l} \hline \text { 荌 } \\ \hline \end{array}$ |  | $\begin{aligned} & \text { zo } \\ & \dot{\hat{i}} \\ & \hline \end{aligned}$ |  |  | ＋ $\begin{array}{r}\text { ¢ } \\ \text { i } \\ \hline\end{array}$ | $\begin{aligned} & \text { z률 } \\ & \dot{j} \\ & \hline \end{aligned}$ | 京 | 旁 |  | 产 | $\begin{aligned} & \text { R⿳亠丷厂犬心㇒ } \\ & \hline \end{aligned}$ | $\begin{aligned} & \text { 䒼 } \\ & \hline \end{aligned}$ | － | $$ | 管 | 颜 | $\stackrel{\text { ¢ }}{\substack{\text { ¢ }}}$ | 3 | $\stackrel{7}{\dot{\circ}}$ | 崗 | 管 |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| （SKU－60．001 | ${ }_{310}^{46}$ | ${ }_{22}^{52}$ | 50 322 | 534 | ${ }_{504}^{33}$ | 413 | ${ }_{269}^{45}$ | ${ }_{374}^{46}$ | ${ }_{284}^{43}$ | $\stackrel{41}{262}$ | ${ }_{352}^{28}$ | ${ }_{213}^{42}$ | ${ }_{330}^{51}$ | $\stackrel{44}{382}$ | ${ }_{450}^{46}$ | ${ }_{326}^{62}$ | ${ }_{527}^{46}$ | $\stackrel{45}{45}$ | ${ }_{456}^{58}$ | ${ }_{498}^{58}$ | 556 | ${ }_{624}^{41}$ | ${ }_{531}^{52}$ | 30 <br> 492 | ${ }_{6}^{44}$ | ${ }_{474}^{27}$ | 41 500 | 38 531 | $\stackrel{43}{564}$ | 33 513 | 526 | ${ }_{568}^{57}$ | 528 | ${ }_{486}$ | ${ }_{561}^{45}$ | 48 486 |
| SKU－60－003 | 62 | 67 | 62 | 54 | ${ }_{93}$ | 57 | ${ }_{72}$ | ${ }_{63}$ | 40 | 52 | 53 | 79 | 52 | 79 | 66 | 40 | ${ }_{79} 7$ | ${ }_{97}$ | 83 | ${ }_{76}$ | 43 | 51 | 531 44 | ${ }_{81} 9$ | ${ }_{85} 8$ | ${ }_{65}$ | 59 | ${ }_{6}^{53}$ | 54 | 513 37 | 526 66 | ${ }_{54}^{568}$ | 528 63 | ${ }_{93}^{486}$ | 561 61 | ${ }^{486}$ |
| SKU－60．004 | 499 | 825 | 455 | 503 | 402 | 310 | 314 | 499 | 298 | 342 | 437 | 458 | 514 | 666 | 431 | 483 | 428 | 470 | 445 | 508 | 369 | 345 | 772 | 492 | 434 | 612 | 336 | 598 | 303 | 283 | 413 | 397 | 260 | 324 | 398 | 301 |
| SKU－60－005 | 185 | 244 | 154 | 214 | 213 | 216 | 199 | 209 | 206 | 176 | 134 | 145 | 122 | 166 | 219 | 233 | 230 | 204 | 197 | 276 | 240 | 251 | 224 | 269 | 174 | 223 | 245 | 198 | 32 | 210 | 130 | 104 | 101 | 135 | 221 | 182 |
| SKU－60．006 | 142 | 169 | 185 | 206 | ${ }_{325}^{231}$ | 161 | ${ }_{291}^{131}$ | 175 | ${ }_{319}^{162}$ | 112 | 124 | 140 | ${ }_{396}^{128}$ | 139 | 159 | 167 | 294 | 198 | 208 | ${ }_{389}^{159}$ | 213 | 326 | 212 | ${ }_{478} 19$ | ${ }_{337}^{237}$ | ${ }_{543}^{223}$ | ${ }_{447}^{240}$ | 225 509 | 244 443 | ${ }_{538}^{181}$ |  | ${ }_{537}^{176}$ | 462 | 209 588 | ${ }_{497}^{225}$ | 220 588 |
| SKU－60－008 | 139 | 179 | 232 | 203 | 204 | 195 | 182 | 170 | 151 | 146 | 232 | 134 | 177 | 162 | 139 | 182 | 184 | 145 | 137 | 168 | 158 | 169 | 149 | 207 | 202 | 179 | 142 | 248 | 133 | 188 | 227 | 175 | 122 | 186 | 166 | 588 <br> 153 |
| SKU－60．009 | 193 | ${ }^{151}$ | 163 | 181 | 170 | 108 | ${ }^{136}$ | 141 | 155 | 167 | 165 | 209 | 161 | 180 | 195 | 193 | 169 | 171 | 170 | 213 | 167 | 187 | 205 | 204 | 215 | 232 | 246 | 231 | 248 | ${ }^{232}$ | 260 | 184 | 213 | 181 | 193 | 144 |
| SKU－60－010 | 105 | 95 | 102 | 129 | 103 | 99 | 72 | 91 | 81 |  | 99 | 71 |  | 88 |  | 100 | 90 | 67 | 55 | 95 | 81 | 52 | 70 | 53 | 59 | 72 | 82 | 77 |  | 45 | 67 | 81 | 81 | 59 | 67 |  |
| $\begin{aligned} & 60 \text { Month Data Set } \\ & \text { Holdout } \end{aligned}$ | 产 | 䓂 | \％ | ¢ | 产 | 若 | 硅 | ＋ | \％ | $\stackrel{8}{i}$ | \％ | $\begin{aligned} & \text { U. } \\ & \hline ⿳ 亠 口 冋 刂 \end{aligned}$ | $\stackrel{C}{\circ}$ | $\begin{aligned} & \text { Z } \\ & \hline ⿳ 亠 口 冋 \end{aligned}$ | $\begin{aligned} & \stackrel{8}{+} \\ & \stackrel{+}{\dot{8}} \\ & \hline \end{aligned}$ | \％ | $\begin{aligned} & \hline \stackrel{\text { O}}{8} \\ & \hline \end{aligned}$ | $\begin{aligned} & \hline 0 \\ & \hline \stackrel{0}{?} \\ & \stackrel{y}{8} \end{aligned}$ | $\begin{aligned} & 0 . \\ & \hline 0 \\ & 0 \\ & 0 \end{aligned}$ | $\begin{aligned} & \hline \stackrel{7}{8} \\ & \stackrel{\circ}{\circ} \end{aligned}$ | 交 | $\frac{8}{i}$ |  | 㲋 |  |  |  |  |  |  |  |  |  |  |  |  |
| SKU－60．001 | 55 | ${ }_{5}$ |  |  |  | ${ }_{47}$ |  |  |  |  |  |  |  |  |  |  |  |  |  |  | 23 |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| SKU－60－002 | 528 | 541 | 510 | 416 | 513 | 510 | 404 | 527 | 324 | 451 | 476 | 349 | 404 | 424 | 232 | 353 | 424 | 321 | 279 | 427 | 373 | 411 | 364 | 292 |  |  |  |  |  |  |  |  |  |  |  |  |
| （ SKU－60．003 | ${ }_{378}^{91}$ | ${ }_{467}^{64}$ | 79 357 | ${ }_{386}^{55}$ | －34 | $\stackrel{44}{25}$ | ${ }_{224}^{627}$ | ${ }_{351}^{62}$ | ${ }_{238}^{29}$ | 81 331 | ${ }_{328}^{60}$ | 474 | ${ }_{263}^{62}$ | 76 305 | －60 | ＋${ }^{56}$ | ${ }^{76}$ | ${ }_{223}^{43}$ | 40 179 | ${ }_{232}^{62}$ | 142 | ${ }^{174}$ | 731 | ${ }_{137}^{65}$ |  |  |  |  |  |  |  |  |  |  |  |  |
| （SKU－60－005 | 268 268 | 287 | 244 | 216 | 167 | 204 | 117 | 134 | 105 | 149 | 123 | 195 | 128 | 101 | 126 | 67 | 88 | 66 | 109 | 117 | 69 | 113 | 144 | 51 |  |  |  |  |  |  |  |  |  |  |  |  |
| SKU－60－006 | 237 | 257 | 240 | 268 | 207 | 209 | 213 | 199 | 204 | 201 | 241 | 184 | 218 | 175 | 233 | 170 | 208 | 206 | 190 | 195 | 234 | 254 | 242 | 231 |  |  |  |  |  |  |  |  |  |  |  |  |
| SKU－60－007 | 572 | 515 | 675 | 456 | 506 | 537 | 538 | 493 | 334 | 447 | 327 | 453 | 579 | 345 | 417 | 448 | 436 | 393 | 273 | 484 | 284 | 266 | 305 | 362 |  |  |  |  |  |  |  |  |  |  |  |  |
| Ste－60．008 | 184 | 210 | 178 | 153 | 135 | 163 | 139 | 172 | 113 | 141 | 200 | 156 | 131 | 113 | 147 | 134 | 125 | －67 | 75 | 107 | 89 92 | 99 | 109 | 118 |  |  |  |  |  |  |  |  |  |  |  |  |
| （ SKU－60．009 | 192 59 | 245 86 | 196 53 | 175 78 | 134 61 | 192 64 | 152 <br> 35 | 176 84 | 143 58 | 177 <br> 46 | 243 75 | 223 67 | 166 62 | $\begin{array}{r}173 \\ 53 \\ \hline\end{array}$ | $\begin{array}{r}188 \\ 78 \\ \hline\end{array}$ | 162 31 | $\begin{array}{r}122 \\ 56 \\ \hline\end{array}$ | 133 46 | 172 39 | 125 52 | 92 <br> 44 | 80 <br> 47 | $\begin{array}{r}169 \\ 58 \\ \hline\end{array}$ | 117 <br> 64 |  |  |  |  |  |  |  |  |  |  |  |  |
| 24 Month Data Set | ting |  |  |  |  |  |  |  |  |  |  | Idout |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
|  | $\stackrel{\stackrel{L}{\dot{\omega}}}{\substack{\text { a }}}$ | 宮 | $\begin{aligned} & \text { ¢8 } \\ & \text { ¢ } \\ & \hline \mathbf{\omega} \end{aligned}$ | ¢ | $\begin{array}{r} \hline \mathbf{2} \\ \hline ⿳ 亠 口 冋 彡 心 \\ \hline \end{array}$ | $\begin{aligned} & \hline \begin{array}{l} 0 \\ \text { Be } \\ \hline \end{array} \end{aligned}$ | － | $\begin{aligned} & \hline \frac{\square}{\dot{\circ}} \\ & \hline \end{aligned}$ |  | $\begin{aligned} & \hline \stackrel{\rightharpoonup}{i} \\ & \dot{i} \\ & \hline \end{aligned}$ | $\begin{aligned} & \hline \frac{3}{8} \\ & \vdots \\ & \hline \end{aligned}$ | $\stackrel{\ddots}{\dot{\delta}}$ | $\stackrel{\square}{5}$ |  | $\begin{aligned} & 88 \\ & \hline \stackrel{8}{\dot{8}} \\ & \hline \end{aligned}$ | $\begin{aligned} & \hline \stackrel{\circ}{\dot{8}} \\ & \hline \end{aligned}$ | $\begin{aligned} & \hline \stackrel{\rightharpoonup}{\dot{\delta}} \\ & \hline \end{aligned}$ | $\begin{aligned} & \hline \stackrel{\circ}{?} \\ & \hline \end{aligned}$ |  | $\stackrel{\square}{\circ}$ | $\begin{aligned} & 2 \frac{2}{8} \\ & \frac{1}{9} \end{aligned}$ | $\begin{aligned} & 7 \\ & \frac{8}{i} \\ & \dot{B} \end{aligned}$ |  | 䎜 |  |  |  |  |  |  |  |  |  |  |  |  |
| SKU－24－001 | ${ }^{17}$ | ${ }^{8}$ | 19 | 18 | 23 |  | 6 | ${ }^{14}$ | 12 | 4 | 10 | 23 | 14 |  | 14 |  | 19 | 12 |  | 20 | ${ }^{18}$ | 10 | 10 | ${ }^{14}$ |  |  |  |  |  |  |  |  |  |  |  |  |
| （SKU－24．002 |  | ${ }_{174}{ }^{3}$ | ${ }^{9}$ | ${ }^{6}$ | 18 | ${ }^{12}$ | 16 113 | ${ }_{12}^{12}$ | 177 | 10 184 | ${ }_{333}^{13}$ | 128 | 164 | 58 98 | 15 321 | 8 199 | 366 | ${ }_{71}{ }_{1}$ | 21 116 | 10 164 | 76 | 77 | 193 | 10 163 |  |  |  |  |  |  |  |  |  |  |  |  |
| （SKU－24－004 | ${ }_{76}^{163}$ | ${ }_{92}^{174}$ | ${ }_{87}^{163}$ | ${ }_{179}^{194}$ | 81 | 112 | 74 | ${ }_{95}^{175}$ | 118 | 185 | 231 | 250 | 162 | 176 | 269 | 191 | ${ }_{295}^{366}$ | 204 | 104 | 129 | 156 | 163 | 145 | ${ }_{244}^{163}$ |  |  |  |  |  |  |  |  |  |  |  |  |
| SKU－24－005 |  | 127 |  |  | 47 |  | 72 | 127 |  | 126 | 126 |  |  |  | 114 |  |  |  | 50 |  | 51 |  | 42 | 81 |  |  |  |  |  |  |  |  |  |  |  |  |
|  | 1，179 | ${ }_{21} 9$ | 1，000 | 1，034 | 744 | ${ }^{946}$ | 1，032 | ${ }_{46}^{822}$ | $\begin{array}{r}701 \\ 31 \\ \hline\end{array}$ | 1，252 | 1，113 | ${ }^{1,268} 4$ | 1，284 | 1，432 | 1，147 | 1，057 | 1，456 | 1，039 | 769 27 | ${ }_{45}^{916}$ | ${ }_{42}^{989}$ | 816 | 967 30 | ${ }^{662}$ |  |  |  |  |  |  |  |  |  |  |  |  |
| （SKU－24－008 | ${ }_{43}$ | 29 | 22 | 50 | 49 | 52 | 26 | 28 | 35 | 80 | 43 | 68 | 59 | 61 | 21 | 20 | 95 | 57 | 21 | 90 | 27 | 41 | 28 | 36 |  |  |  |  |  |  |  |  |  |  |  |  |
| SKU－24－009 | 26 | 17 | 17 | 25 | 14 | 13 | 12 | 14 | 12 | 19 | 10 | 17 | 9 | 27 | 26 | 19 | 9 | 10 | 28 | 24 | 21 | 17 | ${ }_{21}$ | 32 |  |  |  |  |  |  |  |  |  |  |  |  |
| SKU－24－010 | 65 | 86 | 78 | ${ }^{83}$ | 33 | 81 | 55 | 91 | 43 | ${ }^{23}$ | 39 | ${ }^{37}$ | 50 | 58 | 20 | 27 | 52 | 42 | 40 | 32 | 36 | 19 | 39 | 17 |  |  |  |  |  |  |  |  |  |  |  |  |
| （ $\begin{aligned} & \text { SKU－24－011 } \\ & \text { SKU－24－012 }\end{aligned}$ | 288 | 36 35 |  | 29 | 12 39 | 27 32 | 65 | 30 75 | 23 40 | 77 31 | 59 48 | 20 4 | 24 <br> 54 | 474 | 38 28 | 28 38 | ${ }_{43}^{27}$ | 31 28 | ${ }_{41}^{17}$ | 52 49 | $\begin{aligned} & 54 \\ & 26\end{aligned}$ | 42 37 | 33 <br> 25 | 18 20 |  |  |  |  |  |  |  |  |  |  |  |  |
| SKU－24－013 | 21 | 11 | 13 | 26 | 12 | 18 | 28 | 24 | 12 | 15 | 17 | ${ }_{16}$ | 154 | 20 | 15 | 19 | ${ }_{21}$ | 20 | ${ }_{23}$ | ${ }_{31}$ | 26 | 17 | ${ }_{18}^{25}$ | 17 |  |  |  |  |  |  |  |  |  |  |  |  |
| SKU－24－014 | 51 | 34 | 86 | 50 | 54 | 63 | 122 | 118 | 43 | 38 | 63 | 59 | 55 | 74 | 95 | 63 | 106 | 20 | 45 | 141 | 33 | 19 | 57 | 53 |  |  |  |  |  |  |  |  |  |  |  |  |
| （ $\begin{aligned} & \text { SKU－24．015 } \\ & \text { SKU－24－016 }\end{aligned}$ | 87 68 68 | ${ }^{76}$ | 27 51 | ${ }_{46}^{18}$ | 12 | ${ }_{77}^{18}$ | 24 55 | 80 | ${ }_{68}^{81}$ | ${ }^{87}$ | －56 | 22 | 43 75 | 77 | 37 64 | 55 | ${ }_{74}^{137}$ | 588 | 49 | 㐌 | 32 31 | 36 68 | 14 87 | 17 97 97 |  |  |  |  |  |  |  |  |  |  |  |  |
| （ex $\begin{aligned} & \text { SKU－24－016 } \\ & \text { SKU－24－017 }\end{aligned}$ | ${ }_{17}^{68}$ | ${ }_{27}^{129}$ | 29 | ${ }_{34}^{46}$ | ${ }_{17} 6$ | 16 | 48 | ${ }_{44}^{145}$ | ${ }_{23}^{68}$ | 12 | 108 29 | ${ }_{23}^{78}$ | ${ }_{28}^{75}$ | 63 | 264 | ${ }_{29}^{68}$ | 74 | ${ }_{17} 8$ | ${ }_{27}^{97}$ | ${ }_{46}^{56}$ | 21 21 | ${ }_{43}^{68}$ | 4 | ${ }_{33} 9$ |  |  |  |  |  |  |  |  |  |  |  |  |
| SKU－24－018 | 132 | 153 | 109 | ${ }^{166}$ | 160 | 113 | 136 | 114 | ${ }_{27} 7$ | 104 | 88 | ${ }^{68}$ | 94 | 101 | 129 | 106 | 67 | 82 | ${ }_{6}^{63}$ | ${ }_{48}^{48}$ | 55 | 122 | 40 | 139 |  |  |  |  |  |  |  |  |  |  |  |  |
| （ $\begin{aligned} & \text { SKU－24．019 } \\ & \text { SKU－24－2020 }\end{aligned}$ | 33 15 15 | 18 7 7 | 27 16 | 37 16 | ${ }_{26}^{26}$ | 38 23 | 42 19 | 313 | ${ }_{9}^{25}$ | 41 17 | 220 | 27 4 | 323 | 4 | 31 16 | ${ }_{18}^{40}$ | 438 | 189 | ［ 35 | 38 38 | 25 | 314 | 81 9 | 34 9 |  |  |  |  |  |  |  |  |  |  |  |  |
| SKU－24－021 | 27 | 33 | 11 | 44 | 59 | 40 | 16 | 22 | 21 | 31 | 7 | 27 | 39 | 75 | 21 | 19 | 13 | 28 | 52 | 37 | 15 | 11 | 33 | 26 |  |  |  |  |  |  |  |  |  |  |  |  |
| SKU－24－022 | 59 | 52 | 66 | 46 | 94 | 44 | 42 | 35 | 45 | ${ }^{63}$ | 87 | 65 | 69 | 52 | 77 | 72 | 36 | 72 | ${ }^{68}$ | 96 | 47 | ${ }^{63}$ | 157 | 56 |  |  |  |  |  |  |  |  |  |  |  |  |
| （ $\begin{aligned} & \text { SKU－24．023 } \\ & \text { SKU－24－024 }\end{aligned}$ | ［ 27 | 73 10 | ${ }_{42}^{52}$ | 38 108 | －60 101 | －33 | 49 6 | ${ }_{38}^{107}$ | 41 25 | 59 69 | 71 | 64 | 26 103 | 39 | 47 85 | 29 59 | 67 6 | 75 71 | 200 | 28 28 | 40 | ＋89 | 144 | ［ ${ }_{48}^{57}$ |  |  |  |  |  |  |  |  |  |  |  |  |
| SKU－24－025 | 16 | 10 | 26 | 33 | 66 | 57 | 23 | 53 | 36 | 43 | 65 | 28 | 25 | 33 | 49 | 89 | 24 | 45 | ${ }_{40}$ | ${ }_{98}$ | 55 |  | 23 | 36 |  |  |  |  |  |  |  |  |  |  |  |  |
| SKU－24．026 | 47 | 57 | ${ }^{68}$ | 130 | ${ }^{36}$ | 71 | 41 | 44 | ${ }^{38}$ | ${ }_{78}^{68}$ | ${ }_{6}^{63}$ | 74 | ${ }_{86}^{86}$ | ${ }_{78} 8$ | ${ }_{52}^{68}$ | 52 | 72 | 115 | 57 | ${ }_{71}^{41}$ | 67 | ${ }_{6}^{62}$ | 76 | 89 |  |  |  |  |  |  |  |  |  |  |  |  |
| （ $\begin{aligned} & \text { SKU－24－027 } \\ & \text { SKU－24－028 }\end{aligned}$ | 37 29 | 59 64 |  | 105 | 60 27 | 104 59 | 30 34 |  | 59 40 |  | 64 41 | ${ }_{41}^{69}$ | 4888 | 78 114 |  | $4{ }_{4}^{40}$ |  | 73 51 |  | 73 22 | 27 34 | 24 43 | 48 | 58 39 |  |  |  |  |  |  |  |  |  |  |  |  |
| SKU－24－029 | 13 | 28 | 22 | 28 | 8 | 9 | 6 | 14 | 6 | 40 | 19 | 9 | 23 | 18 | 13 | 17 | 57 |  | 5 | 4 | 6 | 25 | 11 | 28 |  |  |  |  |  |  |  |  |  |  |  |  |
| （ely $\begin{aligned} & \text { SKU－24．030 } \\ & \text { SKU－24－031 }\end{aligned}$ | ［18 |  | 24 40 | 36 57 | 18 16 | 23 36 | 17 23 | 40 4 | 31 31 | 21 45 45 | 28 28 | 14 | 29 | 27 | ${ }_{22}^{44}$ | 34 17 | 41 <br> 54 | 37 56 56 | 34 | 43 16 | ${ }_{27}^{96}$ | 523 | ［186 | ${ }_{43}^{97}$ |  |  |  |  |  |  |  |  |  |  |  |  |
| SKU－24－032 | 11 | 30 | 12 | 21 | 14 | 16 | 11 | 23 | 14 | 27 | 31 | 9 | 16 | 18 |  | 15 | 19 | 23 | 18 | 38 | 13 | 27 | 22 | 12 |  |  |  |  |  |  |  |  |  |  |  |  |
| SKU－24－033 |  | 10 |  | 11 |  | 10 |  |  |  |  |  |  | ${ }^{11}$ |  |  |  |  |  |  |  | 22 | 14 | 18 | 14 |  |  |  |  |  |  |  |  |  |  |  |  |
| SKU－24－034 | ${ }^{23}$ | 36 | 58 | 47 | 54 | 38 | 33 | 28 | 23 | 51 | 61 | 38 | 79 | 48 | 68 | 43 | 42 | 44 | 23 | 47 | 51 | 72 | 75 | 36 |  |  |  |  |  |  |  |  |  |  |  |  |
| SKU－24－035 | 17 | 19 | 16 | 21 | 12 | ${ }^{12}$ | 12 | 10 | ${ }^{13}$ | 27 | 13 | 17 | ${ }^{23}$ | 12 | ${ }^{13}$ | ${ }^{20}$ | 20 | 18 | 12 | 17 | ${ }^{28}$ | 28 | ${ }^{24}$ | 14 |  |  |  |  |  |  |  |  |  |  |  |  |
| （ele $\begin{aligned} & \text { SKU－24－036 } \\ & \text { SKU－24－037 }\end{aligned}$ | 423 | 28 28 | 20 30 | 37 20 | 21 30 | ${ }_{33}^{10}$ | 22 24 | 22 | 36 11 | ${ }_{23}^{11}$ | 37 27 | 18 | 211 | 41 31 |  | 31 28 | 28 |  | 12 | 124 | 25 | 19 | 15 | 17 26 |  |  |  |  |  |  |  |  |  |  |  |  |
| ${ }^{\text {SKU－24－038 }}$ | 234 | 116 | 410 | 203 | 404 | 637 | 346 | ${ }^{669}$ | 729 | 789 | ${ }^{647}$ | 312 | 294 | 837 | 759 | ${ }^{217}$ | ${ }^{656}$ | ${ }^{351}$ | 820 | 837 | 456 | 587 | 798 | 758 |  |  |  |  |  |  |  |  |  |  |  |  |
| （ely $\begin{aligned} & \text { SKO－24－039 } \\ & \text { SKU－24－040 }\end{aligned}$ | ${ }_{382}$ | ${ }_{329}$ | ${ }_{413}^{406}$ | ${ }_{242}^{54}$ | 404 | ${ }_{907}^{403}$ | 309 446 | ${ }_{688} 5$ | ${ }_{616}^{376}$ | －669 | 588 | ${ }_{566}^{632}$ | 702 | ${ }_{625}^{469}$ | ${ }_{735}^{667}$ | 1，125 | ${ }_{883}^{261}$ | ${ }_{701}^{593}$ | ${ }_{613}^{623}$ | ${ }_{955}^{668}$ | － 7.033 | 1,067 1.579 | － 51.344 | 1，158 |  |  |  |  |  |  |  |  |  |  |  |  |

Appendix B - Sales History Linear Regression and Autocorrelation (ACF) graphs








































Appendix C - Model Fitting Parameters

## Model Fitting Parameters

## 24 Month Model

Constant model (1st order exponential smoothing) Constant model (1st order exponential smoothing) Constant model (1st order exponential smoothing) Moving Average Model
Moving Average Mode
Weighted Moving Average Model
Weighted Moving Average Model
Trend model (1st order exponential smoothing) Trend model (1st order exponential smoothing) Trend model (2nd order exponential smoothing) Trend model (2nd order exponential smoothing) Trend model (2nd order exponential smoothing) Seasonal model (Winters' method) Seasonal Tred (Winters method) Seasonal Trend Model (Holt-Winters' method) Seasonal Trend Model (Holt-Winters' method) Naïve 1 SKU (combinat Naïve 1

## 60 Month Models

Constant model (1st order exponential smoothing) Constant model (1st order exponential smoothing) Constant model (1st order exponential smoothing) ving Average Mode
oving Average Mode
Weighted Moving Average Model
Weighted Moving Average Model
Trend model (1st order exponential smoothing) Trend model (1st order exponential smoothing) rend model (2nd order exponential smoothing) rend model (2nd order exponential smoothing) Seasonal mol (Winters' method) Seasonal model (Winters' method)
Seasonal Trend Model (Holt Wi
Seasonal Trend Mod (Holt Winters' method) Sedividual SKU (combination of best fit med best fit methods) Naïve 1

## Parameters

Alpha 0.2 (SAP default)
Alpha Fitted
Smoothing Factor Adaptation
24 Historical Values (SAP Default)
Historical Values Fitted
Weighting Group 1 (SAP default)
Weighting Group Fitted
Alpha 0.2, Beta 0.1 (SAP default)
Alpha, Beta Fitted
Alpha 0.2 (SAP default)
Alpha Fitted
Optimised Alpha
Alpha 0.2, Gamma 0.3 (SAP default)
Alpha, Gamma Fitted
Alpha 0.2, Beta 0.1, Gamma 0.3 (SAP default) Alpha, Beta, Gamma Fitted
Various
t+3

## Parameters

Alpha 0.2 (SAP default)
Alpha Fitted
Smoothing Factor Adaptation
24 Historical Values (SAP Default)
Historical Values Fitted
Weighting Group 1 (SAP default)
eighing Group
Alpha 0.2 , Betite (SAP default)
Alpha, Beta Fitte
default)
Alpha Fitted
Aphised Alpha
Alpha, Gamma Fitted
0.3 (SAP default) Beta, Gamma Fitted

Various
t+3

| Alpha | Beta | Gamma | Periods / Weighting Factors | Fitted MAE |
| :---: | :---: | :---: | :---: | :---: |
| 0.2 | * | * |  | 35.63 |
| 0.5 | * | * |  | 35.52 |
| * | * | * |  | 37.47 |
| * | * | * | 24 | 35.78 |
| * | * | * | 8 | 35.92 |
| * | * | * | $0.4,0.3,0.2,0.1$ | 37.74 |
| * | * | * | $0.4,0.3,0.2,0.1$ | 37.74 |
| 0.2 | 0.1 | * |  | 34.27 |
| 0.5 | 0.1 | * |  | 32.90 |
| 0.2 | * | * |  | 37.81 |
| 0.1 | * | * |  | 35.87 |
| * | * | * |  | 44.12 |
| 0.2 | * | 0.3 |  | 108.27 |
| 0.2 | * | 0.3 |  | 108.27 |
| 0.2 | 0.1 | 0.3 |  | 108.27 |
| 0.2 | 0.1 | 0.3 |  | 108.27 |
| * | * | * |  | 30.44 |
| * | * | * |  | 39.07 |
| Alpha | Beta | Gamma | Periods / Weighting Factors | Fitted MAE |
| 0.2 | 0.0 | 0.0 |  | 40.16 |
| 0.4 | 0.0 | 0.0 |  | 39.25 |
| * | * | * |  | 42.53 |
| * | * | * | 24 | 45.98 |
| * | * | * | 2 | 147.20 |
| * | * | * | $0.4,0.3,0.2,0.1$ | 59.97 |
| * | * | * | $0.5,0.3,0.1,0.1$ | 59.57 |
| 0.2 | 0.1 | * |  | 40.37 |
| 0.5 | 0.1 | * |  | 37.74 |
| 0.2 | 0.0 | * |  | 45.68 |
| 0.1 | 0.0 | * |  | 42.52 |
| * |  | * |  | 53.05 |
| 0.2 | * | 0.3 |  | 63.09 |
| 0.2 | * | 0.7 |  | 62.10 |
| 0.2 | 0.1 | 0.3 |  | 66.92 |
| 0.3 | 0.1 | 0.8 |  | 65.09 |
| * | * | * |  | 36.71 |
| * | * | * |  | 45. |

## SAP Automatic Model Parameters (24 Month)

| Material | M | Alpha | ta | na | Material | M | Alpha | Beta | Gamma | Material | M | Alpha | Beta | Gamma | Material | M | Alpha | Beta | Gamma | Material | M | Alpha | Beta | Gamma |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| SKU-24-001 | D | 0.20 | 0.00 | 0.00 | SKU-24-004 | T | 0.10 | 0.10 | 0.00 | SKU-24-007 | D | 0.10 | 0.00 | 0.00 | SKU-24-010 | D | 0.20 | 0.00 | 0.00 | SKU-24-013 | D | 0.20 | 0.00 | 0.00 |
| SKU-24-001 | D | 0.20 | 0.00 | 0.00 | SKU-24-004 | D | 0.20 | 0.00 | 0.00 | SKU-24-007 | D | 0.20 | 0.00 | 0.00 | SKU-24-010 | D | 0.20 | 0.00 | 0.00 | SKU-24-013 | D | 0.20 | 0.00 | 0.00 |
| SKU-24-001 | D | 0.20 | 0.00 | 0.00 | SKU-24-004 | D | 0.20 | 0.00 | 0.00 | SKU-24-007 | D | 0.20 | 0.00 | 0.00 | SKU-24-010 | D | 0.20 | 0.00 | 0.00 | SKU-24-013 | D | 0.20 | 0.00 | . 0 |
| SKU-24-001 | D | 0.20 | 0.00 | 0.00 | SKU-24-004 | D | 0.20 | 0.00 | 0.00 | SKU-24-007 | D | 0.20 | 0.00 | 0.00 | SKU-24-010 | D | 0.20 | 0.00 | 0.00 | SKU-24-013 | D | 0.20 | 0.00 | 0.00 |
| SKU-24-001 | D | 0.20 | 0.00 | 0.00 | SKU-24-004 | D | 0.20 | 0.00 | 0.00 | SKU-24-007 | D | 0.20 | 0.00 | 0.00 | SKU-24-010 | D | 0.20 | 0.00 | 0.00 | SKU-24-013 | D | 0.20 | 0.00 | 0.00 |
| SKU-24-001 | D | 0.20 | 0.00 | 0.00 | SKU-24-004 | D | 0.20 | 0.00 | 0.00 | SKU-24-007 | D | 0.20 | 0.00 | 0.00 | SKU-24-010 | D | 0.20 | 0.00 | 0.00 | SKU-24-013 | D | 0.20 | 0.00 | 0.00 |
| SKU-24-001 | D | 0.20 | 0.00 | 0.00 | SKU-24-004 | D | 0.20 | 0.00 | 0.00 | SKU-24-007 | D | 0.20 | 0.00 | 0.00 | SKU-24-010 | D | 0.20 | 0.00 | 0.00 | SKU-24-013 | D | 0.20 | 0.00 | 0.00 |
| SKU-24-001 | D | 0.20 | 0.00 | 0.00 | SKU-24-004 | D | 0.20 | 0.00 | 0.00 | SKU-24-007 | D | 0.20 | 0.00 | 0.00 | SKU-24-010 | D | 0.20 | 0.00 | 0.00 | SKU-24-013 | D | 0.20 | 0.00 | 0.00 |
| SKU-24-001 | D | 0.20 | 0.00 | 0.00 | SKU-24-004 | D | 0.20 | 0.00 | 0.00 | SKU-24-007 | D | 0.10 | 0.00 | 0.00 | SKU-24-010 | D | 0.20 | 0.00 | 0.00 | SKU-24-013 | D | 0.20 | 0.00 | 0.00 |
| SKU-24-001 | D | 0.20 | 0.00 | 0.00 | SKU-24-004 | D | 0.20 | 0.00 | 0.00 | SKU-24-007 | D | 0.20 | 0.00 | 0.00 | SKU-24-010 | D | 0.20 | 0.00 | 0.00 | SKU-24-013 | T | 0.50 | 0.50 | 0.00 |
| SKU-24-001 | D | 0.20 | 0.00 | 0.00 | SKU-24-004 | D | 0.20 | 0.00 | 0.00 | SKU-24-007 | D | 0.20 | 0.00 | 0.00 | SKU-24-010 | D | 0.10 | 0.00 | 0.00 | SKU-24-013 | D | 0.20 | 0.00 | 0.00 |
| SKU-24-001 | D | 0.10 | 0.00 | 0.00 | SKU-24-004 | D | 0.20 | 0.00 | 0.00 | SKU-24-007 | D | 0.20 | 0.00 | 0.00 | SKU-24-010 | D | 0.20 | 0.00 | 0.00 | SKU-24-013 | D | 0.20 | 0.00 | 0.00 |
| SKU-24-002 | D | 0.20 | 0.00 | 0.00 | SKU-24-005 | D | 0.10 | 0.00 | 0.00 | SKU-24-008 | D | 0.10 | 0.00 | 0.00 | SKU-24-011 | D | 0.20 | 0.00 | 0.00 | SKU-24-014 | D | 0.20 | 0.00 | 0.00 |
| SKU-24-002 | D | 0.20 | 0.00 | 0.00 | SKU-24-005 | D | 0.20 | 0.00 | 0.00 | SKU-24-008 | D | 0.20 | 0.00 | 0.00 | SKU-24-011 | D | 0.20 | 0.00 | 0.00 | SKU-24-014 | D | 0.20 | 0.00 | 0.00 |
| SKU-24-002 | D | 0.20 | 0.00 | . 00 | SKU-24-005 | D | 0.20 | 0.00 | 0.00 | SKU-24-008 | D | 0.20 | 0.00 | 0.00 | SKU-24-011 | D | 0.20 | 0.00 | 0.00 | SKU-24-014 | D | 0.20 | 0.00 | 0.00 |
| SKU-24-002 | D | 0.20 | 0.00 | 0.00 | SKU-24-005 | D | 0.20 | 0.00 | 0.00 | SKU-24-008 | D | 0.20 | 0.00 | 0.00 | SKU-24-011 | D | 0.20 | 0.00 | 0.00 | SKU-24-014 | D | 0.20 | 0.00 | 0.00 |
| SKU-24-002 | D | 0.20 | 0.00 | 0.00 | SKU-24-005 | D | 0.20 | 0.00 | 0.00 | SKU-24-008 | D | 0.20 | 0.00 | 0.00 | SKU-24-011 | D | 0.20 | 0.00 | 0.00 | SKU-24-014 | D | 0.20 | 0.00 | 0.00 |
| SKU-24-002 | D | 0.20 | 0.00 | . 00 | SKU-24-005 | D | 0.20 | 0.00 | 0.00 | SKU-24-008 | D | 0.20 | 0.00 | 0.00 | SKU-24-011 | T | 0.10 | 0.10 | 0.00 | SKU-24-014 | D | 0.20 | 0.00 | 0.00 |
| SKU-24-002 | D | 0.20 | 0.00 | 0.00 | SKU-24-005 | D | 0.20 | 0.00 | 0.00 | SKU-24-008 | D | 0.20 | 0.00 | 0.00 | SKU-24-011 | D | 0.20 | 0.00 | 0.00 | SKU-24-014 | D | 0.20 | 0.00 | 0.00 |
| SKU-24-002 | D | 0.20 | 0.00 | 0.00 | SKU-24-005 | D | 0.20 | 0.00 | 0.00 | SKU-24-008 | D | 0.20 | 0.00 | 0.00 | SKU-24-011 | D | 0.20 | 0.00 | 0.00 | SKU-24-014 | D | 0.20 | 0.00 | 0.00 |
| SKU-24-002 | D | 0.10 | 0.00 | 0.00 | SKU-24-005 | D | 0.20 | 0.00 | 0.00 | SKU-24-008 | D | 0.20 | 0.00 | 0.00 | SKU-24-011 | D | 0.20 | 0.00 | 0.00 | SKU-24-014 | D | 0.20 | 0.00 | 0.00 |
| SKU-24-002 | D | 0.10 | 0.00 | 0.00 | SKU-24-005 | D | 0.20 | 0.00 | 0.00 | SKU-24-008 | D | 0.20 | 0.00 | 0.00 | SKU-24-011 | D | 0.20 | 0.00 | 0.00 | SKU-24-014 | D | 0.20 | 0.00 | 0.00 |
| SKU-24-002 | D | 0.20 | 0.00 | 0.00 | SKU-24-005 | D | 0.20 | 0.00 | 0.00 | SKU-24-008 | T | 0.10 | 0.10 | 0.00 | SKU-24-011 | D | 0.20 | 0.00 | 0.00 | SKU-24-014 | D | 0.20 | 0.00 | 0.00 |
| SKU-24-002 | D | 0.10 | 0.00 | 0.00 | SKU-24-005 | D | 0.20 | 0.00 | 0.00 | SKU-24-008 | D | 0.20 | 0.00 | 0.00 | SKU-24-011 | D | 0.20 | 0.00 | 0.00 | SKU-24-014 | D | 0.20 | 0.00 | 0.00 |
| SKU-24-003 | T | 0.10 | 0.10 | 0.00 | SKU-24-006 | D | 0.20 | 0.00 | 0.00 | SKU-24-009 | D | 0.20 | 0.00 | 0.00 | SKU-24-012 | D | 0.20 | 0.00 | 0.00 | SKU-24-015 | D | 0.20 | 0.00 | 0.00 |
| SKU-24-003 | D | 0.10 | 0.00 | 0.00 | SKU-24-006 | D | 0.20 | 0.00 | 0.00 | SKU-24-009 | D | 0.20 | 0.00 | 0.00 | SKU-24-012 | D | 0.20 | 0.00 | 0.00 | SKU-24-015 | D | 0.20 | 0.00 | 0.00 |
| SKU-24-003 | D | 0.20 | 0.00 | 0.00 | SKU-24-006 | D | 0.20 | 0.00 | 0.00 | SKU-24-009 | D | 0.20 | 0.00 | 0.00 | SKU-24-012 | D | 0.20 | 0.00 | 0.00 | SKU-24-015 | D | 0.20 | 0.00 | 0.00 |
| SKU-24-003 | D | 0.10 | 0.00 | 0.00 | SKU-24-006 | D | 0.20 | 0.00 | 0.00 | SKU-24-009 | D | 0.20 | 0.00 | 0.00 | SKU-24-012 | D | 0.10 | 0.00 | 0.00 | SKU-24-015 | D | 0.20 | 0.00 | 0.00 |
| SKU-24-003 | D | 0.20 | 0.00 | 0.00 | SKU-24-006 | D | 0.20 | 0.00 | 0.00 | SKU-24-009 | D | 0.20 | 0.00 | 0.00 | SKU-24-012 | D | 0.20 | 0.00 | 0.00 | SKU-24-015 | D | 0.20 | 0.00 | 0.00 |
| SKU-24-003 | D | 0.20 | 0.00 | 0.00 | SKU-24-006 | D | 0.20 | 0.00 | 0.00 | SKU-24-009 | T | 0.10 | 0.10 | 0.00 | SKU-24-012 | D | 0.20 | 0.00 | 0.00 | SKU-24-015 | D | 0.20 | 0.00 | 00 |
| SKU-24-003 | D | 0.20 | 0.00 | 0.00 | SKU-24-006 | D | 0.20 | 0.00 | 0.00 | SKU-24-009 | D | 0.20 | 0.00 | 0.00 | SKU-24-012 | D | 0.20 | 0.00 | 0.00 | SKU-24-015 | D | 0.20 | 0.00 | 0.00 |
| SKU-24-003 | D | 0.10 | 0.00 | 0.00 | SKU-24-006 | D | 0.20 | 0.00 | 0.00 | SKU-24-009 | D | 0.10 | 0.00 | 0.00 | SKU-24-012 | D | 0.20 | 0.00 | 0.00 | SKU-24-015 | D | 0.20 | 0.00 | 0.00 |
| SKU-24-003 | D | 0.10 | 0.00 | 0.00 | SKU-24-006 | D | 0.20 | 0.00 | 0.00 | SKU-24-009 | D | 0.20 | 0.00 | 0.00 | SKU-24-012 | D | 0.10 | 0.00 | 0.00 | SKU-24-015 | D | 0.20 | 0.00 | 0.00 |
| SKU-24-003 | D | 0.20 | 0.00 | 0.00 | SKU-24-006 | T | 0.50 | 0.40 | 0.00 | SKU-24-009 | D | 0.20 | 0.00 | 0.00 | SKU-24-012 | D | 0.20 | 0.00 | 0.00 | SKU-24-015 | D | 0.20 | 0.00 | 0.00 |
| SKU-24-003 | D | 0.20 | 0.00 | 0.00 | SKU-24-006 | D | 0.20 | 0.00 | 0.00 | SKU-24-009 | D | 0.20 | 0.00 | 0.00 | SKU-24-012 | D | 0.20 | 0.00 | 0.00 | SKU-24-015 | D | 0.20 | 0.00 | 0.00 |
| SKU-24-003 | D | 0.10 | 0.00 | 0.00 | SKU-24-006 | T | 0.20 | 0.50 | 0.00 | SKU-24-009 | D | 0.20 | 0.00 | 0.00 | SKU-24-012 | D | 0.20 | 0.00 | 0.00 | SKU-24-015 | D | 0.20 | 0.00 | 0.00 |

KEY: $\mathrm{M}=\mathrm{MODEL}, \mathrm{D}=\mathrm{CONSTANT}$ MODEL, $\mathrm{T}=$ TREND MODEL, $\mathrm{S}=\mathrm{SEASONAL}$ MODEL, $\mathrm{X}=\mathrm{SEASONAL}$ TREND MODEL

| Material | M | Alpha | Beta | Gamma | Material | M | Alpha | Beta | Gamma | Material | M | Alpha | Beta | Gamma | Material | M | Alpha | Beta | Gamma | Material | M | Alpha | Beta | Gamma |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| SKU-24-016 | T | 0.50 | 0.50 | 0.00 | SKU-24-019 | D | 0.20 | 0.00 | 0.00 | SKU-24-022 | D | 0.30 | 0.00 | 0.00 | SKU-24-025 | D | 0.20 | 0.00 | 0.00 | SKU-24-028 | D | 0.20 | 0.00 | 0.00 |
| SKU-24-016 | D | 0.20 | 0.00 | 0.00 | SKU-24-019 | D | 0.20 | 0.00 | 0.00 | SKU-24-022 | D | 0.20 | 0.00 | 0.00 | SKU-24-025 | D | 0.20 | 0.00 | 0.00 | SKU-24-028 | D | 0.20 | 0.00 | 0.00 |
| SKU-24-016 | T | 0.10 | 0.10 | 0.00 | SKU-24-019 | D | 0.20 | 0.00 | 0.00 | SKU-24-022 | D | 0.20 | 0.00 | 0.00 | SKU-24-025 | D | 0.20 | 0.00 | 0.00 | SKU-24-028 | D | 0.10 | 0.00 | 0.00 |
| SKU-24-016 | D | 0.20 | 0.00 | 0.00 | SKU-24-019 | D | 0.10 | 0.00 | 0.00 | SKU-24-022 | D | 0.20 | 0.00 | 0.00 | SKU-24-025 | D | 0.20 | 0.00 | 0.00 | SKU-24-028 | D | 0.20 | 0.00 | 0.00 |
| SKU-24-016 | D | 0.20 | 0.00 | 0.00 | SKU-24-019 | D | 0.20 | 0.00 | 0.00 | SKU-24-022 | D | 0.20 | 0.00 | 0.00 | SKU-24-025 | D | 0.20 | 0.00 | 0.00 | SKU-24-028 | D | 0.20 | 0.00 | 0.00 |
| SKU-24-016 | D | 0.20 | 0.00 | 0.00 | SKU-24-019 | D | 0.10 | 0.00 | 0.00 | SKU-24-022 | D | 0.20 | 0.00 | 0.00 | SKU-24-025 | T | 0.10 | 0.10 | 0.00 | SKU-24-028 | D | 0.20 | 0.00 | 0.00 |
| SKU-24-016 | D | 0.20 | 0.00 | 0.00 | SKU-24-019 | D | 0.20 | 0.00 | 0.00 | SKU-24-022 | D | 0.20 | 0.00 | 0.00 | SKU-24-025 | D | 0.20 | 0.00 | 0.00 | SKU-24-028 | D | 0.20 | 0.00 | 0.00 |
| SKU-24-016 | D | 0.20 | 0.00 | 0.00 | SKU-24-019 | D | 0.20 | 0.00 | 0.00 | SKU-24-022 | D | 0.20 | 0.00 | 0.00 | SKU-24-025 | D | 0.20 | 0.00 | 0.00 | SKU-24-028 | D | 0.20 | 0.00 | 0.00 |
| SKU-24-016 | D | 0.20 | 0.00 | 0.00 | SKU-24-019 | D | 0.20 | 0.00 | 0.00 | SKU-24-022 | D | 0.20 | 0.00 | 0.00 | SKU-24-025 | D | 0.20 | 0.00 | 0.00 | SKU-24-028 | T | 0.10 | 0.10 | 0.00 |
| SKU-24-016 | D | 0.20 | 0.00 | 0.00 | SKU-24-019 | D | 0.50 | 0.00 | 0.00 | SKU-24-022 | D | 0.20 | 0.00 | 0.00 | SKU-24-025 | D | 0.10 | 0.00 | 0.00 | SKU-24-028 | D | 0.20 | 0.00 | 0.00 |
| SKU-24-016 | D | 0.20 | 0.00 | 0.00 | SKU-24-019 | D | 0.20 | 0.00 | 0.00 | SKU-24-022 | D | 0.10 | 0.00 | 0.00 | SKU-24-025 | D | 0.20 | 0.00 | 0.00 | SKU-24-028 | D | 0.20 | 0.00 | 0.00 |
| SKU-24-016 | D | 0.20 | 0.00 | 0.00 | SKU-24-019 | D | 0.10 | 0.00 | 0.00 | SKU-24-022 | D | 0.10 | 0.00 | 0.00 | SKU-24-025 | D | 0.20 | 0.00 | 0.00 | SKU-24-028 | D | 0.20 | 0.00 | 0.00 |
| SKU-24-017 | D | 0.20 | 0.00 | 0.00 | SKU-24-020 | D | 0.20 | 0.00 | 0.00 | SKU-24-023 | D | 0.10 | 0.00 | 0.00 | SKU-24-026 | D | 0.20 | 0.00 | 0.00 | SKU-24-029 | D | 0.20 | 0.00 | 0.00 |
| SKU-24-017 | D | 0.10 | 0.00 | 0.00 | SKU-24-020 | D | 0.20 | 0.00 | 0.00 | SKU-24-023 | D | 0.20 | 0.00 | 0.00 | SKU-24-026 | D | 0.10 | 0.00 | 0.00 | SKU-24-029 | D | 0.20 | 0.00 | 0.00 |
| SKU-24-017 | D | 0.10 | 0.00 | 0.00 | SKU-24-020 | D | 0.20 | 0.00 | 0.00 | SKU-24-023 | D | 0.10 | 0.00 | 0.00 | SKU-24-026 | D | 0.10 | 0.00 | 0.00 | SKU-24-029 | D | 0.20 | 0.00 | 0.00 |
| SKU-24-017 | D | 0.20 | 0.00 | 0.00 | SKU-24-020 | D | 0.20 | 0.00 | 0.00 | SKU-24-023 | D | 0.20 | 0.00 | 0.00 | SKU-24-026 | D | 0.20 | 0.00 | 0.00 | SKU-24-029 | D | 0.20 | 0.00 | 0.00 |
| SKU-24-017 | D | 0.20 | 0.00 | 0.00 | SKU-24-020 | D | 0.20 | 0.00 | 0.00 | SKU-24-023 | D | 0.20 | 0.00 | 0.00 | SKU-24-026 | T | 0.10 | 0.10 | 0.00 | SKU-24-029 | D | 0.20 | 0.00 | 0.00 |
| SKU-24-017 | D | 0.20 | 0.00 | 0.00 | SKU-24-020 | D | 0.10 | 0.00 | 0.00 | SKU-24-023 | D | 0.20 | 0.00 | 0.00 | SKU-24-026 | D | 0.20 | 0.00 | 0.00 | SKU-24-029 | T | 0.10 | 0.10 | 0.00 |
| SKU-24-017 | D | 0.20 | 0.00 | 0.00 | SKU-24-020 | D | 0.10 | 0.00 | 0.00 | SKU-24-023 | T | 0.10 | 0.10 | 0.00 | SKU-24-026 | D | 0.20 | 0.00 | 0.00 | SKU-24-029 | D | 0.20 | 0.00 | 0.00 |
| SKU-24-017 | D | 0.20 | 0.00 | 0.00 | SKU-24-020 | D | 0.20 | 0.00 | 0.00 | SKU-24-023 | D | 0.20 | 0.00 | 0.00 | SKU-24-026 | D | 0.20 | 0.00 | 0.00 | SKU-24-029 | D | 0.20 | 0.00 | 0.00 |
| SKU-24-017 | D | 0.20 | 0.00 | 0.00 | SKU-24-020 | D | 0.20 | 0.00 | 0.00 | SKU-24-023 | D | 0.20 | 0.00 | 0.00 | SKU-24-026 | D | 0.20 | 0.00 | 0.00 | SKU-24-029 | D | 0.20 | 0.00 | 0.00 |
| SKU-24-017 | D | 0.20 | 0.00 | 0.00 | SKU-24-020 | D | 0.20 | 0.00 | 0.00 | SKU-24-023 | D | 0.20 | 0.00 | 0.00 | SKU-24-026 | D | 0.10 | 0.00 | 0.00 | SKU-24-029 | D | 0.20 | 0.00 | 0.00 |
| SKU-24-017 | D | 0.20 | 0.00 | 0.00 | SKU-24-020 | D | 0.20 | 0.00 | 0.00 | SKU-24-023 | D | 0.20 | 0.00 | 0.00 | SKU-24-026 | D | 0.20 | 0.00 | 0.00 | SKU-24-029 | D | 0.20 | 0.00 | 0.00 |
| SKU-24-017 | D | 0.20 | 0.00 | 0.00 | SKU-24-020 | D | 0.20 | 0.00 | 0.00 | SKU-24-023 | D | 0.20 | 0.00 | 0.00 | SKU-24-026 | D | 0.20 | 0.00 | 0.00 | SKU-24-029 | D | 0.20 | 0.00 | 0.00 |
| SKU-24-018 | D | 0.10 | 0.00 | 0.00 | SKU-24-021 | D | 0.10 | 0.00 | 0.00 | SKU-24-024 | D | 0.20 | 0.00 | 0.00 | SKU-24-027 | D | 0.20 | 0.00 | 0.00 | SKU-24-030 | D | 0.20 | 0.00 | 0.00 |
| SKU-24-018 | D | 0.20 | 0.00 | 0.00 | SKU-24-021 | D | 0.20 | 0.00 | 0.00 | SKU-24-024 | D | 0.20 | 0.00 | 0.00 | SKU-24-027 | D | 0.20 | 0.00 | 0.00 | SKU-24-030 | D | 0.20 | 0.00 | 0.00 |
| SKU-24-018 | D | 0.20 | 0.00 | 0.00 | SKU-24-021 | D | 0.20 | 0.00 | 0.00 | SKU-24-024 | D | 0.20 | 0.00 | 0.00 | SKU-24-027 | D | 0.20 | 0.00 | 0.00 | SKU-24-030 | D | 0.20 | 0.00 | 0.00 |
| SKU-24-018 | D | 0.20 | 0.00 | 0.00 | SKU-24-021 | D | 0.20 | 0.00 | 0.00 | SKU-24-024 | D | 0.20 | 0.00 | 0.00 | SKU-24-027 | D | 0.20 | 0.00 | 0.00 | SKU-24-030 | D | 0.20 | 0.00 | 0.00 |
| SKU-24-018 | D | 0.20 | 0.00 | 0.00 | SKU-24-021 | D | 0.20 | 0.00 | 0.00 | SKU-24-024 | D | 0.20 | 0.00 | 0.00 | SKU-24-027 | D | 0.20 | 0.00 | 0.00 | SKU-24-030 | D | 0.20 | 0.00 | 0.00 |
| SKU-24-018 | D | 0.20 | 0.00 | 0.00 | SKU-24-021 | D | 0.20 | 0.00 | 0.00 | SKU-24-024 | D | 0.20 | 0.00 | 0.00 | SKU-24-027 | D | 0.20 | 0.00 | 0.00 | SKU-24-030 | D | 0.20 | 0.00 | 0.00 |
| SKU-24-018 | D | 0.20 | 0.00 | 0.00 | SKU-24-021 | T | 0.30 | 0.20 | 0.00 | SKU-24-024 | D | 0.20 | 0.00 | 0.00 | SKU-24-027 | D | 0.20 | 0.00 | 0.00 | SKU-24-030 | D | 0.20 | 0.00 | 0.00 |
| SKU-24-018 | T | 0.50 | 0.50 | 0.00 | SKU-24-021 | D | 0.20 | 0.00 | 0.00 | SKU-24-024 | D | 0.20 | 0.00 | 0.00 | SKU-24-027 | D | 0.20 | 0.00 | 0.00 | SKU-24-030 | T | 0.50 | 0.20 | 0.00 |
| SKU-24-018 | D | 0.10 | 0.00 | 0.00 | SKU-24-021 | D | 0.20 | 0.00 | 0.00 | SKU-24-024 | D | 0.20 | 0.00 | 0.00 | SKU-24-027 | T | 0.50 | 0.30 | 0.00 | SKU-24-030 | D | 0.20 | 0.00 | 0.00 |
| SKU-24-018 | D | 0.20 | 0.00 | 0.00 | SKU-24-021 | D | 0.20 | 0.00 | 0.00 | SKU-24-024 | D | 0.10 | 0.00 | 0.00 | SKU-24-027 | D | 0.20 | 0.00 | 0.00 | SKU-24-030 | D | 0.20 | 0.00 | 0.00 |
| SKU-24-018 | D | 0.20 | 0.00 | 0.00 | SKU-24-021 | D | 0.10 | 0.00 | 0.00 | SKU-24-024 | D | 0.20 | 0.00 | 0.00 | SKU-24-027 | D | 0.20 | 0.00 | 0.00 | SKU-24-030 | D | 0.20 | 0.00 | 0.00 |
| SKU-24-018 | D | 0.20 | 0.00 | 0.00 | SKU-24-021 | D | 0.20 | 0.00 | 0.00 | SKU-24-024 | D | 0.20 | 0.00 | 0.00 | SKU-24-027 | D | 0.20 | 0.00 | 0.00 | SKU-24-030 | D | 0.20 | 0.00 | 0.00 |

KEY: $\mathrm{M}=\mathrm{MODEL}, \mathrm{D}=\mathrm{CONSTANT}$ MODEL, $\mathrm{T}=$ TREND MODEL, $\mathrm{S}=\mathrm{SEASONAL}$ MODEL, $\mathrm{X}=\mathrm{SEASONAL}$ TREND MODEL

| Material | M | Alpha | Beta | Gamma | Material | M | Alpha | Beta | Gamma | Material | M | Alpha | Beta | Gamma | Material | M | Alpha | Beta | Gamma |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| SKU-24-031 | D | 0.20 | 0.00 | 0.00 | SKU-24-034 | D | 0.20 | 0.00 | 0.00 | SKU-24-037 | D | 0.20 | 0.00 | 0.00 | SKU-24-040 | T | 0.40 | 0.40 | 0.00 |
| SKU-24-031 | D | 0.20 | 0.00 | 0.00 | SKU-24-034 | D | 0.20 | 0.00 | 0.00 | SKU-24-037 | D | 0.20 | 0.00 | 0.00 | SKU-24-040 | D | 0.20 | 0.00 | 0.00 |
| SKU-24-031 | D | 0.20 | 0.00 | 0.00 | SKU-24-034 | D | 0.20 | 0.00 | 0.00 | SKU-24-037 | T | 0.40 | 0.30 | 0.00 | SKU-24-040 | D | 0.20 | 0.00 | 0.00 |
| SKU-24-031 | D | 0.20 | 0.00 | 0.00 | SKU-24-034 | D | 0.20 | 0.00 | 0.00 | SKU-24-037 | D | 0.20 | 0.00 | 0.00 | SKU-24-040 | D | 0.20 | 0.00 | 0.00 |
| SKU-24-031 | D | 0.20 | 0.00 | 0.00 | SKU-24-034 | D | 0.20 | 0.00 | 0.00 | SKU-24-037 | D | 0.20 | 0.00 | 0.00 | SKU-24-040 | T | 0.50 | 0.40 | 0.00 |
| SKU-24-031 | D | 0.20 | 0.00 | 0.00 | SKU-24-034 | D | 0.20 | 0.00 | 0.00 | SKU-24-037 | D | 0.20 | 0.00 | 0.00 | SKU-24-040 | D | 0.20 | 0.00 | 0.00 |
| SKU-24-031 | D | 0.20 | 0.00 | 0.00 | SKU-24-034 | D | 0.20 | 0.00 | 0.00 | SKU-24-037 | D | 0.10 | 0.00 | 0.00 | SKU-24-040 | D | 0.20 | 0.00 | 0.00 |
| SKU-24-031 | D | 0.20 | 0.00 | 0.00 | SKU-24-034 | D | 0.20 | 0.00 | 0.00 | SKU-24-037 | D | 0.20 | 0.00 | 0.00 | SKU-24-040 | D | 0.10 | 0.00 | 0.00 |
| SKU-24-031 | D | 0.10 | 0.00 | 0.00 | SKU-24-034 | D | 0.20 | 0.00 | 0.00 | SKU-24-037 | D | 0.20 | 0.00 | 0.00 | SKU-24-040 | D | 0.20 | 0.00 | 0.00 |
| SKU-24-031 | D | 0.20 | 0.00 | 0.00 | SKU-24-034 | D | 0.10 | 0.00 | 0.00 | SKU-24-037 | D | 0.10 | 0.00 | 0.00 | SKU-24-040 | D | 0.20 | 0.00 | 0.00 |
| SKU-24-031 | D | 0.10 | 0.00 | 0.00 | SKU-24-034 | D | 0.20 | 0.00 | 0.00 | SKU-24-037 | D | 0.20 | 0.00 | 0.00 | SKU-24-040 | T | 0.10 | 0.10 | 0.00 |
| SKU-24-031 | D | 0.10 | 0.00 | 0.00 | SKU-24-034 | D | 0.20 | 0.00 | 0.00 | SKU-24-037 | D | 0.20 | 0.00 | 0.00 | SKU-24-040 | D | 0.20 | 0.00 | 0.00 |
| SKU-24-032 | T | 0.10 | 0.10 | 0.00 | SKU-24-035 | D | 0.20 | 0.00 | 0.00 | SKU-24-038 | D | 0.20 | 0.00 | 0.00 |  |  |  |  |  |
| SKU-24-032 | D | 0.20 | 0.00 | 0.00 | SKU-24-035 | D | 0.20 | 0.00 | 0.00 | SKU-24-038 | D | 0.20 | 0.00 | 0.00 |  |  |  |  |  |
| SKU-24-032 | T | 0.10 | 0.10 | 0.00 | SKU-24-035 | D | 0.20 | 0.00 | 0.00 | SKU-24-038 | D | 0.20 | 0.00 | 0.00 |  |  |  |  |  |
| SKU-24-032 | D | 0.20 | 0.00 | 0.00 | SKU-24-035 | D | 0.20 | 0.00 | 0.00 | SKU-24-038 | D | 0.20 | 0.00 | 0.00 |  |  |  |  |  |
| SKU-24-032 | D | 0.20 | 0.00 | 0.00 | SKU-24-035 | T | 0.40 | 0.20 | 0.00 | SKU-24-038 | D | 0.20 | 0.00 | 0.00 |  |  |  |  |  |
| SKU-24-032 | D | 0.10 | 0.00 | 0.00 | SKU-24-035 | D | 0.20 | 0.00 | 0.00 | SKU-24-038 | T | 0.10 | 0.10 | 0.00 |  |  |  |  |  |
| SKU-24-032 | D | 0.20 | 0.00 | 0.00 | SKU-24-035 | D | 0.20 | 0.00 | 0.00 | SKU-24-038 | D | 0.20 | 0.00 | 0.00 |  |  |  |  |  |
| SKU-24-032 | D | 0.20 | 0.00 | 0.00 | SKU-24-035 | D | 0.20 | 0.00 | 0.00 | SKU-24-038 | D | 0.20 | 0.00 | 0.00 |  |  |  |  |  |
| SKU-24-032 | D | 0.20 | 0.00 | 0.00 | SKU-24-035 | T | 0.10 | 0.10 | 0.00 | SKU-24-038 | T | 0.10 | 0.10 | 0.00 |  |  |  |  |  |
| SKU-24-032 | D | 0.20 | 0.00 | 0.00 | SKU-24-035 | D | 0.20 | 0.00 | 0.00 | SKU-24-038 | D | 0.20 | 0.00 | 0.00 |  |  |  |  |  |
| SKU-24-032 | D | 0.20 | 0.00 | 0.00 | SKU-24-035 | D | 0.20 | 0.00 | 0.00 | SKU-24-038 | D | 0.20 | 0.00 | 0.00 |  |  |  |  |  |
| SKU-24-032 | D | 0.20 | 0.00 | 0.00 | SKU-24-035 | D | 0.20 | 0.00 | 0.00 | SKU-24-038 | D | 0.20 | 0.00 | 0.00 |  |  |  |  |  |
| SKU-24-033 | T | 0.10 | 0.10 | 0.00 | SKU-24-036 | D | 0.20 | 0.00 | 0.00 | SKU-24-039 | D | 0.10 | 0.00 | 0.00 |  |  |  |  |  |
| SKU-24-033 | D | 0.20 | 0.00 | 0.00 | SKU-24-036 | D | 0.20 | 0.00 | 0.00 | SKU-24-039 | D | 0.20 | 0.00 | 0.00 |  |  |  |  |  |
| SKU-24-033 | D | 0.20 | 0.00 | 0.00 | SKU-24-036 | D | 0.20 | 0.00 | 0.00 | SKU-24-039 | D | 0.20 | 0.00 | 0.00 |  |  |  |  |  |
| SKU-24-033 | D | 0.20 | 0.00 | 0.00 | SKU-24-036 | D | 0.20 | 0.00 | 0.00 | SKU-24-039 | D | 0.20 | 0.00 | 0.00 |  |  |  |  |  |
| SKU-24-033 | D | 0.20 | 0.00 | 0.00 | SKU-24-036 | D | 0.20 | 0.00 | 0.00 | SKU-24-039 | D | 0.20 | 0.00 | 0.00 |  |  |  |  |  |
| SKU-24-033 | D | 0.20 | 0.00 | 0.00 | SKU-24-036 | D | 0.20 | 0.00 | 0.00 | SKU-24-039 | D | 0.20 | 0.00 | 0.00 |  |  |  |  |  |
| SKU-24-033 | D | 0.20 | 0.00 | 0.00 | SKU-24-036 | D | 0.20 | 0.00 | 0.00 | SKU-24-039 | D | 0.20 | 0.00 | 0.00 |  |  |  |  |  |
| SKU-24-033 | D | 0.20 | 0.00 | 0.00 | SKU-24-036 | D | 0.20 | 0.00 | 0.00 | SKU-24-039 | D | 0.20 | 0.00 | 0.00 |  |  |  |  |  |
| SKU-24-033 | D | 0.10 | 0.00 | 0.00 | SKU-24-036 | D | 0.20 | 0.00 | 0.00 | SKU-24-039 | D | 0.20 | 0.00 | 0.00 |  |  |  |  |  |
| SKU-24-033 | D | 0.20 | 0.00 | 0.00 | SKU-24-036 | D | 0.20 | 0.00 | 0.00 | SKU-24-039 | D | 0.20 | 0.00 | 0.00 |  |  |  |  |  |
| SKU-24-033 | D | 0.20 | 0.00 | 0.00 | SKU-24-036 | D | 0.20 | 0.00 | 0.00 | SKU-24-039 | D | 0.10 | 0.00 | 0.00 |  |  |  |  |  |
| SKU-24-033 | D | 0.20 | 0.00 | 0.00 | SKU-24-036 | D | 0.20 | 0.00 | 0.00 | SKU-24-039 | D | 0.20 | 0.00 | 0.00 |  |  |  |  |  |

KEY: $\mathrm{M}=\mathrm{MODEL}, \mathrm{D}=\mathrm{CONSTANT}$ MODEL, $\mathrm{T}=$ TREND MODEL, $\mathrm{S}=\mathrm{SEASONAL}$ MODEL, $\mathrm{X}=\mathrm{SEASONAL}$ TREND MODEL

## SAP Automatic Model Parameters (60 Month)

| Material | M | Alpha | Beta | amma | Material | M | Alpha | Beta | Gam | aterial | M | Alpha | Beta | Gamma | Materia | M | Alpha | Beta | an | Material | M | Alpha | Beta | Gamm |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| SKU-60-001 | D | 0.20 | 0.00 | 0.00 | SKU-60-003 | D | 0.20 | 0.00 | 0.00 | SKU-60-005 | D | 0.20 | 0.00 | 0.00 | SKU-60-007 | D | 0.20 | 0.00 | 0.00 | SKU-60-009 | D | 0.20 | 0.00 | 0.00 |
| SKU-60-001 | D | 0.20 | 0.00 | 0.00 | SKU-60-003 | S | 0.20 | 0.00 | 0.40 | SKU-60-005 | D | 0.20 | 0.00 | 0.00 | SKU-60-007 | D | 0.20 | 0.00 | 0.00 | SKU-60-009 | D | 0.20 | 0.00 | 0.00 |
| SKU-60-001 | D | 0.20 | 0.00 | 0.00 | SKU-60-003 | S | 0.10 | 0.00 | 0.10 | SKU-60-005 | D | 0.20 | 0.00 | 0.00 | SKU-60-007 | D | 0.20 | 0.00 | 0.00 | SKU-60-009 | D | 0.20 | 0.00 | 0.00 |
| SKU-60-001 | D | 0.20 | 0.00 | 0.00 | SKU-60-003 | D | 0.20 | 0.00 | 0.00 | SKU-60-005 | D | 0.20 | 0.00 | 0.00 | SKU-60-007 | D | 0.20 | 0.00 | 0.00 | SKU-60-009 | D | 0.20 | 0.00 | 0.00 |
| SKU-60-001 | D | 0.20 | 0.00 | 0.00 | SKU-60-003 | D | 0.20 | 0.00 | 0.00 | SKU-60-005 | D | 0.20 | 0.00 | 0.00 | SKU-60-007 | D | 0.20 | 0.00 | 0.00 | SKU-60-009 | D | 0.20 | 0.00 | 0.00 |
| SKU-60-001 | D | 0.20 | 0.00 | 0.00 | SKU-60-003 | $\times$ | 0.20 | 0.20 | 0.20 | SKU-60-005 | D | 0.20 | 0.00 | 0.00 | SKU-60-007 | D | 0.20 | 0.00 | 0.00 | SKU-60-009 | D | 0.20 | 0.00 | 0.00 |
| SKU-60-001 | D | 0.20 | 0.00 | 0.00 | SKU-60-00 | D | 0.20 | 0.00 | 0.00 | SKU-60-005 | D | 0.20 | 0.00 | 0.00 | SKU-60-00 | x | 0.10 | 0.10 | 0.10 | SKU-60-009 | D | 0.20 | 0.00 | . 00 |
| SKU-60-001 | D | 0.20 | 0.00 | 0.00 | SKU-60- | D | 0.20 | 0.00 | 0.00 | SKU-60-005 | D | 0.20 | 0.00 | 0.00 | SKU-60-00 | x | 0.10 | 0.10 | 0.10 | SKU-60-009 | D | 0.20 | 0.00 | . 00 |
| SKU-60-001 | D | 0.20 | 0.00 | 0.00 | SKU-60-003 | D | 0.20 | 0.00 | 0.00 | SKU-60-005 | $\times$ | 0.10 | 0.10 | 0.10 | SKU-60-00 | X | 0.30 | 0.40 | 0.30 | SKU-60-00 | D | 0.20 | 0.00 | 0.00 |
| SKU-60-001 | D | 0.20 | 0.00 | . 0 | SKU-60-0 | D | 0.20 | 0.00 | . 0 | SKU-60-00 | D | 0.20 | 0.00 | 0.00 | SKU-60-00 | D | 0.20 | 0.00 | 0.0 | SKU-60-00 | D | 0.20 | 0.00 | 0.00 |
| SKU-60-001 | D | 0.20 | 0.00 | . 0 | SKU-60-003 | $\times$ | 0.10 | 0.10 | 10 | SKU-60-005 | D | 0.20 | 0.00 | 0.0 | SKU-60-00 | D | 0.20 | 0.00 | 0.0 | SKU-60-00 | D | 0.2 | 0.00 | 0.00 |
| SKU-60-001 | D | 0.20 | 0.00 | . 00 | SKU-60-00 | D | 0.20 | 0.00 | . 00 | SKU-60-005 | D | 0.20 | 0.00 | 0.0 | SKU-60-007 | D | 0.20 | 0.00 | 0.0 | SKU-60-009 | D | 0.20 | 0.00 | 0.00 |
| SKU-60-001 | D | 0.20 | 0.00 | . 00 | SKU-60-00 | D | 0. 20 | 0.00 | . 00 | SKU-60-005 | D | 0.20 | 0.00 | 0.00 | SKU-60-007 | D | 0.20 | 0.00 | 0.00 | SKU-60-009 | D | 0.20 | 0.00 | 0.00 |
| SKU-60-001 | $\times$ | 0.10 | 0.10 | 0.10 | SKU-60-00 | D | 0.20 | 0.00 | . 00 | SKU-60-005 | D | . 20 | 0.00 | 0.00 | SKU-60-007 | D | 0.20 | 0.00 | 0.00 | SKU-60-009 | D | 0.20 | 0.00 | 0.00 |
| SKU-60-001 | $x$ | 0.10 | 0.10 | 0.10 | SKU-60-00 | D | 0.20 | 0.00 | 0.00 | SKU-60-005 | D | . 20 | 0.00 | 0.00 | SKU-60-007 | D | 0.20 | 0.00 | 0.00 | SKU-60-009 | D | 0.20 | 0.00 | 0.00 |
| SKU-60-001 | $x$ | 0.10 | 0.10 | 0.10 | SKU-60-00 | D | 0.20 | 0.00 | 0.00 | SKU-60-005 | D | 0.20 | 0.00 | 0.00 | SKU-60-007 | D | 0.20 | 0.00 | 0.00 | SKU-60-009 | D | 0.20 | 0.00 | 0.00 |
| SKU-60-001 | $x$ | 0.10 | 0.10 | 10 | SKU-60-00 | D | 20 | . 00 | . 0 | SKU-60-00 | D | . 20 | 0.00 | . 00 | SKU-60-007 | D | 0.20 | 0.00 | 0.00 | SKU-60-009 | D | 0.20 | 0.00 | 0.00 |
| SKU-60-00 | x | 10 | 0.10 | 0 | SKU-60 | D | 20 | 00 | 0.00 | SKU-60-00 | D | 20 | 0.00 | 0.00 | SKU-60-007 | D | 0.20 | 0.00 | 0.00 | SKU-60-009 | D | 0.20 | 0.00 | . 00 |
| SKU-60-00 | $\times$ | 0.10 | 0.10 | 0.10 | SKU-6 | D | 0.20 | 0.00 | 0.00 | SKU-6 | D | 20 | . 00 | 0.00 | SKU-60-007 | D | 20 | 0.00 | 0.00 | SKU-60-009 | D | 0.20 | . 00 | 0.00 |
| SKU-60-00 | x | 0.10 | 0.10 | 0.10 | SKU-6 | D | 0.20 | 0.00 | 0.00 | SKU- | D | 0.20 | 00 | 0.00 | SKU-60-007 | D | 0.20 | 0.00 | 0.00 | SKU-60-00 | D | 0.20 | 0.00 | 0.00 |
| SKU-60-00 | x | 0.10 | 0.10 | 0.10 | SKU-6 | D | 0.20 | 00 | 0.00 | SKU-60-005 | D | 20 | . 00 | 0.00 | SKU-60-007 | D | 0.20 | 0.00 | 0.00 | SKU-60-009 | D | 0.20 | 0.00 | 0.00 |
| SKU-60-00 | $\times$ | 0.10 | 0.10 | 0.10 | SKU-6 | D | 0.20 | 0.00 | 0.00 | SKU-6 | D | 0.20 | 0.00 | 0.00 | SKU-60-007 | D | 0.20 | 0.00 | 0.00 | SKU-60-0 | D | 0.20 | 00 | 0.00 |
| SKU-60-00 | $\times$ | 0.10 | 0.10 | 0.10 | SKU-60 | D | 0.20 | 0.00 | 0.00 | SKU-60-00 | D | 0.20 | 0 | 0.00 | SKU-60-00 | D | 0.20 | 0.0 | 0.00 | SKU-60-00 | D | 0.20 | 0.00 | 0.00 |
| SKU-60-00 | x | 0.10 | 0.10 |  | SKU-60 | D | 20 | 0 | 00 | SKU-60 | D | 0.20 | 0.00 | , | SKU-60-00 | D | 0.20 | 0.00 | . 00 | SKU-60-00 | D | 0.20 | 0.00 | 0.00 |
| SKU-6 | D | 0.20 | 0.00 | 0.00 | SKU-6 | D | 0.20 | 0 | 0.00 | SKU | D | . 20 | . 00 | 0.00 | SKU | D | . 20 | . 0 | 0.00 | SKU-60-01 | D | 0.20 | 0.00 | 0.00 |
| SKU-60-0 | D | 0.20 | 0.00 | 0.00 | SKU- | D | 0.20 | 00 | 0.00 | SKU-6 | D | 20 | 0.00 | 0.00 | SKU | D | 0.20 | 0.00 | 0.00 | SKU | D | 0.20 | 0.00 | 0.00 |
| SKU-60-00 | D | 0.2 | 0.00 | 0.00 | SKU-60 | D | 0.20 | 0.00 | 0.00 | SKU-6 | D | 20 | 0.00 | 0.00 | SKU-60-0 | D | 0.20 | 0.00 | 0.00 | SKU | D | 0.20 | 0.00 | 0.00 |
| SKU-60-00 | D | 0.20 | 0.00 | 0.00 | SKU-60-0 | D | . 20 | 0.00 | 0.00 | SKU-60-0 | D | . 20 | . 00 | 0.00 | SKU-60-0 | x | 0.1 | 0.10 | 0.10 | SKU-60-010 | D | 0.20 | 0.00 |  |
| SKU-60-002 | D | 0.20 | 0.00 | 00 | SKU-60-00 | D | 0.20 | . 0 | 00 | SKU-60-00 | D | 0.20 | 0.00 | 0.00 | SKU-60-00 | $\times$ | 0.1 | 0.1 | 0.10 | SKU-60-010 | D | 0.2 | . 0 | 0.00 |
| SKU-60-002 | D | 0.20 | 00 | 0.00 | SKU-60-004 | D | 0.20 | 00 | 0.00 | SKU-60-006 | D | 0.20 | 0.00 | 0.00 | SKU-60-00 | $\times$ | 0.10 | 0.1 | 0.1 | SKU-60-010 | D | 0.20 | 0.00 | 0.00 |
| SKU-60-002 | D | 0.20 | 00 | 0.00 | SKU-60-004 | D | 0.20 | 0.00 | 0.00 | SKU-60-006 | D | 0.20 | 0.00 | 0.00 | SKU-60-00 | S | 0.10 | 0.00 | 0.10 | SKU-60-010 | D | 0.20 | 0.00 | 0.00 |
| SKU-60-002 | D | 0.20 | 0.00 | 0.00 | SKU-60-004 | D | 0.20 | 0.00 | 0.00 | SKU-60-006 | D | 0.20 | 0.00 | 0.00 | SKU-60-008 | S | 0.10 | 0.00 | 0.10 | SKU-60-010 | D | 0.20 | 0.00 | 0.00 |
| SKU-60-002 | D | 0.20 | 0.00 | 0.00 | SKU-60-004 | D | 0.20 | 0.00 | 0.00 | SKU-60-006 | D | 0.20 | 0.00 | 0.00 | SKU-60-008 | S | 0.10 | 0.00 | 0.1 | SKU-60-010 | D | 0.20 | 0.00 | 0.00 |
| SKU-60-002 | D | 0.20 | 0.00 | 0.00 | SKU-60-004 | D | 0.20 | 0.00 | 0.00 | SKU-60-006 | D | 0.20 | 0.00 | 0.00 | SKU-60-008 | D | 0.20 | 0.00 | 0.0 | SKU-60-010 | D | 0.20 | 0.00 | 0.00 |
| SKU-60-002 | D | 0.20 | 0.00 | 0.00 | SKU-60-004 | X | 0.10 | . 10 | 0.10 | SKU-60-006 | D | 0.20 | 0.00 | 0.00 | SKU-60-008 | D | 0.20 | 0.00 | 0.0 | SKU-60-010 | D | 0.20 | 0.00 | 0.00 |
| SKU-60-002 | D | 0.20 | 00 | 0.00 | SKU-60-004 | D | 0.20 | 0.00 | 0.00 | SKU-60-00 | D | 0.20 | 0.00 | 0.00 | SKU-60-008 | D | 0.20 | 0.00 | 0.0 | SKU-60-010 | D | 0.20 | 0.00 | 0.00 |
| SKU-60-002 | D | 0.20 | 00 | 0.00 | SKU-60-004 | D | 0.20 | . 00 | 0.00 | SKU-60-006 | D | 0.20 | 0.00 | 0.00 | SKU-60-008 | D | 0.20 | 0.00 | 0.00 | SKU-60-010 | x | 0.10 | 0.10 | 0.10 |
| SKU-60-002 | D | 0.20 | 0.00 | 0.00 | SKU-60-004 | D | 0.20 | 0.00 | 0.00 | SKU-60-006 | D | 0.20 | 0.00 | 0.00 | SKU-60-008 | D | 0.20 | 0.00 | 0.00 | SKU-60-010 | x | 0.10 | 0.10 | 0.1 |
| SKU-60-002 | D | 0.20 | 0.00 | 0.00 | SKU-60-004 | D | 0.20 | 0.00 | 0.00 | SKU-60-006 | D | 0.20 | 0.00 | 0.00 | SKU-60-008 | D | 0.20 | 0.00 | 0.00 | SKU-60-010 | x | 0.10 | 0.10 | 0.10 |
| SKU-60-002 | D | 0.20 | 0.00 | 0.00 | SKU-60-004 | D | 0.20 | 0.00 | 0.00 | SKU-60-006 | D | 0.20 | 0.00 | 0.00 | SKU-60-008 | D | 0.20 | 0.00 | 0.00 | SKU-60-010 | x | 0.10 | 0.10 | 0.10 |
| SKU-60-002 | D | 0.20 | 0.00 | 0.00 | SKU-60-004 | D | 0.20 | 0.00 | 0.00 | SKU-60-006 | D | 0.20 | 0.00 | 0.00 | SKU-60-008 | D | 0.20 | 0.00 | 0.00 | SKU-60-010 | x | 0.10 | 0.10 | 0.10 |
| SKU-60-002 | D | 0.20 | 0.00 | 0.00 | SKU-60-004 | D | 0.20 | 0.00 | 0.00 | SKU-60-006 | D | 0.20 | 0.00 | 0.00 | SKU-60-008 | D | 0.20 | 0.00 | 0.00 | SKU-60-010 | x | 0.10 | 0.10 | 0.10 |
| SKU-60-002 | D | 0.20 | 0.00 | 0.00 | SKU-60-004 | D | 0.20 | 0.00 | 0.00 | SKU-60-006 | D | 0.20 | 0.00 | 0.00 | SKU-60-008 | D | 0.20 | 0.00 | 0.00 | SKU-60-010 | X | 0.10 | 0.10 | 0.10 |
| SKU-60-002 | D | 0.20 | 0.00 | 0.00 | SKU-60-004 | D | 0.20 | 0.00 | 0.00 | SKU-60-006 | D | 0.20 | 0.00 | 0.00 | SKU-60-008 | D | 0.20 | 0.00 | 0.00 | SKU-60-010 | X | 0.10 | 0.10 | 0.10 |
| SKU-60-002 | D | 0.20 | 0.00 | 0.00 | SKU-60-004 | D | 0.20 | 0.00 | 0.00 | SKU-60-006 | x | 0.40 | 0.40 | 0.20 | SKU-60-008 | D | 0.20 | 0.00 | 0.00 | SKU-60-010 | X | 0.10 | 0.10 | . 10 |
| SKU-60-002 | D | 0.20 | 0.00 | 0.00 | SKU-60-004 | D | 0.20 | 0.00 | 0.00 | SKU-60-006 | x | 0.40 | 0.40 | 0.20 | SKU-60-008 | D | 0.20 | 0.00 | 0.00 | SKU-60-010 | x | 0.10 | 0.10 | 0.10 |
| SKU-60-002 | D | 0.20 | 0.00 | 0.00 | SKU-60-004 | D | 0.20 | 0.00 | 0.00 | SKU-60-006 | X | 0.40 | 0.40 | 0.20 | SKU-60-008 | D | 0.20 | 0.00 | 0.00 | SKU-60-010 | - | 0.10 | 0.10 | 0.10 |
| SKU-60-002 | D | 0.20 | 0.00 | 0.00 | SKU-60-004 | D | 0.20 | 0.00 | 0.00 | SKU-60-006 | D | 0.20 | 0.00 | 0.00 | SKU-60-008 | D | 0.20 | 0.00 | 0.00 | SKU-60-010 | x | 0.10 | 0.10 | 0.1 |

KEY: M = MODEL, D = CONSTANT MODEL, T = TREND MODEL, S = SEASONAL MODEL, X = SEASONAL TREND MODEL

Appendix D - Summary Forecast Error Measures
Mean SKU MAE, MAPE, RW-MAPE, MW-MAPE, and CFE for total hold-out period

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| MODEL（1＋3） |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
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| PARAMETERS | 咅 |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| ${ }^{\text {80－MONTH }}$ |  |  | Revenue Weighted MAPE | $\begin{gathered} \text { Magin } \\ \text { Weighed } \\ \text { Mape } \end{gathered}$ | ${ }_{\text {cost }}^{\text {Total }}$ |  | MAPE | $\begin{aligned} & \text { Revenue } \\ & \text { Weighted } \\ & \text { MAPE } \end{aligned}$ | $\begin{gathered} \text { Margin } \\ \text { Weighed } \\ \text { MAPE } \end{gathered}$ | ${ }_{\text {cost }}^{\text {Total }}$ |  |  | $\begin{gathered} \text { Revenue } \\ \text { Weifhed } \\ \text { MAPE } \end{gathered}$ | $\begin{gathered} \text { Margin } \\ \text { Weighed } \\ \text { MAPE } \end{gathered}$ | ${ }_{\text {cost }}^{\text {Total }}$ |  |  | $\begin{gathered} \text { Revenue } \\ \text { Weiphede } \\ \text { MADE } \end{gathered}$ | $\begin{gathered} \text { Maging } \\ \text { Weighed } \\ \text { MAPE } \end{gathered}$ | ${ }_{\text {Total }}^{\text {cost }}$ | maE |  | $\begin{gathered} \text { Revenue } \\ \text { Wegnhed } \\ \text { WAPE } \end{gathered}$ | $\begin{gathered} \text { Magin } \\ \text { Meighed } \\ \text { MAPE } \end{gathered}$ | ${ }_{\text {cost }}^{\text {Total }}$ |
| $\begin{aligned} & \text { SKU-60-001 } \\ & \text { SKU-60-001-EM } \end{aligned}$ | ${ }_{\substack{\text { MAE } \\ 7.11 \\ 7.11}}$ | $\xrightarrow[\substack{\text { MAPE } \\ 10.9 \% \\ 19.8 \%}]{\text { a }}$ | $\xrightarrow[\substack{\text { MAPE } \\ 0.4 \% \\ 0.4 \%}]{\text { cem }}$ |  |  | $\underset{\substack { \text { MAE } \\ \begin{subarray}{c}{10.24 \\ 10.24{ \text { MAE } \\ \begin{subarray} { c } { 1 0 . 2 4 \\ 1 0 . 2 4 } }\end{subarray}}{ }$ | $\substack { \text { MAPE } \\ \begin{subarray}{c}{6.5 \% \\ 26.5 \%{ \text { MAPE } \\ \begin{subarray} { c } { 6 . 5 \% \\ 2 6 . 5 \% } } \end{subarray}$ |  |  |  | ${ }_{9}^{\text {MAE }}{ }_{9.33}$ |  |  |  | $\begin{gathered} { }_{5}^{\text {cost }}{ }_{4}^{4411} \\ \hline 441 \end{gathered}$ | （ |  |  |  | ${ }_{s}^{\text {cosit }}{ }_{4787}^{4787}$ | ${ }_{\text {MAE }}^{9.58}$ |  |  |  | $\begin{gathered} \text { cost } \\ 45.56 \\ 45.26 \end{gathered}$ |
|  | ${ }_{\text {c }}^{13749}$ | 38．70\％ | ${ }_{\substack{3.6 \% \\ 3}}^{\text {e．}}$ | come | （e） | cictice | ${ }_{\text {1 }}^{1.55 \%}$ | ${ }_{\text {1．5\％}}^{\substack{\text { 1．5\％}}}$ | ${ }^{1.60 \%}$ | $\begin{gathered} 8 \\ \hline \end{gathered}$ | ${ }^{7} 70.72$ | 19， | ${ }_{1}^{1.8 \%}$ |  | ${ }_{5}^{5} \quad 256.86$ |  | ${ }_{\text {16，}}^{\text {1．4\％}}$ | － |  | ${ }_{8}^{5}$ 21.87 <br>  21.27 | ${ }_{\text {ckich }}^{7}$ | 边 |  |  |  |
|  | － $\begin{aligned} & 137.49 \\ & 1256\end{aligned}$ | ${ }^{38.70 \%}$ | ${ }_{\text {l }}^{3.0 \%}$ |  | （ | 56.69 16.25 | ${ }_{\substack{16.5 \% \%}}^{1311 \%}$ | ${ }_{1.2 \%}^{1.5 \%}$ |  |  | － 15.738 | cemer | ${ }_{1.2 \%}^{1.2 \%}$ |  |  | ${ }_{\text {cke }}^{59.27}$ | － | ${ }_{\text {1．2\％}}^{1.5 \% \%}$ | － $1.10 \%$ s | ［ |  | ${ }_{\text {cke }}^{\text {1．9\％\％}}$ | 1．8\％\％ $1.3 \%$ 1.8 | ＋1．9\％s | ${ }_{\$}^{27.70} 7$ |
| SKU．60．003．EM | ${ }^{12.56}$ | ${ }^{26.0 \%}$ | ${ }^{1.0 \%}$ | ${ }^{1.50 \%}$ |  | ${ }_{1}^{16.25}$ | ${ }_{\substack{31.19 \% \\ \\ \text { 32，}}}$ | ${ }_{1}^{122 \%}$ | ${ }_{\text {1．80\％}}^{1.085}$ |  | ${ }_{\text {ckise }}^{15.58}$ | 30．8\％ | 1．2\％ | 1．88\％ | \％${ }^{\text {c }}$ | 16.39 <br> 1．39 | ${ }^{31.99 \%}$ | ${ }_{1}^{122 \%}$ | ${ }_{\text {1，}}^{1.90 \%}$ | ［ | － 11.6 .28 | 边 3 32．5\％ | ＋1．3\％ | 1.96 | 79．88 |
| SKUL．60．004 | 46.37 <br> 36.21 | ${ }_{\substack{20.19 \% \\ 15.2 \%}}$ | 20\％ |  | \％${ }_{\text {s }}$ | （ $\begin{gathered}65.02 \\ 58.12\end{gathered}$ | ${ }_{\text {cher }}^{22.97 \%}$ | 2．6\％ |  | s 384.55 <br> s 34.74 |  | －24．2\％\％ | － | 2．6\％${ }^{2.6 \%}$ | ¢ | 55.14 55.14 | cereme |  | ${ }^{2.5 \%}$ 2．5 | ¢ | ${ }_{46.95}^{46.95}$ | cisem | $1.8 \%$ <br> $\substack{1.8 \%}$ | $1.9 \%$ s | ${ }_{277.66}^{27.76}$ |
| Sku ．60．005 | 56．27 | ${ }_{522}^{122 \%}$ | ${ }_{3.75}^{1.75 \%}$ | ${ }_{3.6 \%}^{10.65}$ | ${ }_{\text {¢ }}{ }^{531.36}$ | ${ }_{50.23}$ | ${ }^{29.3 \%}$ | ${ }_{2.8 \%}^{2.25 \%}$ | ${ }_{2}^{2} .740 \%$ s | ${ }_{\text {¢ }}{ }^{\text {¢ }}$ 474，33 | ${ }_{5159} 5$ | ${ }_{\text {4，}}^{24.8 \%}$ | ${ }_{3.2 \%}^{2.2 \%}$ | 3．10\％${ }^{20.15}$ | 4857．17 | ${ }_{50.95}^{55.4}$ | ${ }_{43.4 \%}^{2.46 \%}$ | ${ }_{3.1 \%}$ | 3．0\％ | ¢ | ${ }_{50.30}^{40.35}$ | ${ }_{\text {33．0\％}}^{1320 \%}$ | 2．8\％ | ${ }_{2} 1.7 \%$ | ${ }_{474.96}$ |
|  | ${ }_{3}^{53.52}$ | － $48.89 \%$ | ${ }_{2}^{3.5 \%}$ |  |  | 46.65 30.04 | $\underset{\substack{36.0 \% \% \\ 13.9 \%}}{\text { a }}$ | $2.6 \% \%$ 1.89 2， | ，$2.5 \%$ <br> $1.80 \%$ | ［ |  | － | －${ }_{\text {3，0\％}}^{\text {2．0\％}}$ |  | ［10． | 50.10 27.22 | ${ }_{\text {cher }}^{42.37 \%}$ | －${ }_{\text {3，}}^{\text {3，7\％}}$ |  |  | ${ }_{\substack{4.904 \\ 36.15}}$ |  |  |  | ${ }_{\substack{46878 \\ 34127}}$ |
| Stuctiole |  |  | ${ }_{\substack{2.3 \% \\ 7.6 \%}}^{2.20}$ |  |  | 30．04 |  | － |  | （ex |  | （1500\％ | coize |  |  | － 27.722 |  |  |  |  | 寺36．15 |  |  |  | （enter |
|  | ${ }_{9}^{94.711}$ | ${ }_{\text {cke }}^{25.56 \%}$ | ${ }_{7}^{7.6 \%}$ |  |  | ${ }_{\text {con }}^{101.11}$ | ${ }_{\text {cher }}^{25.56 \%}$ | ${ }_{\text {l }}^{7.6 \%}$ |  | \＄ | ${ }_{\substack{86.37 \\ 86.37}}^{824}$ |  |  | 5．6．6\％${ }_{5}^{5.68}$ |  | ${ }_{8}^{840.07}$ | ${ }_{2}^{21.11 \% \%}$ |  | ${ }_{5}^{5.4 \% \%}$ s． | crers | ${ }_{0}^{90.19}$ | cone | c．7．79\％ | 5．7．70 5 |  |
| SKU．60．008 | ${ }_{3918}^{3918}$ | －${ }_{\text {3 }}$ | 3，3\％\％ | 3．5\％s | \％ 465.07 | ${ }^{37.32}$ | ${ }_{\substack{\text { and } \\ 3 \\ 31.6 \% \%}}$ | ${ }_{2}^{2.9 \%}$ | 3，0\％${ }^{3}$ | \％ 442.98 | ${ }^{28.97}$ | 20．0\％\％ | ${ }_{2}^{2.3 \% \%}$ | ${ }_{2}^{2.40 \%}$ \＄ | ¢ ${ }_{\text {s }}$ | 29．50 | ${ }^{25.0 \% \%}$ | ${ }_{23 \%}^{2.3 \% \%}$ | $2.4 \%$ | s－ 350.20 | 26．59 | 2．2．490 | ${ }_{20 \%}^{2.00 \%}$ | 2， $2.2 \%$ \＄ | 315.67 |
|  | 3918 <br> 37.09 | ${ }^{35799 \%}$ |  |  |  |  | ${ }_{\substack{31.1 . \% \% \\ 31.1 \%}}^{\text {and }}$ | ${ }_{\substack{2.6 \% \\ 3.6 \%}}^{2.20}$ | ${ }^{3.0 \% \%}{ }^{3.0 \%}$ |  | ${ }_{3}^{28.97}$ | ${ }_{\text {20，4．}}^{250 \% \%}$ | ${ }_{\substack{2.8 \% \\ 2.8 \%}}^{\text {a }}$ | ， | s  <br> ${ }_{8}$ 343.36 <br> 13.98  | ${ }_{3}^{29.50}$ | ${ }^{25.5 \%}$ | ${ }_{\text {2，}}^{2.95 \%}$ | ，${ }_{\text {2．1\％\％}}$ | （lly | 26．59 |  | ${ }_{2.68}^{2.0 \% \%}$ | ${ }_{\text {2，}}^{2.20 \%}$ \＄ | 315.67 40297 |
| STuL |  | ${ }^{27.9 \%}$ | ${ }_{\text {3，}}^{3}$ | 3．49\％${ }^{3}$ | \＄ 433.08 | 46．08 | ${ }_{\substack{3.1 .19 \% \\ 291 \%}}$ |  |  | （ | －3497 | ${ }_{\text {che }}^{24.49 \%}$ |  |  | （tar | － 37.74 | ${ }_{\text {25，}}^{250 \%}$ |  |  | ［ | －3404 | ${ }_{\substack{\text { 22，5\％\％}}}^{22.75}$ |  |  | 402．97 |
| SkU－60．010－EM | ${ }_{12.49}^{13,19}$ | ${ }_{2}^{22.0 \% \%}$ | ${ }_{\text {cosem }}^{0.98 \%}$ |  | （ | ${ }_{1}^{14.97}$ | ${ }_{27.7}^{29.7 \%}$ | ${ }_{1.12 \%}^{1.20 \%}$ |  | （170．20 | ${ }_{12.62}^{1211}$ | ${ }_{\text {chem }}^{24.95 \%}$ | ${ }_{\text {1．0\％}}^{1.0 \%}$ | － $0.90 \%$ ¢ | ［ | ${ }_{13,54}^{1234}$ | ${ }_{\text {20，}}^{25 \%}$ | ${ }_{\text {li．1\％}}$ | 1．0\％ | （er | ${ }_{12.75}^{12.03}$ | ${ }_{\text {24，}}^{2.5 \%}$ | ${ }_{\text {l }}$ |  | 1432．64 |
|  | $\operatorname{MEAN}_{\substack{47.9 \\ 4.6}}$ | $\underset{\substack{\text { MEAN } \\ 28.6 \% \\ 2,5 \%}}{ }$ | $\underset{\substack{\text { TOTAL } \\ 20,0 \% \\ 2720}}{\substack{ \\\hline}}$ | TOTAL $\begin{array}{ll}28.0 \% & \$ \\ 27.2 \% & \$\end{array}$ |  | $\underset{\substack{\text { MEAN } \\ 417 \\ 417}}{ }$ | MEAN <br> 2．7．0\％ <br> $263 \%$ | $\underset{\substack{\text { TOTAL } \\ 25.70 \%}}{2.50}$ | TOTAL ${ }_{25.3 \%}^{25.9 \%}$ \＄ | TOTAL <br> $\$ 3.843 .33$ <br> $\$$ <br> ancer | MEAN | $\begin{gathered} \text { MEAN } \\ 25.5 \% \\ 25464 \end{gathered}$ | TOTAL $23.7 \%$ $2.3 \%$ | TOTAL $23.9 \%$ $23.8 \%$ | TOTAL <br> $\$$ <br> $\$ 3.448 .11$ <br> 3.4358 | $\underset{\substack{38.3 \\ 38}}{\substack{38,3 \\ 3}}$ | MEAN $25.2 \%$ $25.2 \%$ | $\begin{aligned} & \text { TOTAL } \\ & 22.9 \% \\ & 22.9 \% \end{aligned}$ | TOTAL $23.2 \%$ $23.2 \%$ |  |  | MEAN $24.3 \%$ $24.4 \%$ | $\stackrel{\text { TOTAL }}{\substack{\text { 227\％} \\ 2.2020}}$ | Total ${ }_{230 \%}^{22,9 \%}$ | TOTAL \＄ $3,428.01$ <br> $3,428.01$ $3,430.48$ |



Appendix E - Detailed Forecast Error Tables
SKU level absolute error and absolute percentage error for each hold-out period





































## Appendix F - Assessing the Cost of Forecast Error

Foresight: The International Journal of Applied Forecasting - Summer 2007, Issue 7

# ASSESSING THE COST OF FORECAST ERROR A PRACTICAL EXAMPLE 

Peter Maurice Catt

## PREVIEW

Peter provides a detailed futorial on the calculation of the costs associated with forecast arrors. His procedure considers inventory costs, including safoty stock, as woll as the costs of lost sales attributable to poor service (out-of-stock). He shows how the cost of forecast error (CFE) can be used to determine appropriate safoty stock levels.

## INTRODUCTION

Forecastaccuracy canplay a central roleinincreasing shareholder value, particularly when the firm is reliant on long-fulfillment lead-times. However, forecast error metrics, such as the Mean Absolute Error (MAE) and Mean Absolute Percentage Error (MAPE), do not reveal the financial impact of forecast error.

Flores et al. (1993, p. 140) state that "statistical measures of forecast accuracy are not designed to capture the economic implications associated with managing aninventory system." Roberts and Whybark (1974, p. 638) consider forecast cost implications as "probably the most essential measure." Hence, although measures of forecast accuracy serve an important purpose, it is also highly desirable to determine the financial costs associated with forecast error.

This article will show how to calculate a cost of forecast error (CFE) and will examine the key issues and choices involved in the calculation. By applying the CFE one can compare the financial performance of different forecasting methods and also see the cost implications of specifying different service levels.

## KEY POINTS

- Traditional forecast error metrics, auch as the MAE and MAPE, do not reveal the financial impact of forecast error. Better decisions can be made if we have an actual Cost of Forecast Error (CFE) metric.
- A CFE calculation should include both inventory costs and the costs of poor service (stock-outs). Importantly, it will incorporate the costs of holding safety stock and maintaining a deaired service level.
- Applying a cost to forecast error helps to show the trade-offs inherent in varying the service level and also helps to determine optimal safety stocks.

The assessment of the costs of forecast error should include both inventory costs and the costs of poor service. Mitigating forecasterrorhelps maintain desired levels of customer service while controlling the costs associated with excess inventory.

The balance between service level and inventory costs is achieved through safety stock, defined by Silver et al (1998, p. 31) as "the amount of inventory keptonhand, on the average, to allow for the uncertainty of demand and the uncertainty of supply. ..." Too much safety stock means that inventory costs will be high, while too little safety stock means that customer service levels may suffer. The right amount of safety stock strikes a balance between these two costs.

INVENTORY COSTS AND SAFETY STOCKS
Inventory costs are the costs associated with procuring, producing, and carrying inventory. The procurement'


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production cost per unit is called the unit variable cost. For purchased items, it includes the purchase price plus freight costs. Formanufactureditems, it includes production and other costs associated with making the item available for sale.

The costs incurred by carrying inventory include storage, insurance, investment, obsolescence, damage, deterioration, and the opportunity cost of the funds tied up in inventory. Some perishable items have remarkably short life-cycles measured in days, while many fashion items and high-tech consumer products have life-cycles measured in months. Such items have extremely high carrying costs due to their inherent obsolescence.

In the illustrative examples, I will assume an inventory carrying charge equivalent to $2.5 \%$ per month ( $30 \%$ per anmum) of the inventory value, e.g., a $\$ 5.00$ item will incur a monthly carrying charge of $\$ 0.125$ ( $\$ 1.50$ per annum). This may seem relatively high, but capital alone is typically worth $10 \%$, and the life-cycle of high fashion/technology and perishable goods can frequently be measured in weeks. For a good introduction to calculating inventory carrying costs, I suggest the Timme and Williams-Timme (2003) paper "The Real Cost of Holding Inventory."

Exhibit 1 defines the traditional safety stock (SS) calculation. The key factors are:

- the safety factor (k), which increases with the desired service level,
- the variance (standard deviation) of the forecast emror $(\sigma)$, which is related to the size of the mean absolute error of the forecasts (MAE), and
- the lead-times in reviewing and replenishing product ( $\mathrm{R}+\mathrm{L}$ ).

The correspondence between the safety factor and the desired service level is traditionally determined from a table of the Normal Distribution, excerpts of which are shown in Table 1.
$P_{1}$ is the probability of no stock-out occurring during the replenishment cycle. The table also provides the normal loss function, which we will later use to calculate the expected shortages per replenishment cycle. A complete table can be found in Silver, p. 724. [Ed. note: See Paul Goodwin's Hot New Research column beginning on page 53 of this issue for a discussion of new alternatives to the use of the normal distribution for determining stock-out risks.]

| Service Level\% ( $\mathrm{P}_{7}$ ) | $k$ | Nomsl Loss Frection $G_{\Delta}(k)$ |
| :---: | :---: | :---: |
| 9998\% | 3.60 | 0.00003911 |
| 9993\% | 3.20 | 0.0001852 |
| 99.74\% | 2.80 | 0.0007611 |
| 99.15\% | 2.40 | 0.00272 |
| 97.73\% | 2.00 | 0.008491 |
| 94.52\% | 1.60 | 0.02324 |
| 88.48\% | 1.20 | 0.0561 |
| 73.82\% | 0.80 | 0.1202 |
| 65.54\% | 0.40 | 0.2304 |
| 50.0\%\% | 0.00 | 0.3989 |

To illustrate the safety stock calculation, consider the 12 months of data plotted in Figure 1, next page. Here we see the sales history of a product and the forecasts produced 2 months before the actual sales were known. By subtracting the forecast from the actual sales value for each month and ignoring any negative (minus) signs, we get the absolute error for each month. The average of the absolute forecast errors, the Mean Absolute Error (MAE) over the 12 months, is 10 units.

The key inputs to the safery stock calculation are:
[1] Mean Absolute Error: MAE = 10 units/month
[2] Review Period + Lead-Time: R+L = 2 months
[3] Service Level, set at approx. $98 \%$, implies a safety factor, $\mathrm{k}=2.0$ (See Table 1 ).

Exhibit 1. Safoty Stock Calculation

$$
\begin{aligned}
& S S=k \sigma \sqrt{\boldsymbol{R + \mathbf { L }}} \quad \text { where } \\
& S S=\text { Safty stock in units } \\
& k=\text { Safery fictor from a table of } \sigma=1.25 * \mathrm{MAE} \text { (moan aboolute arroc) } \\
& \sigma=\text { An approximation of the stridard deviation, or variability, of foceosst erxor } \\
& \sqrt{\boldsymbol{K}+\boldsymbol{\Sigma}}=\text { The square root of the review period ( } \mathrm{R} \text { ) and the replenishment lead-time (L), in moets } \\
& \text { The review period is the frequency with which a parchasing (repleminhment) decision is made. } \\
& \text { Often this decision talkes place moethly as past of the Sales \& Opentioes Planning cycle. }
\end{aligned}
$$

Using the formula for the safety stock in Exhibit 1,

$$
\begin{aligned}
\mathrm{SS}= & (\text { safety factor * } 1.25 * \mathrm{MAE} * \text { the square root } \\
& \text { of the (review period + lead-time)) } \\
\mathrm{SS}= & 2.0 * 1.25 * 10 * \mathrm{SQRT}(2)=\mathbf{3 5 . 3 6} \text { units }
\end{aligned}
$$

So with a mean absolute forecast error of 10 units and a combined review period and lead-time of 2 months, we need to hold around 36 units (always round up) of stock to maintain a service level of $98 \%$.

## STOCK-OUTS AND THE COST OF LOST SALES

For retail companies, costs of inadequate stock can be punitive. In their paper "Stock-Outs Cause Walkouts," Corsten and Gruen (2004) report results of a survey of 71,000 retail consumers worldwide. They found that if the desired item is not in stock (ie. a stock-out), $31 \%$ of the customers will leave the store to buy it elsewhere, while another $9 \%$ will choose not to make the purchase at all. Their study also found that worldwide stock-out rates sit at approximately $8 \%$.

The longer-term effects of stock-outs are difficult to quantify, however, research has indicated that customer loyalty and hence the likelihood of repeat business, is also diminished (Schwartz, 1968).

In the case of a retailer it appears unrealistic to assume that a stock-out will lead to a $100 \%$ loss in margin, as the customer may accept a substitute for the original product. It is more reasonable to assume that stock-outs have differing marginloss impacts depending on situational factors, such as the ease of substitution for the product in question. The Corsten and Gruen study does provide some guidelines for retailers.

In my illustrative example, I have set the percentage of lost product margin, $\mathrm{B}_{5}$ (using the notation of Silver), at $50 \%$. This percentage reflects the sum of the $40 \%$ figure reported in the Corsten and Gruen study plus a further $10 \%$ to account for the ongoing loss of customer loyalty (future margin).

I will also assume that the product margin per unit is $\$ 2.50$. So each unit of sales lost incurs an opportunity cost of $50 \%$ of $\$ 2.50$ or $\$ 1.25$.


Exhibit 2, presents the formula for the calculation of the volume of lost sales. The calculation has two components and these are multiplied together.

- The standard deviation of the forecast error over the review period and replenishment lead-time,
$\boldsymbol{\pi} \cdot \sqrt{R+L}=1.25 * \mathrm{MAE} * \mathrm{SQRT}(\mathrm{R}+\mathrm{L})$.
- A function that provides the statistical probability of lost sales at the desired service level (See Table 1, Normal Loss Function).

The normal loss function, $G_{u}(k)$, can either be calculated using standard Excel ${ }^{\text {b }}$ functions (Silver, p. 735) or taken from a table of normal distribution functions (Silver, p. 724).
[1] Mean Absolute Error: MAE = 10 units/month
[2] Review Period + Lead-Time: R+L = 2 months
[3] Service Level, set at approx $98 \%$, implies a safety factor, $\mathrm{k}=2.0$, and normal loss function, $G_{\|}(k)=0.008491$.

$$
\begin{aligned}
\mathrm{VLS}= & 1.25 * 10 * \mathrm{SQRT}(2) * 0.008491=0.15 \text { units } \\
& \text { per month }
\end{aligned}
$$

Table 1 shows that, at $k=2.0$, the service level or probability of no stock-out is $97.73 \%$. However, the standard deviation of forecast errors over the replenishment cycle ( 1.25 * 10 * $\mathrm{SQRT}(2)=17.68$ ) times the normal loss function ( 0.008491 ) indicates that only about $0.8 \%$ of the forecast error volume will be lost sales.

Extibit 2 Volume of Lost Sales (VLS)
$V L S=\mathbf{\sigma} \sqrt{\boldsymbol{R}+\boldsymbol{L}}{ }^{\bullet} \boldsymbol{G}_{\mathbf{a}}(\mathbf{L})$ wbere
$\sigma \sqrt{\boldsymbol{R}+\boldsymbol{Z}}=$ strindard devintion of foxecast erxors, in units, over the
replenikhment cycle (See Exhibit 1)
$G_{u}(k)$ = the normal loess fuestion used to calkulate sbortages por replenibtment cycle

We can now determine the lost sales margin (LSM) as the product of [1] percentage charge for lost margin (50\%), [2] product margin (\$2.50 per unit), and [3] lost sales per month (0.15).

$$
\mathrm{LSM}=(50 \% * \$ 2.50) * 0.15=\$ 0.19 \text { per month }
$$

CALCULATING THE CFE
So far we have taken a single sales forecast with an MAE of 10 units, calculated the necessary safety stock to achieve our desired service level of $98 \%$, and worked out our lost sales margin. Now we need to bring these elements together and add stockholding costs to get a comprehensive cost of forecast error.

My formulation for the cost calculation, shown in Exhibit 3, is a modification of that developed by Silver (p. 263). The CFE formula utilizes product margin to ascertain the cost of lost sales. Silver had used unit cost, but lost margin better reflects the opportunity cost of poor service.

To illustrate the CFE calculation, let us assume:
[1] Mean Absolute Error: MAE $=10$ units/month
[2] Service Level = aprox $98 \%$, implying a safety factor, $\mathbf{k}=2.0$, and normal loss function, $G_{\mathbf{z}}(k)=0.008491$
[3] Review Period + Lead-Time: $\mathrm{R}+\mathrm{L}=2$ months
[4] Unit Cost: $v=\$ 5.00$
[5] Inventory Carrying Charge: $\mathrm{r}=\$ 0.125$
[6] Lost Sales Margin per unit: $B_{5}=50 \%$
[7] Product Margin in \$/unit: $m_{p}=\$ 2.50$
[8] Period Multiplier to convert from monthly to annual cost of forecast emror: $P=12$

Here are the steps in performing the CFE calculation:

Step 1: Estimate the safety stock using the formula in Exhibit 1.

$$
\mathrm{SS}=2.0 * 1.25 * 10 * \operatorname{SQRT}(2)=35.36 \text { units }
$$

Step 2: Multiply the safety stock by the monthly inventory carrying charge (per unit of safety stock).

$$
\begin{aligned}
& 35.36 \text { units } * \$ 0.125=\$ 4.42 \\
& \text { per month (holding cost of } \\
& \text { safety stock) }
\end{aligned}
$$

Step 3: Calculate the expected volume of lost sales (VLS) due to stock-outs using the formula in Exhibit 2.

$$
\begin{aligned}
& \text { VLS }=1.25 * 10 * \mathrm{SQRT}(2) * 0.00849=0.15 \\
& \text { expected units per month of lost sales }
\end{aligned}
$$

Step 4: Calculate the lost sales margin as the product of percentage charge for lost margin (50\%), product margin ( $\$ 2.50$ per unit), and lost sales per month $(0.15)=\$ 0.19$ per month

$$
\begin{aligned}
& \mathrm{LSM}=(50 \% * \$ 2.50) * 0.15=\$ 0.19 \\
& \text { per month }
\end{aligned}
$$

Step 5: Add the holding cost of safety stock and lost sales margin, then multiply by 12 to annualize.

$$
\mathrm{CFE}=(\$ 4.42+\$ 0.19) * 12=\$ 55.32
$$

per annum

Exhl bit 3 Annual Cost of Forocast Error


[^2]The result in Step 5 is the cost of forecast error (CFE) for the item in question. By breaking down the two major components of the $\$ 55.32 \mathrm{CFE}$, we can see that $\$ 53.04$ $(96 \%)$ ) of the cost is attributed to the safety stock component while the remaining $\$ 2.28$ (4\%) consists of lost margin due to stock-outs. In this example, the cost of maintaining a relatively high service level is significant, particularly if one considers the total cost over all products.

Step 6: Repeat the process for every other item to derive the aggregate cost of forecast emror (aggregate CFE).

## DETERMINATION OF OPTIMAL SAFETY STOCK

Our illustration of the CFE calculation assumed $998 \%$ service level, which, given a particular replenishment cycle (review and lead-time equal to 2 months), resulted in a certain level of safety stock ( 36 units). But how can you decide what the appropriate safety stock should be? One way is to apply the CFE calculation across a range of service levels parameters (from Table 1). A plot of the results will be a cost curve showing CFE as a function of service level. The minimum point on the curve tells us the service level associated with the minimum cost of forecast error, ie. the lowest combined cost of safety stock and lost sales.

Figure 2 shows the cost curve resulting from our illustrative example. We can see that the lowest cost of forecast error is achieved at a service level of approximately $88 \%$. Our arbitrarily chosen service level of $98 \%$ resulted in an annual CFE of $\$ 55.32$. The optimum service level of $88 \%$ resulted in an annual CFE of $\$ 46.70$, providing a potential cost reduction of $\$ 8.62$ (a $16 \%$ decrease) on this one item.

However, the "strategic availability" of products should not be underestimated; for example, product families may contain some low-margin items that impact the sales of the entire family. In addition, poor product availability (relative to competitors) is likely to seriously harm customer loyalty.

> COMPARISON WITH THE GÖTZ-KÖHLER SIMULATION

In their article in the Fall 2006 issue of Foresight, Norman Götz and Carsten Köhler (2006) simulated the cost of forecast error for forecast models implemented in SAP. Using their methodology, inventory carrying costs were much lower and the cost of lost sales much higher than in my CFE calculation.

Götz and Köhler (GK) set inventory carrying costs at $10 \%$ per annum, whereas my CFE calculation assumes a carrying cost of 30\% per annum. My figure is higher because I consider the costs incurred by carrying inventory to include $10 \%$ alone for the cost of capital plus $20 \%$ for storage, insurance, obsolescence, damage, deterioration, and opportumity costs.

While my CFE procedure has incorporated safety stock to achieve a target service level, GK simulated the stock-out effects of forecast errors without the protection offered by safety stock. As a result, GK's simulation assumes that a forecast error results in a stock-out and lost sale, whereas the CFB applies a more pragmatic approach and minimizes the disruption of forecast errors through the use of safety stock.

Figure 2. Annual Cost of Forecast Error at Varying Service Levels

The assessment of the costs of
forecasterrorshouldincludeboth
inventory costs and the costs of
poor service. Mitigating forecast
error helps maintain desired
levels of customer service while
controlling the costs associated
with excess inventory.

With respect to stock-out costs, GK assume a $100 \%$ lost product margin, whereas my CFE assumed a $50 \%$ figure. As noted, Corsten and Gruen had assumed a $40 \%$ lost margin, to which I added $10 \%$ as a loss of future margin. In light of the Corsten and Gruen survey, the GK figure of $100 \%$ seems excessive since the majority of customers will substitute for the out-of-stock item with the purchase of another product. The substitution produces a margin for the retailer, albeit reduced. GK also used a blanket gross margin of $20 \%$, as opposed to using individual product margins as per the CFE approach.

## CONCLUSIONS

The ability to quantify the costs associated with forecast error yields an appreciation of the costs and benefits of a desired service level. It also allows an objective comparison between competing forecast methods.

Statistical measures of forecast accuracy do not make cost trade-offs explicit and hence need to be augmented with financial figures. Without knowing the costs associated with a forecast error, one cannot determine the acceptability of the available methods.

Consider downloading the necessary data from your ERP system to an Excel8 spreadsheet for calculation. Better yet, consider developing a template within your business intelligence or ERP application.

The information garnered from the CFE calculations could well mitigate the need to invest in very costly software that may only offer relatively small gains in forecast accuracy.

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[^0]:    * $S A P^{\circledR}$ All-in-One is a templated version of $S A P ~^{\circledR}{ }^{\circledR} S A P ®$ Enterprise Resource Planning System Core Component (ECC), formerly known as R/3, developed for small to medium sized enterprises (SMEs). The

[^1]:    "A set of techniques that uses bill of material data, inventory data, and the master production schedule to calculate requirements for materials. It makes recommendations to release replenishment orders for materials. Further, because it is time phased, it makes recommendations to reschedule open orders when due dates and need dates are not in phase. Time-phased MRP begins with the items listed on the MPS (Master Production Schedule) and determines (1) the quantity of all components and materials required to fabricate those items and (2) the date that the components and material are required. Time-phased MRP is

[^2]:    8 FORESIGHT loove 7 Oummer 2007

