DOKUZ EYLÜL UNIVERSITY
GRADUATE SCHOOL OF NATURAL AND APPLIED SCIENCES

APPLICATIONS OF SPARE PARTS MANAGEMENT IN AN INTERNATIONAL TV MANUFACTURING COMPANY

by
Mustafa DEĞİRMENCİOĞLU

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İZMİR

APPLICATIONS OF SPARE PARTS MANAGEMENT IN AN INTERNATIONAL TV MANUFACTURING COMPANY

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We have read the thesis entitled **"APPLICATIONS OF SPARE PARTS MANAGEMENT IN AN INTERNATIONAL TV MANUFACTURING COMPANY"** completed by **MUSTAFA DEGIRMENCIOGLU** under supervision of **ASSOC. PROF. HASAN SELİM** and we certify that in our opinion it is fully adequate, in scope and in quality, as a thesis for the degree of Master of Science.

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APPLICATIONS OF SPARE PARTS MANAGEMENT IN AN INTERNATIONAL TV MANUFACTURING COMPANY

ABSTRACT

The aim of this study is to reduce inventory and transportation costs at the spare parts warehouse of a TV manufacturing company. This aim can be reached by proper forecasting method and optimum storage of the spare parts. In this concern, first, features of spare parts and complexities in spare parts management are explained. Then, related forecasting methods are introduced and compared. In the analysis, we employ Trend Analysis, Single Exponential Smoothing, Double Exponential Smoothing and Auto-Regressive Integrated Moving Average (ARIMA) methods. The results are evaluated comparatively by using Mean Absolute Percentage Error. Finally, using the best forecast values, the automated warehouse system, which is called “Kardex”, is optimized by using a linear programming model.

Keywords: Spare parts management, forecasting, warehouse layout optimization.

TELEVİZYON ÜRETİCİSİ ULUSLARARASI BİR FİRMADA YEDEK PARÇA YÖNETİMİ UYGULAMALARI

ÖZ

Bu çalışmanın amacı TV üreten bir firmanın yedek parça deposundaki depolama ve taşıma maliyetlerini azaltmaktır. Bu amaca uygun tahminleme metodu ve optimum depolama şekli ile ulaşılabilir. Çalışmada öncelikle yedek parçaların özellikleri ve yedek parça yönetimimin zorluklarından bahsedilmiştir. Daha sonra buna ilişkin olarak tahminleme metotları tanıtılmış ve karşılaştırma yapılmıştır. Analiz kısmında ise Trend Analizi, Tek Üstel Düzgünleştirme, Çift Üstel Düzgünleştirme ve ARIMA metotları uygulanmıştır. Sonular Ortalama Mutlak Hata Oranlarına göre değerlendirildi. Son olarak da en iyi tahminleme metodu kullanılarak "Kardex" ismi verilen otomatik depolama sisteminin lineer programlama modeli aracılığı ile optimizasyonu yapılmıştır.

Anahtar Sözcükler: Yedek parça yönetimi, tahminleme, depo yerleşimi optimizasyonu.

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CHAPTER ONE
INTRODUCTION

Spare Parts Management (SPM) plays a major role for companies. First of all after-sales satisfaction is very important for customers. Durability of orders, it is very important. Many of companies can provide quick response and fast shipment but few of them can provide good service after sales. In this context, SPM has critical role.

On the other hand, companies focus on order quantities and shipments. They force fast shipments. Producing spare parts slow down major production. Because quantities of spare parts are low and variation of them are very high. Also these orders belonging to old products. Therefore, some of them can't be supplied and inventory should be done.

For all of these reasons, companies should organize and plan spare parts operations well. In this respect, maximum customer satisfaction and optimum inventory level are the main goals for all companies.

The remainder of this study is organized as follows. In Chapter 2, spare parts management and spare parts demand structure are the main focus. In Chapter 3, an overview of spare parts demand forecasting methods is presented. Additionally, related forecasting methods are explained and compared. In Chapter 4, real life-applications on spare parts management are presented. Finally, concluding remarks are presented in Chapter 5.

CHAPTER TWO
SPARE PARTS MANAGEMENT AND ANALYSIS OF SPARE PARTS DEMAND

2.1 Literature Review

The spare parts requirement prediction and management is so important in industries but researches focus on demand forecasting of spare parts is still very under-developed, there are not many investigations focus on the CSP requirement prediction. Prakash et al. (1994) used analytic hierarchy process (AHP) method to evaluate the criticality of spare parts. Kabir (1996) developed a simulation model to determine the optimal value of the decision variable by minimizing the total cost of replacement and inventory. Dekker (1998) pointed out that spare parts can be classified into critical and non-critical demand, and proposed a stocking policy verified by simulation. Ghobbar (2003) experimented 13 forecasting methods to predict spare parts demand for airline fleets. Aronis (2004) calculated the required stock levels and determine the distributions of demand for spare parts by Bayesian approach. Caglar (2004) investigated a spare parts inventory problem and formulated a model to minimize the inventory cost subjected to a response time constraint at each field depot. Based on the above literatures, subject and research on spare parts management mostly focused on the consideration of safe inventory level. Investigations on the actual number of spare parts required are very rare. If the actual required number can be correctly predicted, there will be no problem of controlling inventory level and purchasing quantities. Hence, this investigation applied grey prediction model, BPN, MA to predict the critical spare parts requirement accurately and reduce the unnecessary costs and slack risks (Fei-Long Chen, 2009).

There have been numerous papers discussing the fast and slow moving parts inventory models. For slow moving spare parts, Vereecke and Verstraeten (1994) have developed an inventory management system based on the assumption that demand of spare parts follows a Poisson distribution. Segerstedt (1994) and Yeh (1997) focus on the parts in intermittent demand situation. They assumed that the three variables, the time between two consecutive demands, the demand size and the lead time, are all Gamma distributed. Burgin (1975) proposed demand size during lead time is Gamma distributed if data are positively skewed. For fast moving spare parts, Dilworth (1992) proposed many inventory control systems using normal distribution to approximate the demand during lead time. In addition, Vereecke and Verstraeten (1994), Silver et al. (1985) also indicated that fast moving spare parts demand should be normal distributed during the lead time. (Pao-Long Chang, 2008)

Methods for forecasting and determining the re-supply of wholesale, retail and manufacture stocks are easily found in books and inventory management courses. In such cases, the demand and the response time frequently have good adherence to the normal distribution, and time series methods are adequate for forecasting the demand. However, in the case of spare parts for maintenance, the problem is clearly different. When compared with retail items, spare parts are usually more expensive, of sporadic need and low consumption rate; the availability is critical (high stock out costs). This intermittent demand rules out the normal distribution as a reasonable representation, and the time series methods, designed for continuous distribution, becomes inappropriate in face of high probabilities of zero demand (Guilherme, 2008).

Frequently, time intervals between failures are completely random, and many studies found in literature employ mainly Gamma and Poisson distributions to represent the demand for spare parts (Croston, 1972). These distributions are associated with the known Poisson process characteristic of phenomena in which age or wear of the component does not affect the likelihood that it will fail, and also the fact that given that a failure has just occurred has no influence on the time elapsed until the next failure. The characteristic of the Poisson distribution that makes it easy to use is that its average is equal to its variance and completely characterizes the distribution. Therefore, if the failure process has the characteristics of a Poisson process, it is enough to use the average demand of historical data to estimate the probability of any given number of failures to occur in any time interval. Strijbosch et al. (2000) discuss the selection of adequate distribution for spare parts for an (s, Q) control system, and use a compound Bernoulli distribution (Guilherme, 2008).

Forecasting the future is a critical element of management decision making. The final effectiveness of any decision depends upon the consequence of events following this decision. The ability to forecast the uncontrollable aspects of these events earlier to making the decision should permit an improved choice over that which would otherwise be made (Montgomery, 1990). The need for forecasting is increasing as management attempts to decrease its dependence on chance and becomes more scientific in dealing with its environment (Pour, 2008).

Statistical methods, such as exponential smoothing and regression analysis, have been used by analysts in forecasting demand for a number of decades. Many of these methods may perform poorly when demand for an item is lumpy. Lumpy demand patterns are characterized by intervals in which there is no demand and, for periods with actual demand occurrences, by a large variation in demand levels (Bartezzaghi, 1999). The problem of modeling the future consumption becomes especially difficult for lumpy patterns which are common for the spare parts inventory systems. Forecasting the lumpy demand requires special techniques in comparison with the smooth and continuous case, since the assumptions for continuity and normal demand distribution do not hold (Dolgui, 2005). Lumpy demand patterns are very common, particularly in organizations that hold many spare parts. In the aerospace, and automotive sectors, for example, organizations may have thousands or tens of thousands of stock keeping units (SKUs) classified as intermittent or lumpy For instance, lumpy demand has been observed in the automotive industry, in durable goods spare parts, in aircraft maintenance service parts and in telecommunication systems, large compressors, and textile machines (Pour, 2008).

Deshpande et al. (2003) look at the conflict between minimization of cost and maximization of system availability through the use of priority codes. They assign fill rate objectives to the different priority codes in order to include this in the stocking models as constraints. When fill rate percentage is higher for high priority spare parts one acknowledges the challenge of setting the correct priority code. Kalchschmidt et al. (2003) study how to design a spare parts solution in order to manage uncertain and extremely variable demand. Four alternatives/scenarios with orders based on differentiating forecasting and inventory management, based upon whether the part has stable or unstable demand are presented. Cost versus availability/service level graphs for different scenarios is one of the results. Finally, Razi (2003) look at how to implement an inventory management model for spare parts in an Enterprise Resource Planning (ERP) environment. Simulation of the proposed model is compared to simulation of a standard ERP inventory management model. The proposed model uses pooled distribution of parts instead of statistical distributions and performs better than the ERP solution (Tysseland, 2004).

Several methods have been employed to forecast the demand quantity of spare parts, and the grey prediction method and back-propagation network (BPN) have good prediction performance in many fields. Sheu and Kuo (2006) apply grey prediction model to forecast the timing of prevent maintenance accurately. Lin and Yang (2003) forecast accurately the output value of Taiwan's opto-electronics industry through grey forecasting model. Ansuj et al. (1996) used time series models and BPN to predict the behaviors of sales, the result indicated BPN had better prediction performance than time series models. Law (2000) utilized BPN to forecast the demand of tourism, the result indicated that the BPN has higher forecasting accuracy than time-series models, feed-forward neural networks, and regression models. Thus, this paper applied grey prediction model, BPN to forecast the demand of critical spare parts (CSP) (Chen, 2009). His research framework is illustrated in Figure 2.1.

With regard to demand forecast model, Buzacott (1999) and Jun (1989) both use exponential smoothing to estimate the demand. It requires only two pieces of data, the last forecast and the observation of the latest period. It is claimed to be the method most frequently used for forecasting low and intermittent demand. Croston (1972) developed a method for forecasting in intermittent demand situations which he showed the method has lower variance than the exponential smoothing forecast. Willemain et al. (1994) emphasize the key role of demand forecasting in planning production, inventories and work force and economic lot sizing. They conclude that Croston's method is robustly superior to exponential smoothing. Foote (1995) discussed the implementation of forecasting system for aircraft spare parts. He used *ARIMA* forecasting lead time demand and average monthly demand. Researchers such as Tsay (1988) looking at outliers, level shifts and variance changes for ARIMA series. When forecasts using judgment and different models are combined, a simple average method is shown by Kang (1986) to be the best. Lawrence et al. (1986) also show that simple models and averaging of different forecasts are likely to be most effective. Sani et al. (1997) described several forecasting methods for low demand items, including exponential smoothing method, moving average method and other simple empirical methods (Chang, 2008).

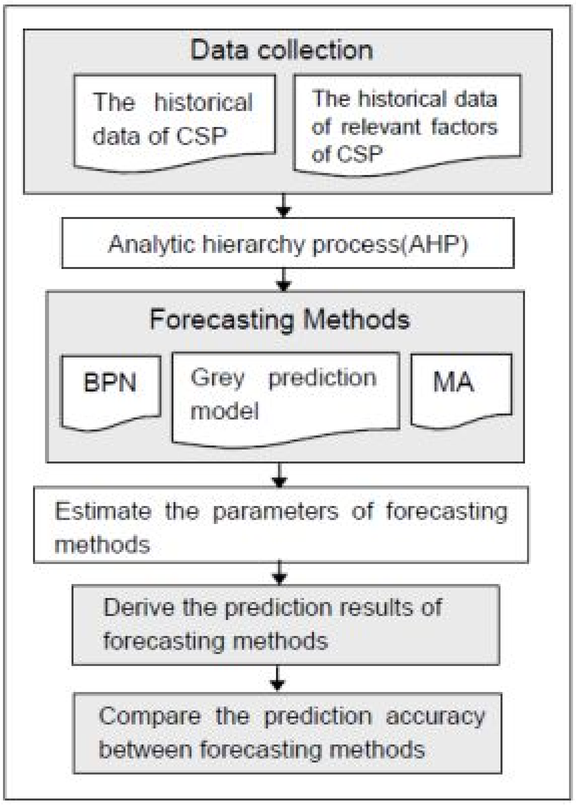

Figure 2.1 Research framework

Studying the case of a manufacturer of electronic products in Taiwan, Yeh (1997) adopted the premise of the Gamma distribution for demand to determine the spare parts stock policy. As usual, the normal distribution proved to be inadequate by the fact that most of the items studied presented annual demand less than ten units. The Poisson distribution also showed little adherence to data since the variances and average historical demands were significantly different. Wanke (2005) studied the case of a Brazilian manufacturer of agricultural equipments and used the Gamma distribution for modeling the consumption of spare parts adjusting the actual data to test alternative methods based on the key characteristics of the spare parts. In another study, Wanke (2006) noted that the demand for spare parts had good adherence to the Poisson distribution. He also pointed out that the properties of this distribution become particularly interesting when examining how different safety stock levels would affect the likelihood of lack of material, especially in environments where the annual consumption is between 1 and 300 units (Neves, 2008).

Croston (1972) implied that traditional forecasting methods such as single exponential smoothing (SES) may lead to suboptimal stocking decisions and proposed an alternative forecasting method. In proposed procedure, two forecasts for the mean demand-interval and the mean demand-size have been done. The forecast for the demand per period is then calculated as the ratio of the forecasts for demand size and demand interval. Modifications of the original Croston (1972)'s method were later proposed by several other authors. An important contribution is that by Syntetos and Boylan (2001). They show that Croston (1972)’s method leads to a biased estimate of demand per unit of time. They also proposed a modified method and demonstrated the improvement in a simulation experiment. Ghobbar and Friend (2002) compared various forecasting methods using real data of aircraft maintenance repair parts from an airlines operator. The data is lumpy in nature and they showed that moving average, Winters and Holt (1986)’s and Croston (1972)’s forecasting methods, are superior to other methods such as the exponential smoothing (Nasiri, 2008).

The forecast methods, including single exponential smoothing, Croston (1972)'s method, *ARIMA*, moving average method and so on, are all based on the mean and variance of past demand data. In general, demand of spare parts is increasing along with the machine quantity and its usage time. Moreover, when equipment design changed, parts reliability will be increased and hence the spare parts demand size is decreased. Therefore, one must consider the above mentioned factors of equipment in building the demand forecast model for spare parts (Chang, 2008).

2.2 Features and Life Cycle of Spare Parts

Spare Parts have large space in production periods. Because in one final product, it has lots of materials and all of these materials can be spare parts. For example, TV has averagely 500 parts as LCD panel, front cover, back cover, chassis, power cards, metal frame, snow box, carton box, foot assy, speakers etc. In Figure 2.2, some of LCD parts are located.

Figure 2.2 Some of LCD Spare Parts

Spare materials have unique characteristics which separate it from all the other materials used in a main production systems. They have changeable demands and types. Variations of them are generally high and quantities are generally small.

A successful SPM implies the availability of right type of parts in right quantity at the right time. Often the key element to successful procurement is spare part demand forecasting. Other relevant inputs include (see Figure 2.3) unit item costs (for e.g. procurement, warehousing and disposal), internal requirements (such as 95% service level or inventory turnover time of 1 month) and external factors (such as supplier contracts or delivery times). Obviously, if the spare part demand is deterministic, external factors are very restrictive (such as regulations that require a certain amount of spare parts in stock) or if the requirements dominate (such as service levels of luxury automobiles no matter what the costs), the role of SPM changes and the demand forecasting loses its importance. In most cases, however, the demand is not completely deterministic, requirements and external factors exist but do not dominate, and cost structure of items is realistic. SPM framework is illustrated in Figure 2.3 (K’aki, 2007).

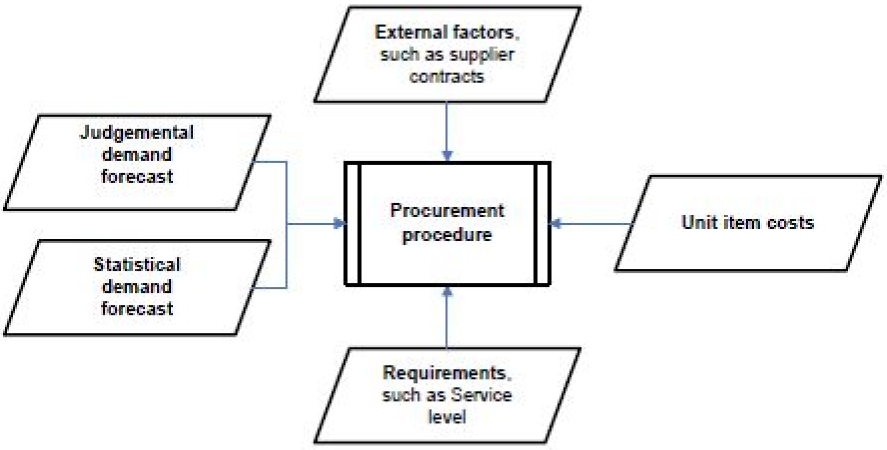

Figure 2.3 SPM framework

Spare part life cycle phases can be gathered in three main heading (K’aki, 2007).

- The initial phase: No historical demand is available so demand forecasting relies purely on data from other items (and judgmental forecasting).

- The normal phase: Demand is somewhat predictable and at least for fast-movers (parts with high demand), statistical forecasts can be reliable.

- The final phase: The product and spare part manufacturing have ended, but service obligations exist and therefore demand does not drop to zero. As the items might not be available for long, a final order must be placed.

Life cycles of spare parts phases are shown in Figure 2.4.

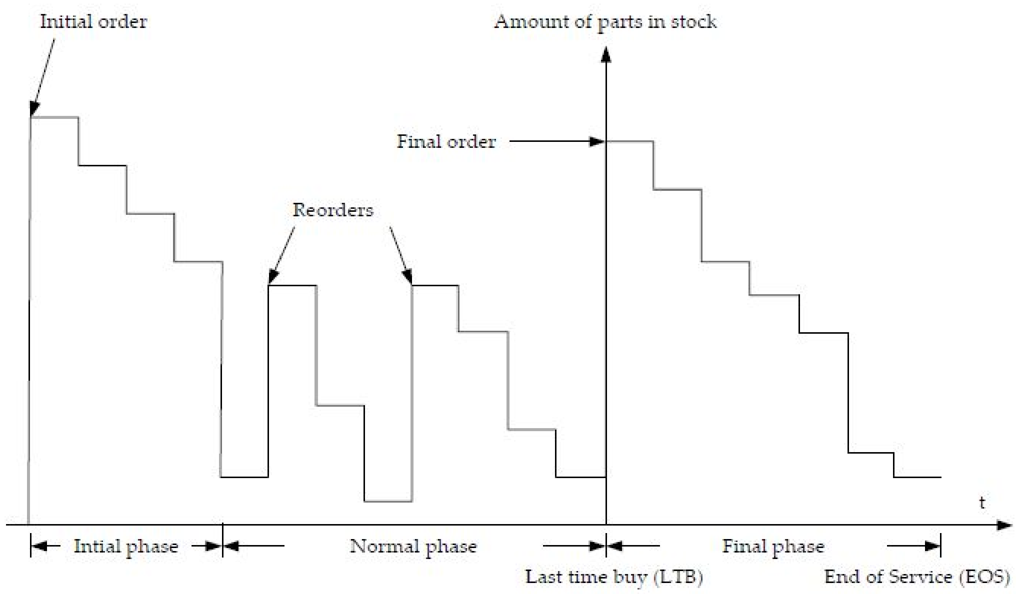

Figure 2.4 Life cycles of spare parts phases

Also, we can gather spare parts cycle at the beginning of the life time, end of life and end of service (see Figure 2.5).

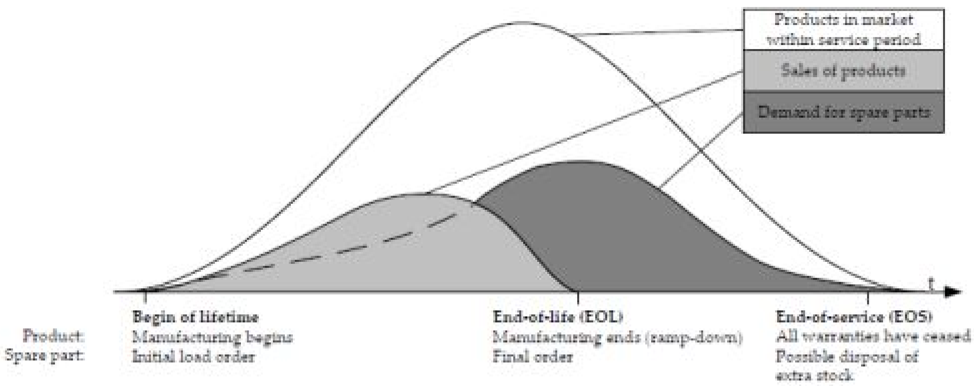

Figure 2.5 Spare part life cycle

Boylan, Syntetos and Karakostas (2008) showed an application of the method above in a software enterprise. Spare parts are classified in Table 2.1 (Regoa, 2011).

Table 2.1 Classification of spare parts

Variability of			Category
Frequency	Amount	Lead-time	
Low	Low		Smooth
	High		Irregular
High	Low		Slow moving
	High	Low	Slightly intermittent
		High	Highly intermittent

2.3 Spare Parts Demand and Classifications

Spare parts demand is very important for stock keeping unit (SKU). It should ve known the demand pattern to maximize customer satisfaction, and optimize stock level.

Demand for consumable spare parts tends to be divided into two categories. Firstly, erratic or intermittent demand patterns are characterized by infrequent transactions with variable demand sizes, and secondly, slow-moving demand patterns which are also characterized by infrequent transactions (Howard, 2002).

- Erratic Demand: Under erratic demand, when a transaction occurs, the request may be for more than a single unit resulting in so-called lumpy demand. Such demand patterns frequently arise in parts and supplies inventory systems. Erratic demand can create significant problems in the manufacturing and supply environment as far as forecasting and inventory control are concerned. This section examines the causes of erratic demand, and the demand for a sample line item illustrates the consequences of one such cause. Alternatively, an actual occasion in which an erratic demand pattern need not be a problem is also considered. Finally, statistical means for assessing erratic demand are introduced.

- Slow Moving Demand: Slow-moving spares are mainly held as insurance against the very high costs that might otherwise be incurred if the item failed in use when a spare was not available. Any inventory control policy for slow-moving spares must take into account the run-out or shortage cost. The run-out cost for a particular spare is defined as the average difference between the cost of a breakdown where a spare is required but is not available and the cost of a similar breakdown when a spare is available.

Classification of Lead Time demand is given at Table 2.2. (Howard, 2002).

Table 2.2 Classification of Lead Time demand

Lead-Time Demand Component			Type of Demand Pattern
Transaction Variability	Demand Size Variability	Lead-Time Variability	
Low			Smooth
High	Low		Slow-moving
High	High	Low	Erratic
High	High	High	Erratic with highly variable lead-time

For characterization of spare parts demand, two parameters are commonly used for (Callegaro, 2010):

- *ADI* - Average inter demand interval: Average interval between two demands of the spare part.

- *CV* - *Coefficient of variation*: standard deviation of the demand divided by the average demand.

$$ADI=\frac{\sum_{i=1}^{N} t_i}{N} \tag{2.1}$$

$$CV=\frac{\sqrt{\frac{\sum_{i=1}^{N}(\varepsilon_i-\varepsilon)^2}{N}}}{\varepsilon} \tag{2.2}$$

$$where\ \varepsilon=\frac{\sum_{i=1}^{N}\varepsilon_i}{N} \tag{2.3}$$

For *ADI*, *N* is the number of periods with non-zero demand, while for *CV* it is the number of all periods.

Ghobbar et al. (2003) suggest some "*cut values*" which allow a more detailed characterization of the intermittent standard of spare parts demand. Figure 2.6 presents the categories of the spare parts demand patterns.

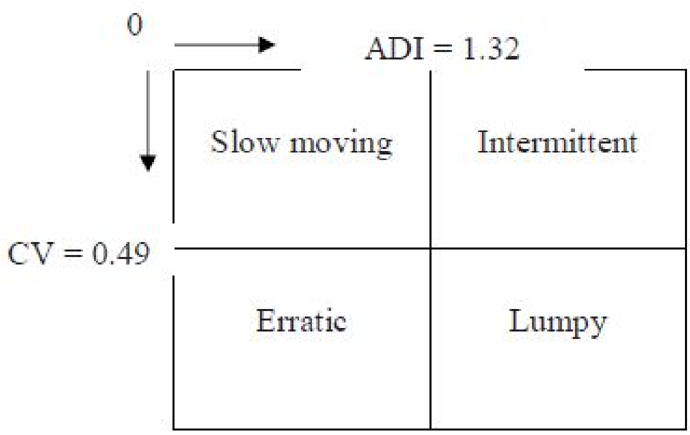

Figure 2.6 Principal patterns for the characterization of the spare parts demand

Four typologies can be recognized (Howard, 2002):

- Slow moving (or smooth): this items have a behavior which is similar to that of the traditional articles, at low rotation, of a productive system;

- Strictly intermittent: they are characterized by extremely sporadic demand (therefore a lot of a period with no demand) with a not accentuated variability in the quantity of the single demand;

- Erratic: the fundamental characteristic is the great variability of the requested quantity, but the demand is approximately constant as distribution in the time;

- Lumpy: it is the most difficult to control category, because it is characterized by a lot of intervals with zero-demand and a great variability in the quantity.

Note that the subclass intermittent has the same name as the overall class of intermittent demand patterns. According to the classification method presented by Ghobbar and Friend (2002), the characteristics of intermittent demand are derived from two measures; the average inter-demand interval (ADI) and the coefficient of variation (CV). ADI measures the average number of time periods between two successive demands for a specific SKU, and CV measures the standard deviation of the period non-zero demands as a proportion of the average period non-zero demand for a SKU. If the non-zero demand observations are invariant, independent of the sizes, the CV is lower than if the sizes vary (Eaves, 2002). To distinguish between the four classes, cut-off values have to be decided for high and low CV and ADI. Some literature proposes values for these cut-off values, but very often, they depend on the context in which the classification is used (Van Kampen, 2012) Demand forecasting for spare parts has been studied for several decades. Several authors have discussed the difference between the normally more smooth demand patterns for regular SKUs and the more intermittent demand patterns for spare part SKUs. In one of the first contributions to this field, Croston (1972) developed a method (hereafter referred to as CM) that takes both the demand size and the time between demand occurrences into account, hereby including the typical structure of intermittent demand patterns. More recently, researchers have identified CM to be biased, and have proposed adjustments to CM, such as Syntetos-Boylan (2001) approximation, hereafter referred to as SBA (Syntetos, 2005). Recent research has also focused on the identification of demand patterns for which either CM or SBA performs better (Heinecke, 2011). In order to obtain more realistic demand patterns, bootstrap methods have also been utilized in forecasting. Next to these specific methods, basic forecasting methods such as (weighted) moving average ((W)MA), and simple exponential smoothing (SES) are often used in practice (Bacchetti and Saccani, 2011), partly due to the fact that they are easier to understand for staff members. In our numerical experiments, we will both use the simple general models and the more advanced models that are specifically developed for intermittent demand patterns. (Ragnarsdóttir, 2008)

2.4 Importance and Complexities of Spare Parts Management

Spare parts inventory management shares many traits with standard inventory management, but requires an extra layer of cost consideration. Whether a Maintenance and Repair Organization (MRO) is internal to a larger business, or providing maintenance services to an external customer, efficient spare parts inventory management plays a critical role in reducing costs and maximizing customer service. We will look at an internal MRO to a production facility. These five steps collect the information you need for executing effective spare parts inventory management (http://www.purchasing-procurement-center.com).

- Step 1. Understanding existing (or projected) consumption: Because repairs happen due to system failures, rather than as part of a production plan, many logistics professionals overlook consumption predictions. Depending on the age of the MRO, spare parts consumption can be based on either actual historic consumption, or projected based on equipment manufacturer preventative maintenance recommendations and fleet records of other system owners.

- Step 2. Calculating system failure costs: In-stock levels and the size of your on-site inventory should be directly linked to costs of system failure or "down time". Every machine in a production facility plays a role. Some have redundancy, like the multiple forklifts in a warehouse, while others act as a single point of failure for the whole building, such as an automated full-building outbound sorter.

- Step 3. Estimate soft cost impact of out-of-stocks: It is a picture familiar to many industry professionals: parts hoarded in toolboxes, a spare motor under a desk in the maintenance supervisor's office, or the "secret stash" closet with thousands of dollars worth of parts. Reducing inventory dollars on the books as part of spare parts inventory management can lead to an off-books rise in inventory costs. You are guaranteed these behaviors will start when your out-of-stock rate in your frequently requested spare parts inventory reaches 4-5%.

- Step 4. Work with vendors for cost-reduction and in-stock improvement: In many instances, leveraging vendor relationships will allow you to reduce your overall inventory dollars and keep better in-stocks. Rather than using your own time and resources to monitor spare parts usage, establish reorder points, and project parts required for preventative maintenance, the manufacturer can often provide you a starting point for your stocking levels. In the best cases, you can find vendors willing to provide spare parts inventory management on a consignment bases: you pay only for parts consumed.

- Step 5. Calculate costs (hard and soft) of expedited orders: It is sometimes impossible to maintain a spare parts inventory for every contingency. The key is to establish an expedited spare parts ordering process and understand the costs involved. This allows subordinate managers and maintenance person to make good decisions on what to expedite and what to order on standard orders. These five steps are just the beginning to achieving optimum spare parts inventory management. From these basics, you can measure, evaluate and further stream line your spare parts inventory control processes. Cost reduction, increased system availability, and improved moral because workers have the tools they need to do their jobs are just some of the benefits you can experience.

Spare parts Management plays an important role in achieving the desired plant availability at an optimum cost. Presently, the industries are going for capital intensive, mass production oriented and sophisticated technology. The downtime for such plant and machinery is prohibitively expensive. It has been observed in many industries that the non-availability of spare parts, as and when required for repairs, contributes to as much as 50% of the total down time. Also, the cost of spare parts is more than 50% of the total maintenance cost in the industry. It is a paradox to note that the maintenance department is complaining of the non-availability of the spare parts to meet their requirement and finance department is facing the problem of increasing locked up capital in spare parts inventory. This amply signifies the vital importance of spare parts management in any organization (Mishra, 2004).

Also, the spares should be of right quality. There are many actions required to ensure the spare parts management effective.

There is a need for systematic actions while managing spare parts as given below. (Mishra, 2004):

- Identification of spare parts
- Forecasting of spare parts requirement
- Inventory analyses
- Formulation of selective control policies for various categories
- Development of inventory control systems
- Stocking policies for capital & insurance spares
- Stocking policies for ratable spares or sub- assemblies.
- Replacement policies for spare parts
- Spare parts inspection
- Indigenization of spares
- Reconditioning of spare parts
- Establishment of spare parts bank
- Computer applications for spare parts management.

A question that often comes up is “Why treat service and spares differently from regular production parts?” The forecasting of spares and service parts as well as the inventory management function is a more complex task because of the following characteristics in Table 2.3 (Kumar, 2006).

Table 2.3 Differences between production parts and spare parts

	Production Parts	Spare parts
1	The demand for production parts is a derived or a dependant demand generated from the production plan and hence is predictable	The demand for spare parts largely depends on the output of preventive and predictive maintenance activities, and is typically based on MTTF (mean time to failure) calculations. Sudden breakdowns due to factors such as wrong operation or failure to perform a routine maintenance activity lead to demand with no assignable predictable causes, thereby imposing a need to maintain buffer inventory.
2	Production parts have a demand based the existence of market demand which is easier to predict	The demand of spares is based on the equipment life cycle and follows the inverted bathtub curve
3	Easier to forecast because of more predictable movement patterns	The sparse nature of usage/ consumption data makes it difficult to generate statistically valid forecasts for spares.
4	Incidence of alternate parts and common parts is handled through substitution relationships in a Bill Of materials	The existence of part alternates and common parts across equipment makes inventory management more complex
5	The component/ part relationships with the supplier are inherently better defined apart from commodity raw materials	Spares are often procured locally and development of indigenous suppliers makes the analysis of failure dependent on a large set of factors. Managing multiple sources of supply for the same part imposes a need for greater rigor and analysis on service maintenance.
6	The demand for a part or a component is in most cases a derived demand based on the customer demand for the end product; which is relatively simple and based on orders received or forecasted	Often the demand for a spare arises from an alternate source of failure. To elaborate, a failure of a key on a gear shaft may cause the gear shaft to be replaced as well as the other meshing parts like gears. Likewise, the demand of spares is a function of the equipment life cycle
7	Production parts are typically the input or output of a production process. Non- availability of input parts can constrain the throughput.	Non-availability of spares impacts the throughput and directly translates into costly machine downtime

2.4.1 Network Structure of Spare Parts Management

The demand driven supply chain story of integrated planning and decision support has been well documented. However, the move to integrated supply chains has not included the service aspects very well and likewise; the integration of execution systems such as plant maintenance systems with planning systems has seldom been focused on. A host of factors are driving the need to take a close look at this vital aspect presented in Figure 2.7 (Kumar, 2006).

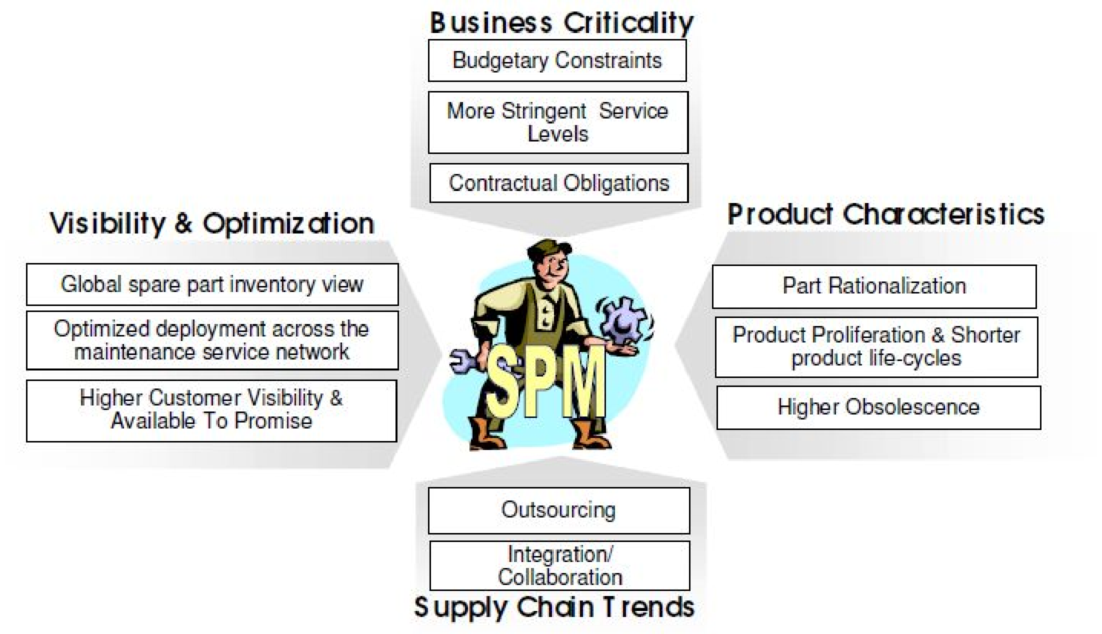

Figure 2.7 Network structure of spare parts management

- *Business criticality:* Lowering the cost of operation and improving service levels is the challenge that both plant and service maintenance folks face. The demand for agility and flexibility has led to more sophistication in manufacturing systems with higher part complexity and greater capital investments, calling for better utilization factors and quality service response.

- *Product Characteristics:* The proliferation of parts and products is making equipment manufacturers rationalize and standardize on their parts and components. A rationalization step in the earthmoving industry could be to try and use the same standard set of accessories across all bulldozers manufactured.

- *Supply chain trends:* The trend towards outsourcing of service functions has huge ramifications on system support for managing service needs. The operational planning process needs to be closely integrated with the service and maintenance planning functions and in a service provider scenario; it becomes vital that there is integration from both a process and a system perspective. As an example, some operational specifics on what and how a batch of steel plates was made in a hot strip mill in a steel plant needs to be made available to a third party maintenance service provider to predict the maintenance requirements from a activity and a part perspective.

- *Visibility and optimization:* Deployment of spare part inventory happens across locations and one way of controlling the spare part inventory is by taking a global view of inventory and then forecasting demand based on statistically significant data. In service operations, the practice of maintaining multi-echelon inventory calls for optimization on inventory decisions based on need and service response.

2.4.2 Some Difficult Questions in Spare Parts Management

In today’s business environment, the importance of after-sales service is high. Lost revenues due to disservice are enormous. Not only is after-sales service valuable as a competitive advantage for manufacturers, but also direct revenue in service is remarkably high (Adrianus, 2006).

- *Is it possible to develop a heuristic that is accurate and fast?*

In models with one or more of the five features incorporated, the resulting optimization problems have non-linear constraints (on service levels) and integer decision variables (like base stock levels). Especially for problems with large numbers of items, optimization is intractable; often only explicit enumeration can be used to solve the problem exactly. For that reason, the focus is on development of heuristics. Aarts and Lenstra (1997) mention that for approximation algorithms running time and solution quality quantify the performance. Approximation algorithms without performance guarantees are also known as heuristics, and for those the solution quality, the accuracy, can be measured as ratio of the empirical worst-case to the optimal solution or to a bound on the optimal value. In our question, we refer to the empirical running time and solution quality with fast and accurate, respectively. If multiple methods would exist with comparable speed and accuracy, then a method that in addition is simple would be preferred over the alternatives. We have in mind that our methods are to be implemented in inventory control methods to be used in practice, and thus methods that are easy to implement are preferred.

- *Which factors determine the magnitude of the expected cost benefits, and what is the magnitude of cost benefits for real-life data sets?*

This question aims to obtain insight into expected cost benefits, where benefits are defined e.g. in comparison to the cost in a model without that feature incorporated. We are interested in which factors are important in terms of their influence on the size of the cost benefits. Besides, using data sets of ASML, with parameter values that are appropriate in those particular cases, we would like to get an indication of the magnitude of the expected cost benefits in practice (Adrianus, 2006).

2.5 Service Parts Industry Success Stories

Siemens VAI has developed a comprehensive spare parts management system available to all customers regardless of location. With a massive inventory of critical mill spare components made from guaranteed original materials and to Siemens VAI original specifications. Customers now have access to the parts they need to ensure maximum mill productivity 24 hours a day 7 days a week and 365 day per year. With warehouse servicing all major regions of the world the spare parts that you rely on for day to day operation are now just a phone call away. Globally located warehouses contain a huge inventory of common high wear parts including; roll pinions, flingers, tapered sleeves and bearings just to list a few. All parts are manufactured to the same exacting specifications as those they are replacing unless improvements have been made to a part in which case the customer benefits from the enhanced design. Spare parts management operation of Siemens can be seen at Figure 2.8. (http://www.industry.siemens.com/industrysolutions).

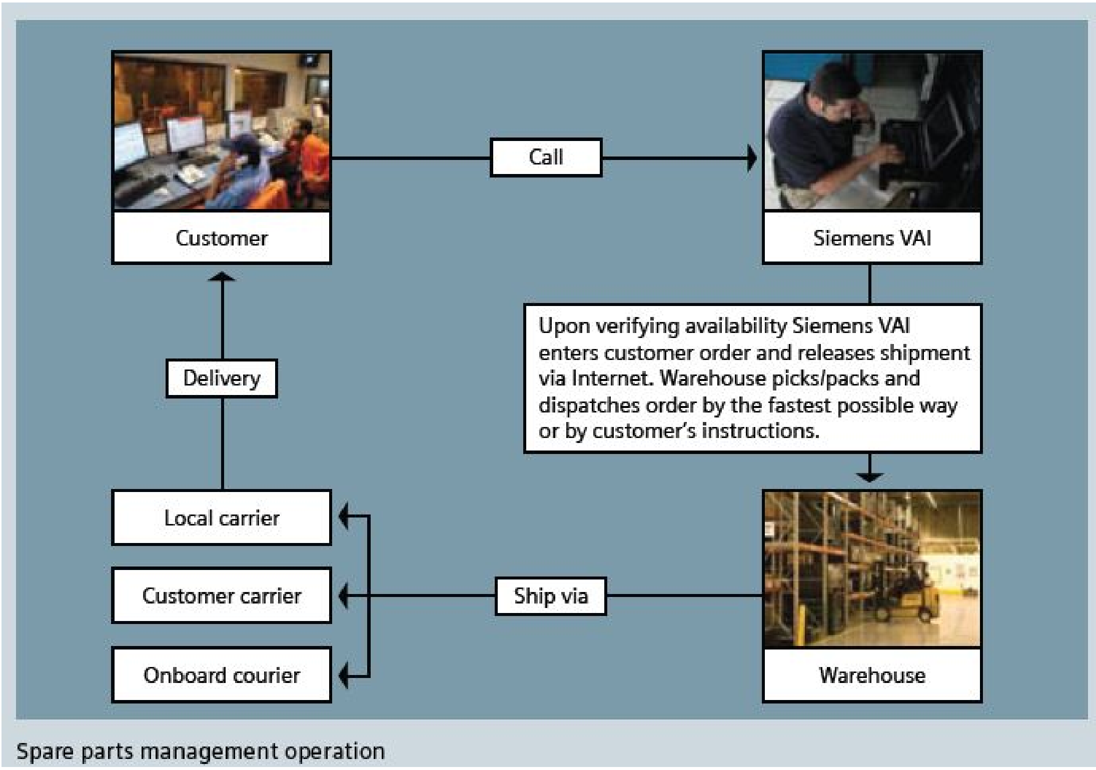

Figure 2.8 Spare parts management operation of Siemens

A number of our customers are using Smart Forecasts to streamline and optimize their service parts operations. The experiences of Prevost Parts and SKF Vehicle Service Market may be of particular interest. Prevost Parts, the parts division of Canadian bus manufacturer Prevost Car, uses Smart Forecasts to more effectively distribute parts to the North American motor coach and transit bus markets. To serve its clients, the company maintains seven North American locations with over 25,000 active parts, 70 percent of which exhibit intermittent demand. Prevost selected SmartForecasts over SAP's demand planning system and several other best-of-breed applications, in good part because of Smart's unique solution to the intermittent demand forecasting problem. In just 3 months following Smart Forecasts' implementation, the company's backorders and lost sales decreased 65% and 59%, respectively, and fill rates increased from 93 to 96%. As Prevost Parts' logistics director commented, "We need to have the right parts in the right place to support our customers. Smart Forecasts helps us to not only improve our inventory allocation but also significantly reduce transportation and inventory costs." (www.smartcorp.com/success_stories.asp).

SKF Vehicle Service Market (SKF-VSM) is the North American automotive aftermarket arm of SKF, a $6.3 billion, publicly traded corporation headquartered in Gothenburg, Sweden. SKF-VSM maintains six distribution centers in North America and stocks approximately 60,000 unique parts, the majority of which exhibit intermittent, slow-moving demand. Within 6 months of implementing Smart Forecasts, the company was able to reduce the net value of its inventory by over a million dollars. The full benefit was seen in 2005 when SKF-VSM was able to reduce its inventory holdings by an impressive 16% while still maintaining targeted 95% customer service levels. As SKF-VSM's manager of aftermarket supply chain planning noted, "Smart Forecasts drives our relationship with suppliers. We [now] have a much better understanding of what our future demand will be, and that reduces a lot of the costly expediting that we had to do in the past." (www.smartcorp.com/success_stories.asp).

2.6 Designing and Operating a Spare Parts Warehouse

2.6.1 General View of the Warehouse

The basic function of a warehouse is to receive customer orders, retrieve required items, and finally prepare and ship those items. There are many ways to organize these operations but the overall process in most warehouses shares the following common phases (Blomqvist, 2010):

- *Receiving*: The process of unloading, checking quality and quantity, and dissembling or repacking items for storage.

- *Put away*: Defining the appropriate location for items and transferring them to the specified storage location to wait for demand.

- *Order Picking*: Retrieving items from their storage locations and transporting them either to a sorting process or straight to the shipping area.

- *Shipping*: Iinspecting, packing, palletizing and loading items into a carrier for further delivery.

Common warehouse operation costs are presented in Figure 2.9.

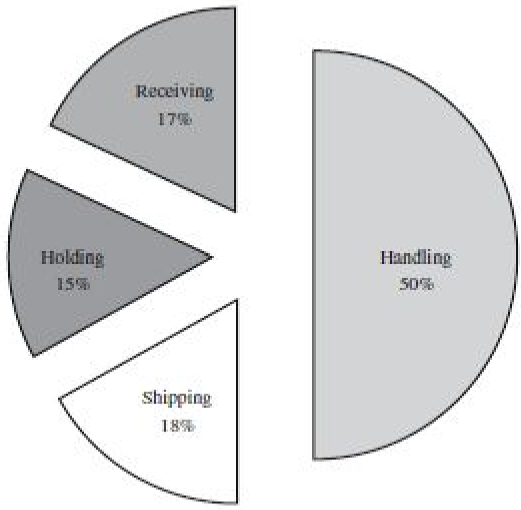

Figure 2.9 Common warehouse costs.

2.6.2 Automating and Mechanizing Processes at Warehouses

Warehouse technologies are used for three main reasons: save storage space, improve productivity, and reduce errors (Aminoff, 2002). Selecting the appropriate level of warehouse automation is a difficult task. Capital investments can be considerable but the rewards often include significant savings in terms of labor costs and productivity, inventory accuracy, or order processing times. A warehousing system refers to the combination of equipment and operating policies that are used in a storage/retrieval environment. The simplest storage method is block stacking which is a typical method for stocking bulk items. Although block stacking is very cheap it results in low accessibility to items due to the honey combing effect. To enhance accessibility, most warehouses consist of parallel aisles with products stored along sides. Small items can usually be placed in bin shelves or modular storage drawers fairly efficiently while larger items are typically placed on pallet racks (Blomqvist, 2010).

With respect to the level of automation it is possible to distinguish three types of warehousing systems (Berg, 1999):

- Manual warehousing systems (picker-to-product): The order picker collects the product in the warehouse by travelling to the storage location.
- Automated warehousing systems (product-to-picker): The picking operation is performed by an automated device, delivering items to a stationary order picker.
- Automatic warehousing systems: This system is similar to the automated warehousing system except that the picker is replaced by a robot.

The choice of a storage medium is strongly affected by the physical characteristics of the goods in stock and by the average number of items of each product in a customer order. Briefly, when storing solid goods three main alternatives are available: stacks, racks and drawers. In the first case, goods are stored as cartons or as pallets, and aisles are typically 3.5–4 m wide (see Figure 2.10). Stacks do not require any capital investment and are suitable for storing low-demand goods, especially in reserve zones. In the second case, goods are stored as boxes or pallets on metallic shelves separated by aisles. Here quick picking of single load units is possible. When SKUs are moved by forklifts, the racks (see Figure 2.11) are usually 5–6 m tall and aisles are around 3.5 m wide. Instead, as explained in the following, in automated storage and retrieval systems (AS/RS), racks are typically 10–12 m tall and aisles are usually 1.5 m wide (see Figure 2.12). Finally, in the third case, items are generally of small size (e.g. metallic small parts), and are kept in fixed or rotating drawers (Ghiani, 2005).

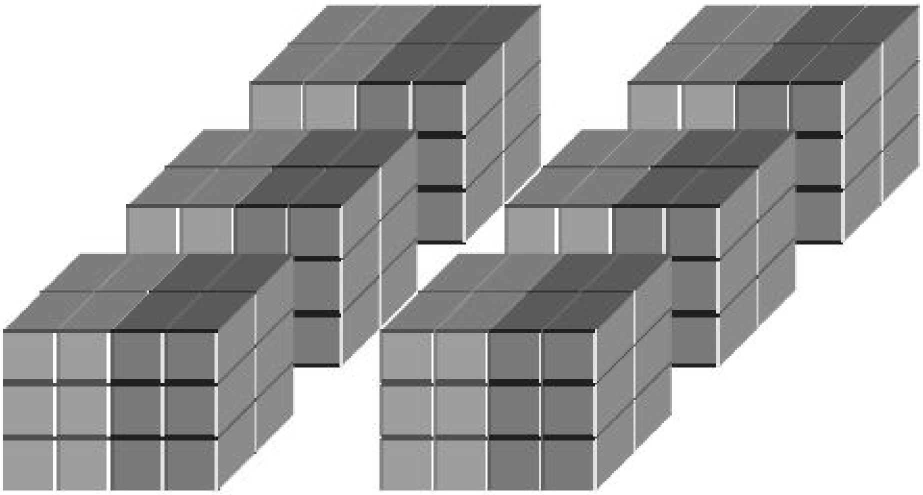

Figure 2.10 Block stacking system.

Figure 2.11 Rack storage.

Figure 2.12 An AS/RS.

2.6.3 Cost Considerations in Spare Parts Management

Costs that need to be considered in the analysis of a spare parts inventory should include all costs that vary as the level of inventory changes, or costs that are incurred according to the inventory policy (and that will be affected by the choice of policy) (Louit, 2006).

Different kinds of costs can be associated to spare parts management. The first cost is the cost of lack: if there is a breakdown and no spare parts in the warehouse, there is a cost associated to the loss of production which can be seen as missed pay-off. Because of the complexity reached by the present productive systems, these costs can be very significant. Sometimes, when the down times are high, some businesses are induced to get on components that aren't adapted. In this case, there is the risk to damage the productive system and to add other costs: reparation costs and further lack costs. It is evident that connected to the storage of technical material such the spare parts are, there is a significant financial cost which, in case of missed use of the item, produces numerous negative effects. This financial cost includes the block of sums of money for the purchase, the maintenance cost and eventually disposal cost in case of missed utilize and turned up obsolescence (often due to the necessity to replace the original productive system) (Ghiani, 2005).

In conclusion, in the spare parts management for productive systems two contrasting aspects have to be considered: the cost of lack and the cost of storage. The formulas approved by the international literature to calculate these two kinds of costs are the following:

$$C_{lack} = P_{lack} \cdot \frac{T}{MTTF} \cdot C_h \cdot MTTR \qquad (2.4)$$

Where:

- P_{lack} is the probability of lack
- $MTTF$ is the mean time to failure
- T is the interval time considered
- C_h is hourly cost of lack of production

- *MTTR* is the mean time to repair or replace

$$C_{storage}=R.T.\overline{S} \tag{2.5}$$

Where:

- *R* is the purchase cost of a spare part
- *t* is financial storage rate
- *S* is the average storage of spare parts

Figure 2.13 exemplifies the contrasting trend of the two costs in function of the level of supply of a spare part and the consequent trend of the total cost.

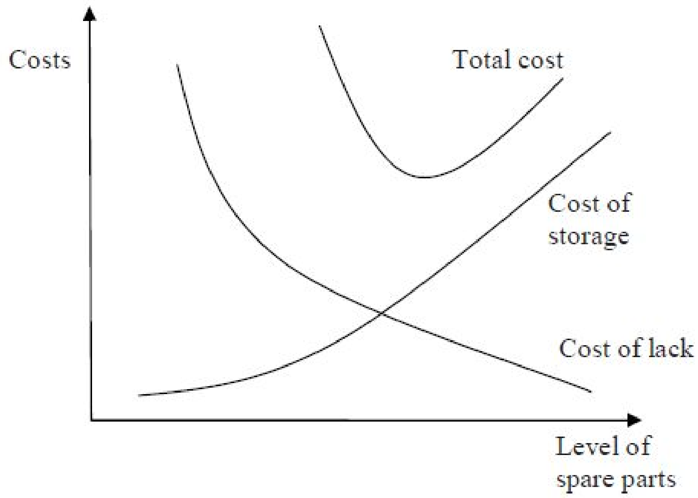

Figure 2.13 Trade off on the level of escort of spare parts

The extent to which these costs are to be included in a particular model and the breakdown which is required to define them will vary considerably between different companies and applications; thus their precise meaning and quantification is not trivial. A large body of literature is available, where numerous inventory cost models are introduced. In this paper we will briefly describe two cost models: one for non-repairable parts and another for repairable parts, selected due to their simplicity (Louit, 2006).

CHAPTER THREE

AN OVERVIEW OF SPARE PARTS DEMAND FORECASTING METHODS

3.1 Importance of Forecasting in Spare Parts Management

Service parts management, or spare parts management as it is more commonly known, is often granted stepchild status relative to its counterpart, production parts management. The fact remains, however, that the service parts business is often the more profitable of the two. Take, for instance, the auto industry, where it is common for parts to sell at three or four times their cost to the supplier, or the high-tech market, where companies often sell printers at or below cost and make money selling print cartridges. The key to effective service parts management lies in being able to optimally plan for availability of spare parts across the supply chain network. So, what makes service parts planning complicated and different from any other supply chain scenario? Answer of this question can be given by convenient forecast methods. Integrated forecasting process is illustrated in Figure 3.1 (Iyer, www.cognizant.com).

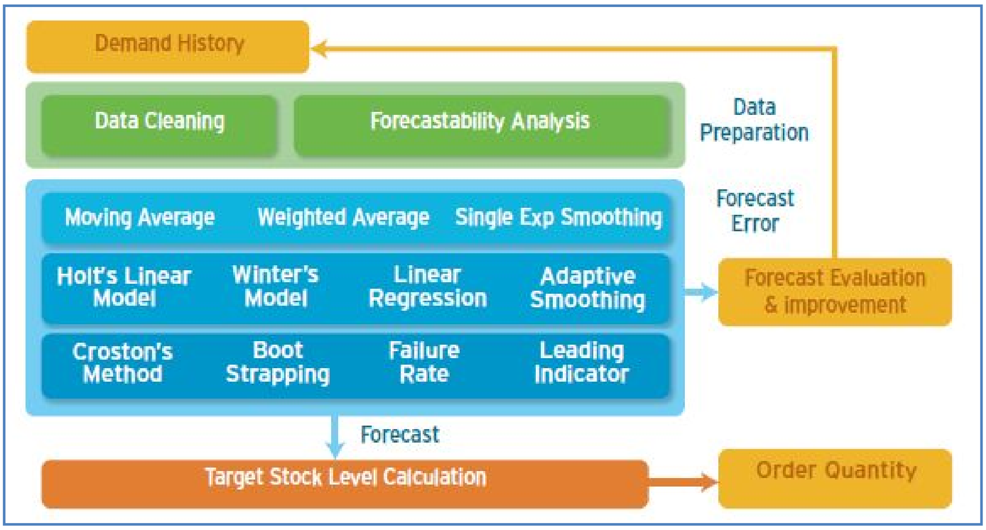

Figure 3.1 Integrated forecasting process

As stated previously, forecasting is the basic stone for good SPM. Benefits of good forecasting are explained as in the following (Iyer, www.cognizant.com):

- *Improved customer service levels*: A result of accurate forecasting is better procurement planning. This ensures the right products are present on the shelves at the right time.

- *Reduced safety stock*: Safety stocks are directly proportional to demand variability. Better forecasts reduce the amount of safety stock that needs to be held, resulting in lower operational costs.

- *Slower build-up of surplus and obsolete stock*: Traditional time series forecasting often results in over-ordering. Over time, this leads to the accumulation of slow-moving products in the warehouse. Methods such as a Croston(1972)'s method for intermittent demand mitigate this.

- *Better forecasts for new products*: Using new product introduction forecasting techniques, such as modeling, produces accurate forecasts.

- *Better management of events and promotions*: A formal event management process after the forecast is generated ensures events and promotions are handled better.

- *Adherence with continuous improvement principles*: A forecast evaluation and improvement process ensures that the process (and hence the forecast accuracy) is improved based on feedback.

3.2 Classification of Forecasting Methods

Future demand plays a very important role in production planning and inventory management of spare parts, fairly accurate forecasts are needed. The manufacturing sector has been trying to manage the uncertainty of spare parts demand for many years, which has brought about the development of many forecasting methods and techniques. In general view, forecasting methods can be divided into two categories: Qualitative and Quantitative methods (Ghiani, 2005).

Qualitative methods can be grouped under three headings:

- Sales force assessment,
- Market research,
- Delphi method.

Quantitative methods can be grouped under two headings:

- Causal Methods,
- Time Series Extrapolation.

Causal methods exploit the strong correlation between the future demand of some items (or services) and the past (or current) values of some causal variables. For example, the demand for economy cars depends on the level of economic activity and, therefore, can be related to the GDP (Gross Domestic Product). Similarly, the demand for spare parts can be associated with the number of installed devices using them (Ghiani, 2005).

Time Series Extrapolation can be grouped under four headings:

- The Constant Trend Case,
- The Linear Trend Case,
- The Seasonal Effect Case,
- Advanced Forecasting Methods.

The Constant Trend Case can be grouped under six headings:

- Time series decomposition method,
- Elementary technique,
- Moving average method,
- Exponential smoothing method,
- Choice of the smoothing constant,
- The demand forecasts for the subsequent time periods.

The Linear Trend Case can be grouped under four headings:

- Elementary technique,
- Linear regression method,
- Double moving average method,
- The Holt method.

The Seasonal Effect Case can be grouped under four headings:

- Elementary technique,
- Linear regression method,
- Double moving average method,
- The Holt method.

Advanced Forecasting Methods can be grouped under six headings:

- Econometric models,
- Input–output models,
- Life-cycle analysis,
- Computer simulation models,
- Neural Networks,
- Box–Jenkins method.

General view of the literature about forecasting methods is reported in Table 3.1 (Callegaro, 2010).

Table 3.1 General view of the literature

AUTHORS	YEAR	SES (SINGLE EXPONENTIAL SMOOTHING)	CR (CROSTON'S METHOD)	MA(MOVING AVERAGE)	WMA(WEIGHTED MOVING AVERAGE)	AW (ADDITIVE WINTER)	MW (MULTIPLICATIVE WINTER)	BOOT (BOOTSTRAP METHOD)	BJ (ARMA-autoregressive and a moving average ARIMA)	GM (GTREY PREDICTI ON MODEL)
Croston	1972		x							
Rao	1973		x							
Mckenzie	1986					x				
Schulz	1987		x							
Bookbinder , Lordahl	1989							x		
Yar, Chatfield	1990					x	x			
Wang, Rao	1992							x		
Willemain et al.	1994		x							
Johnston , Boylan	1996		x							
Sani , Kingsman	1997		x	x						
Ho, Xie	1998								x	
Lawton	1998					x				
Koehler et al.	2001						x			
Syntetos , Boylan	2001	x	x							
Ho et al.	2002								x	
Ramjee , Crato	2002			x						
Snyder	2002		x							
Tseng et al.	2002								x	
Archibald , Koehler	2003					x	x			
Bu Hamra et al.	2003								x	
Ghobbar A.A., Friend	2003	x	x		x	x	x			
Tzeng et al.	2004									x
Willemain et al.	2004	x	x					x		
Syntetos , Boylan	2005	x	x							
Syntetos et al.	2005		x							
Hua, Zhang	2006							x		
Amin-Naseri, Tabar	2008	x								
Gutierrez et al.	2008	x								
Sheu et al.	2009				x					
Teunter, Sani	2009		x							
Chen F.L., Chen Y.C.	2010			x						x

3.3 Explanation of the Forecasting Methods

3.3.1 Single Exponential Smoothing

This method is based on time series analysis; especially it is convenient for short term forecasts. This forecasting method is usually used of all forecasting techniques (Attaran, 1992). It isn't complex. It requires easy calculation. This method can be used when data pattern is horizontal (i.e., there is no trend in the historical data).

The equation of exponential smoothing method is:

$$F_{t+1} = \alpha X_t + (1-\alpha) F_t \tag{3.1}$$

Where, X_t is the actual value of the demand at the snap t, F_{t+1} is the forecast for snap t+1, *and* α is the smoothing parameter which can take different values, usually between 0,1 and 0,4 on the basis of demand features. (Callegaro, 2010).

3.3.2 Double Exponential Smoothing

This method is used when the data shows a trend. Exponential smoothing with a trend works much like simple smoothing except that two components must be updated each period - level and trend. The level is a smoothed estimate of the value of the data at the end of each period. The trend is a smoothed estimate of average growth at the end of each period. The specific formula for simple exponential smoothing is (Kalekar, 2004):

$$S_t = \alpha * y_t + (1-\alpha) * (S_{t-1} + b_{t-1}) \quad 0 < \alpha < 1 \tag{3.2}$$

$$b_t = \gamma * (S_t - S_{t-1}) + (1-\gamma) * b_{t-1} \quad 0 < \gamma < 1 \tag{3.3}$$

Note that the current value of the series is used to calculate its smoothed value replacement in double exponential smoothing. (Kalekar, 2004):

There are several methods to choose the initial values for S_t and b_t .

S_1 is in general set to y_1. Three suggestions for b_1.

$$b_1 = y_2 - y_1 \quad (3.4)$$

$$b_1 = [(y_2 - y_1) + (y_3 - y_2) + (y_4 - y_3)] / 3 \quad (3.5)$$

$$b_1 = (y_n - y_1)/(n-1) \quad (3.6)$$

3.3.3 Croston's Method

Croston (1972)'s method reduces bias of Exponential Smoothing but does not eliminate it completely. Croston (1972)'s method is a forecasting approach that was developed to provide a more accurate estimate for products with intermittent demand.

Croston (1972)'s method consists of two main steps. First, Croston(1972)'s method calculates the mean demand per period by separately applying exponential smoothing. Second, the mean interval between demands is calculated. This is then used in a form of the model to predict the future demand (Vinh, 2010).

Let $Y(t)$ be the estimate of the mean size of a nonzero demand, let $P(t)$ be the estimate of the mean interval between nonzero demands, and let Q be the time interval since the last nonzero demand. Where α is a smoothing constant between 0 and 1 (Vinh, 2010).

If $X(t) = 0$ then,

$$Y(t) = Y(t-1) \quad (3.7)$$

$$P(t) = P(t-1) \quad (3.8)$$

$$Q = Q + 1$$

Else,

$$Y(t) = \alpha X(t) + (1\text{-}\alpha)Y(t\text{-}1) \tag{3.9}$$

$$P(t) = \alpha Q + (1\text{-}\alpha)P(t\text{-}1) \tag{3.10}$$

$$Q = 1 \tag{3.11}$$

The estimate of mean demand per period can be calculated as follow:

$$\mathrm{M(t) = Y(t)/P(t)\ (2)} \tag{3.12}$$

3.3.4 Moving Average

The moving average (MA) method is the mean of the previous n data sets. The formulation of the moving average method can be seen as follow:

$$F_t = MA(n) = \frac{X_{t-1} + X_{t-2} + \ldots + X_{t-n}}{n} \tag{3.13}$$

As it can be seen from the formulation, this method is exactly simple and easy to calculate, but it is convenient for only in slow moving demands. (Callegaro, 2010).

3.3.5 Weighted Moving Average

A weighted k-point moving average can be written as follows (Hyndman, 2009):

$$f(t) = \sum_{j=-k}^{k} a_j y_t + j \tag{3.14}$$

For the weighted moving average to work properly, it is important that the weights sum to one and that they are symmetric, that is $a_j = a_{-j}$. However, we do not require that the weights are between 0 and 1. The advantage of weighted averages is that the resulting trend estimate is much smoother. Instead of observations entering and leaving the average abruptly, they can be slowly down weighted. There are many schemes for selecting appropriate weights (Hyndman, 2009).

3.3.6 Holt –Winters Methods

Additive and multiplicative winter are the methods proposed by Winters and Holt (1986) in order to considerate hypothetical seasonal effects. Assume that we require monthly sales forecasts. To produce a forecast, the Holt-Winters (HW) method needs to estimate up to three components of a forecasting equation (Goodwin, 2010):

- The current underlying level of sales. This is the level that remains after we have deseasonalized the sales and attempted to remove the effect of random factors (noise).

- The current trend in our sales. This is the change in the underlying level that we expect to occur between now and next month. For example, if we estimate our current level is 500 units and we expect this to be 505 units next month, then our estimated trend is +5 units.

- The seasonal index for the month we are forecasting. Let's say our estimate is 1.2; this means that we expect our sales in this month to be 20% above that month's underlying level, showing that our product tends to sell relatively well at that time of year.

Suppose we are in January and we want a sales forecast for March, two months later. HW estimates that our current level is 500, our trend is 5, and March has a seasonal index of 1.2. The forecast for the level in March will be:

$$[\text{Level } (500) + 2 * \text{Trend } (10)] * \text{Seasonal } (1.2) = 612 \text{ units} \qquad (3.15)$$

As soon as a new sales figure arrives, HW updates its estimates of the level, trend, and seasonal index for that month. It does this by taking a weighted average of the previous estimates of the component's value and the value suggested by the new sales figure. The weights used are called the smoothing constants. For each component (level, trend, seasonal) there is a smoothing constant that falls between zero and one. Larger smoothing constants mean more weight is placed on the value suggested by the new sales figure and less on the previous estimate. This means that the method will adapt more quickly to genuine changes in the sales pattern, but it might also overreact to freak sales figures. The graph shows how HW forecasts can effectively track trends and seasonal patterns. Key point of this method is given as below (Goodwin, 2010):

• While Holt-Winters remains a mainstay approach to business forecasting, it has recently been extended to deal with three problem areas.

• One is the presence of unusual values (outliers). Left unattended, outliers can distort HW forecasts.

• Another is the prevalence of multiple seasonal cycles, such as a combination of day-of week patterns and month-of-year patterns. Traditional HW could account for only a single seasonal pattern.

• Third is the need for prediction intervals, which affect safety-stock calculations, among other things. Traditional HW intervals in use tend to be too narrow, misleading us into thinking our forecasts are more precise than they really turn out to be.

3.3.7 Bootstrap Method

The bootstrap method introduced in Efron (1979) is a very general re-sampling procedure for estimating the distributions of statistics based on independent observations. The bootstrap method is shown to be successful in many situations, which is being accepted as an alternative to the asymptotic methods. In fact, it is better than some other asymptotic methods, such as the traditional normal approximation and the Edgeworth expansion. However, there are some counterexamples that show the bootstrap produces wrong solutions, i.e., it provides some inconsistent estimators (Efron, 1979).

Consider the problem of estimating variability of location estimates by the Bootstrap method. If we view the observations $x_1,x_2, \ldots, x_n$ as realizations of independent random variables with common distribution function F, it is appropriate to investigate the variability and sampling distribution of a location estimate calculated from a sample of size *n*. Suppose we denote the location estimate as θ. Note that θ is a function of the random variables X_1, X_2, … , X_n and hence has a probability distribution, its sampling distribution, which is determined by *n* and *F*. (Efron, 1979).

The bootstrap procedure can be explained with the following steps (Callegaro, 2010):

- Take an observed sample (in our case a sample of historical spare parts demand) of number equal to *n*, called $X = (x_1,x_2, \ldots, x_n)$;

- From *X*, resample m other samples of number equal to n obtaining X_1, X_2, …, X_m (in every bootstrap extraction, the data of the observed sample can be extracted more than one time and every data has the probability 1/n to be extracted);

- Given *T* the estimator of θ, parameter of study (in our case it may be the average demand), calculate T for every bootstrap sample. In this way we have m estimates of θ;

- From these estimates calculate the desired value: in our case the mean of T_1, …, T_m can be the demand forecast.

This method can be applied not only to find the average demand but also the intervals between non zero demands or other wanted values.

3.3.8 Grey Prediction Model

The grey prediction was firstly introduced in 1982 (Deng, 1982). It is able to analyze the indeterminate and incomplete data to establish the systematic relations. It assumes the internal structure, parameters, and characteristics of the observed system are unknown. The system state can be predicted by a differential equation from the recently historical measurements. The grey prediction has been widely used in applications of social sciences, agriculture, procreation, power consumption, and management (Chen, 2009).

The procedure of GM (1, 1) which model is the most frequently grey prediction model can be summarized as follows.

- Step 1. Establish the initial sequence from observed data.

$$x^{(0)} = (x^{(0)}(1), x^{(0)}(2), \ldots , x^{(0)}(n)) \tag{3.16}$$

where $x^{(0)}(i)$ represents the base line (state = 0) data with respect to time i.

- Step 2. Generate the first-order accumulated generating operation (AGO) sequence.

$x^{(1)}$ based on the initial sequence $x^{(0)}$

$$x^{(1)} = (x^{(1)} (1), x^{(1)}(2),\ldots, x^{(1)}(n)) \tag{3.17}$$

where $x^{(1)}(k)$ is derived as following formula:

$$x^{(1)}(k)=\sum_{i=1}^{k} x^{(1)}(i) \tag{3.18}$$

- Step 3. Compute the mean value of the first-order AGO sequence:

$$Z^{(1)}(k)=0.5 .x^{(1)}(k)+0.5 . x^{(1)}(k-1) \tag{3.19}$$

- Step 4. Define the first-order differential equation of sequence x(1) as:

$$Z^{(1)}+\frac{dx^{(1)}(k)}{dk}+ax^{(1)}(k)=b \tag{3.20}$$

where a and b express the estimated parameters of grey forecasting model.

- Step 5. Utilizing the least squares estimation, we can derive the estimated first-order.

AGO sequence $x^{(1)}(k+1)$ and the estimated inversed AGO sequence $x^{(0)}(k+1)$ (the forecast) as follows:

$$x^{(1)}(k+1)= \left[x^{(0)}(k)-\frac{b}{a}\right].e^{-ak}+\frac{b}{a} \tag{3.21}$$

$$x^{(0)}(k+1)= x^{(1)}(k+1)-x^{(1)}(k) \tag{3.20}$$

where parameter a and b can be shown by following equations (Callegaro, 2010):

$$\begin{bmatrix} a \\ b \end{bmatrix} =\left(B^T.B\right)^{-1}.B^T.y \tag{3.22}$$

$$\mathrm{B} = \begin{bmatrix} -0.5\ .(x^{(1)}(1)+x^{(1)}(2) & 1 \\ -0.5\ .(x^{(1)}(2)+x^{(1)}(3) & 1 \\ \vdots & \\ -0.5\ .(x^{(1)}\left(n-1\right)+x^{(1)}(n) & 1 \end{bmatrix} \tag{3.23}$$

$$\mathrm{y}=\left[x^{(0)}(2),x^{(0)}(3),\ldots,x^{(0)}(n)\right]^{\mathrm{T}} \tag{3.24}$$

3.3.9 ARMA(p,q) ARIMA(p,d,q)

This is a group of methods which include of two parts: an autoregressive (*AR*) part and a moving average (*MA*) part. An autoregressive model of order p can be seen as below form (Callegaro, 2010):

$$F_t=\rho_1 u_{t-1}+\rho_2 u_{t-2}+\ldots+\rho_p u_{t-p}+\varepsilon_t \tag{3.25}$$

Where:

- u_i is the actual value in the period i;
- ρ_i is a coefficient;
- ε_t is a residual term that represents random events not explained by model.

A moving average forecasting model, $MA(q)$ has the form as below (Callegaro, 2010):

$$F_t = \varepsilon_t + \theta_1 \varepsilon_{t-1} + \theta_2 \varepsilon_{t-2} + \ldots + \theta_q \varepsilon_{t-q} \tag{3.26}$$

Where:

- ε_i is the rest of the period i;
- θ_i is a coefficient;

3.3.9.1 ARMA(p,q)

An autoregressive moving average (*ARMA*) process is obtained by applying a recursive filter to white noise which process has An normally distributed with mean 0, variance σ^2_A , and auto-covariance $\gamma_k = 0$. In terms of the elements of the z_n and a_n sequences.

$$z_n = \phi_1 z_{n-1} + \phi_2 z_{n-2} + \ldots + \phi_p z_{n-p} + a_n - \theta_1 a_{n-1} - \ldots - \theta_q a_{n-q} \tag{3.27}$$

The terms $\phi_1 z_{n-1}$ through $\phi_p z_{n-p}$ are the autoregressive portion of the filter. The terms a_n through $\theta_q a_{n-q}$ are a moving average of the white noise input process. Notice that this has the form of the recursive IIR filter that we previously considered, except that the first coefficients have been normalized to 1 (Borchers, 2001).

3.3.9.2 ARIMA(p,d,q)

ARIMA processes are the mathematical models used for forecasting. *ARIMA* is an acronym for Autoregressive, Integrated, Moving Average. Each of these phrases describes a different part of the mathematical model. *ARIMA* processes have been studied extensively and are a major part of time series analysis. They were popularized by George Box and Gwilym Jenkins in the early 1970s; as a result, *ARIMA* processes are sometimes known as Box-Jenkins models. Box and Jenkins (1970) effectively put together in a comprehensive manner the relevant information required to understand and use *ARIMA* processes. Each *ARIMA* process has three parts: the autoregressive (or *AR*) part; the integrated (or *I*) part; and the moving average (or *MA*) part. The models are often written in shorthand as ARIMA(p,d,q) where p describes the AR part, d describes the integrated part and q describes the *MA* part (Hyndman, 2001).

The model is usually known as an *ARIMA(p,d,q)* model where p, d, and q are integers greater than or equal to zero and refer to the order of the autoregressive, integrated, and moving average parts of the model. When one of the notation is zero, it's usual to transform AR, I or MA. For example, an *I(2)* model is *ARIMA(0,2,0)*, and a *MA(2)* model is *ARIMA(0,0,2*). (Callegaro, 2010):

3.3.9.3 Box-Jenkins Methodology

This procedure, gives a way to decide how to use these two forecasting models. This technique does not assume any particular pattern in the historical data of the series to be forecast. This process is repeated until a satisfactory model is found. Figure 3.2 illustrates the approach. (http://www.colorado.edu/ , 2010).

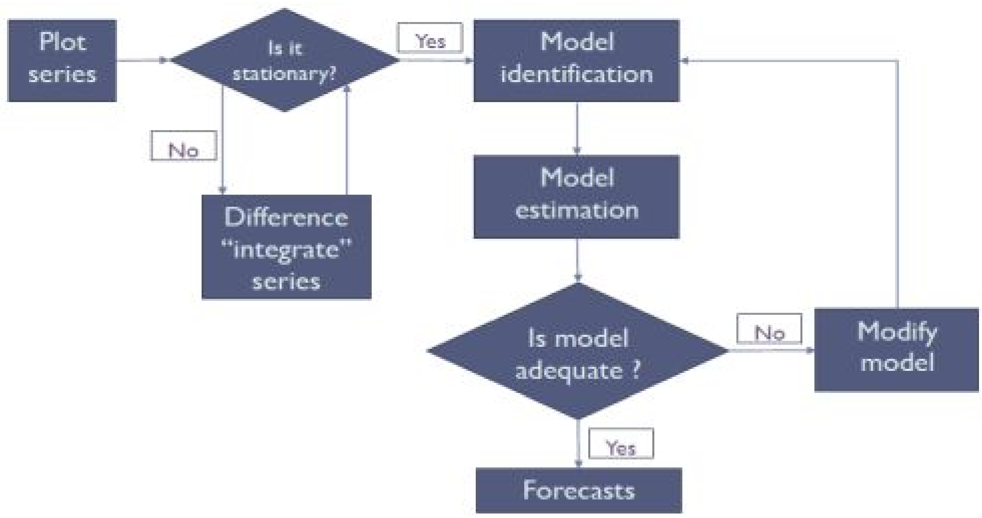

Figure 3.2 Box-Jenkins model building process

3.4 Comparison of the Forecasting Methods

Table 3.2 shows comparison of the forecasting methods in terms of inputs, description, mathematical model, innovative features and limits of them (Callegaro, 2010).

At this table these methods are mentioned: Single Exponential Smoothing, Croston's Method, Moving Average, Weighted Moving Average, Binomial Method, Grey Prediction Method, ARMA, ARIMA and S-ARIMA. (Callegaro, 2010).

Table 3.2 Comparison of the forecasting methods

METHODS	ABBR.	INPUTS	DESCRIPTION	MATHEMATIC MODEL	INNOVATIVE FEATURES	LIMITS
SINGLE EXPONENTIAL SMOOTHING	SES	- historical data -smoothing constant	It adopts a smoothing constant α of the real demands	- Exponential smoothing	- adapt for low-period forecasts -easy to compute	- Deterministic model - few fields of applicability
CROSTON'S METHOD	Croston	- historical data - interval between present and last non-zero demand -smoothing constant	Evolution of SES which also looks on intervals of zero demand	- Exponential smoothing	- adapt to demand with a lot of zero values	- Deterministic model
MOVING AVERAGE	MA	- historical data - number of data to considerate	Mean of the past n demands	- Arithmetic mean	- adapt for the constant demands - easy to compute	- Deterministic model -Few fields of applicability
WEIGHTED MOVING AVERAGE	WMA	- historical data - number of data to considerate	Mean of past n demands with decreasing weights	- Arithmetic mean	- more weight applied to last demands - easy to compute	- Deterministic model - applicable only with low level of lumpiness

Table 3.2 (Cont.)

METHODS	ABBR.	INPUTS	DESCRIPTION	MATHEMATIC MODEL	INNOVATIVE FEATURES	LIMITS
BINOMIAL METHOD	BM	- historical data - interval time T - level of service	It values the forecast demand as sum of two terms, associated at the probability of happening	- probabilistic model (binomial distribution)	- it a values the demand in a probabilistic way	- it give not the exact forecast, but a number of spare parts to guarantee a level of service
GTREY PREDICTION MODEL	GM	- historical data	With probabilistic basis, this algorithm forecasts through the use of cumulative demand and least square method to minimize the error	- accumulative generating operation - least square method	- Ideal when there are few historical data - it performs good in low-period forecasts	- not well performing in the medium and long term
ARMA ARIMA S-ARIMA (BOX- JENKINS METHODS)	BJ	- historical data - degree p of AR - degree q of MA - degree d of residual differencing -other degrees P; D, Q in case of seasonality - AR, MA coefficients	They combine autoregressive and moving average models in an iterative way until the best forecasts are produced	- autoregression - weighted average of residuals	- possibility to consider non-stationarity and seasonality - iterative way until best performances	- they requires a lot of historical data to give good results

3.5 Forecasting Performance

Measure of forecasting performance, is the process of comparing different forecasting methods in order to determinate which has more confirmations in the reality (Lawrence, 2009).

Benchmarks are the parameters, the references with which two or more forecasting methods are evaluated, in connection with the actual demands that occurred. Several types of benchmarks have been used in the literature. These are, Mean absolute error (MAE), Mean Absolute Deviation (MAD), Percent Mean Absolute Deviation (PMAD), Mean squared error (MSE), Root Mean squared error (RMSE), Forecast skill (SS) and Average of Errors (E). One of the most frequently used benchmarks is Mean Absolute Percentage Error (MAPE) is also employed in this study (Callegaro, 2010).

MAPE expresses accuracy as a percentage, and is defined by the formula:

$$\text{MAPE}=\frac{1}{n}\cdot\sum_{t=1}^{N}\left|\frac{A_t-F_t}{A_t}\right| \tag{3.28}$$

where n is number of period, A_t is the actual value, and F_t is the forecast value. (Callegaro, 2010).

CHAPTER FOUR
APPLICATIONS OF SPARE PARTS MANAGEMENT IN AN INTERNATIONAL TV MANUFACTURING COMPANY

4.1 Application I: Forecasting Spare Parts Demand

4.1.1 Problem Description

In this section, Trend Analysis, Single Exponential Smoothing Optimal ARIMA, Single Exponential Smoothing with alpha=0.1, Single Exponential Smoothing with alpha=0.5, Double Exponential Smoothing Optimal ARIMA, Double Exponential Smoothing with alpha=0.5 and gamma=0.2, Double Exponential Smoothing with alpha=0.5 and gamma=0.4, ARIMA(1,1,0), ARIMA(0,1,1), ARIMA(2,1,0) and ARIMA(0,1,2) methods are employed and the results are compared. MAPE values are used for the benchmark measure in the comparison.

A real life problem is dealt with in this study. Spare parts warehouse data of an international TV manufacturing company is used in the analyses. The last twenty four-month demand constitutes the data. Thirteen different chassis group is considered in the analyses. These groups are; MB70, MB65, MB62, MB61, MB60, MB46, MB45M, MB45, MB38, MB37, MB36, MB35 and MB30. Demands for the following 3 months are forecasted (see Table 4.1).

Table 4.1 Chassis demand for the last twenty-four month.

SP Type	MB70	MB65	MB62	MB61	MB60	MB46	MB45M	MB45	MB38	MB37	MB36	MB35	MB30
Jan-10	0	0	0	0	0	0	138	633	0	5	90	1845	20
Feb-10	0	0	0	0	0	0	65	447	0	43	354	1123	54
Mar-10	0	0	0	0	0	0	128	917	0	65	349	1465	6
Apr-10	0	0	0	0	0	0	592	1043	0	52	484	1574	14
May-10	0	0	0	8	0	15	311	2751	5	158	538	891	69
Jun-10	0	0	0	57	0	15	306	1481	10	150	222	988	38
Jul-10	0	0	0	53	15	47	486	1544	1	162	469	1240	50
Aug-10	0	0	0	46	15	63	299	1487	2	87	160	1494	8
Sep-10	0	0	0	131	15	149	455	1319	1	142	455	1288	3
Oct-10	0	0	0	173	47	206	851	1103	16	222	571	1105	185
Nov-10	0	0	0	750	360	528	1645	1460	1	150	555	989	23
Dec-10	30	0	0	1457	964	807	862	2098	23	178	708	1275	68
Jan-11	6	0	0	988	381	179	321	370	10	97	120	676	5
Feb-11	0	0	0	1161	1316	484	779	1267	10	130	608	1344	5
Mar-11	18	0	0	1178	2075	290	555	1086	23	171	440	950	0
Apr-11	35	0	0	979	1808	438	545	754	0	204	174	894	23
May-11	89	0	0	750	1572	780	821	958	68	17	250	677	0
Jun-11	72	6	15	695	1317	524	887	1126	53	139	141	810	1
Jul-11	59	0	22	658	1334	357	704	869	71	88	298	600	6
Aug-11	179	2	56	802	1873	267	742	612	61	151	328	680	0
Sep-11	106	25	364	1091	1846	68	1040	357	52	118	132	788	29
Oct-11	162	173	815	681	1710	246	838	385	174	111	261	882	0
Nov-11	331	173	934	883	1682	277	920	583	109	66	262	485	4
Dec-11	562	348	2746	905	4078	404	1072	707	70	207	249	622	7

4.1.2 Application Methodology

MINITAB 14 statistical software is employed in this study in performing the forecasts. As stated previously, four types of forecasting method are used in the first application. Totally, the following eleven analyses are conducted and the results are compared using MAPE values.

- Trend Analysis
- Single Exp. Smoot. Optimal ARIMA
- Single Exp. Smoot (Alpha=0.1)
- Single Exp. Smoot (Alpha=0.5)
- Double Exp. Smoot (Optimal ARIMA)
- Double Exp. Smoot (Alpha=0.5, Gamma=0.2)
- Double Exp. Smoot. Alpha=0.5, Gamma=0.4)

- ARIMA(1,1,0)
- ARIMA(0,1,1)
- ARIMA(2,1,0)
- ARIMA(0,1,2)

MAPE values are used for Benchmarking. MAPE can be found by equation 3.28.

Where D_t is the actual demand in the period and F_t is the forecasted demand for that period. The forecasts for MB35 chassis obtained by the selected methods are presented in Figures 4.1 to 4.9.

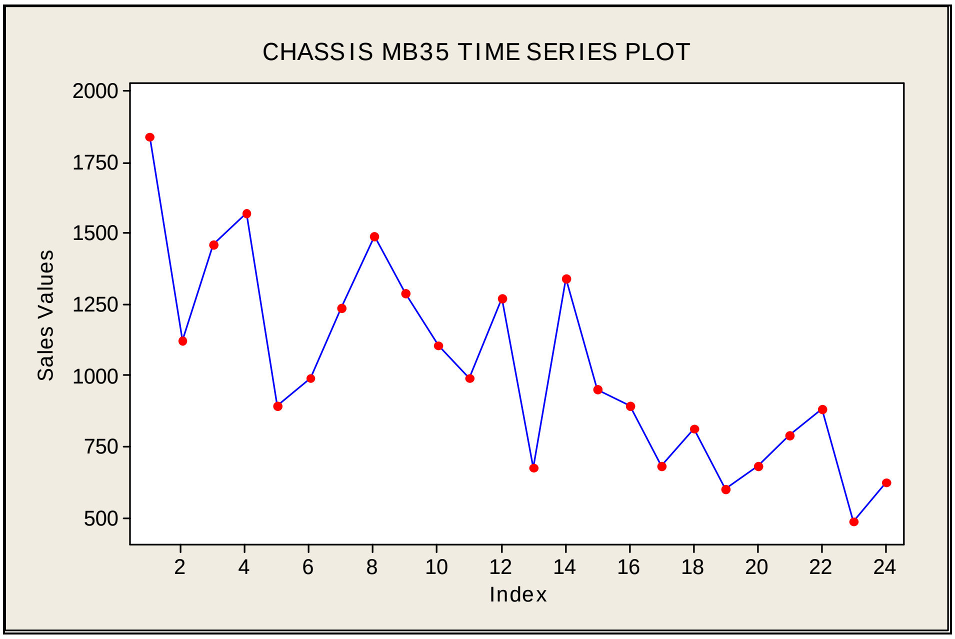

Figure 4.1 Time series plot

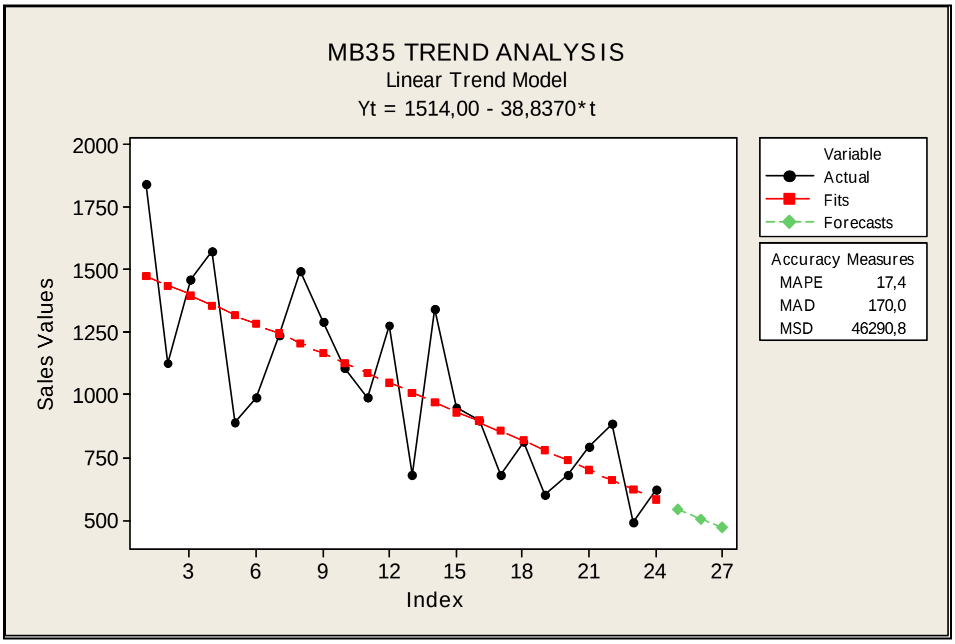

Figure 4.2 Trend analysis

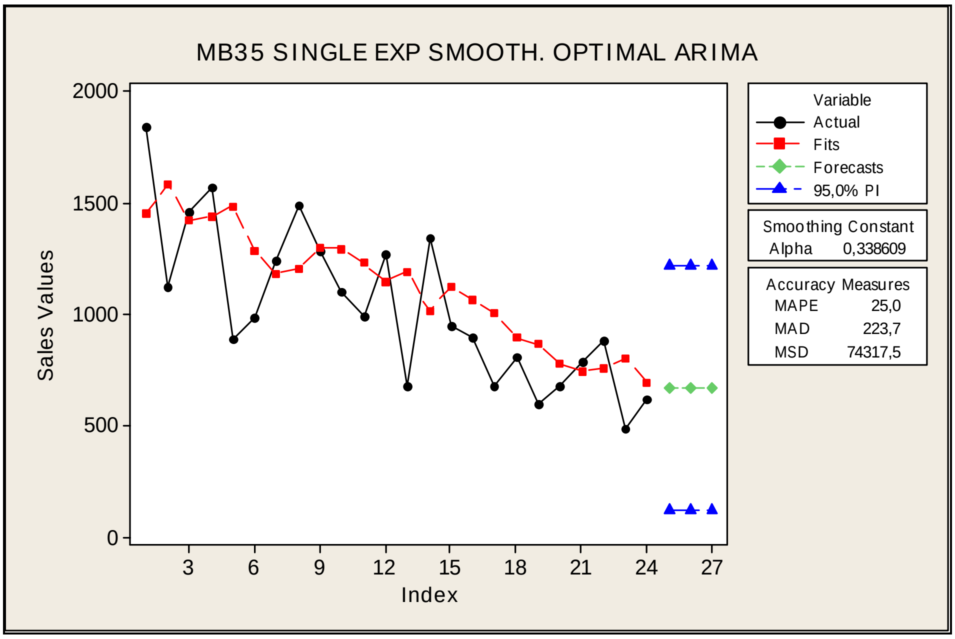

Figure 4.3 Single exp. smooth. optimal ARIMA

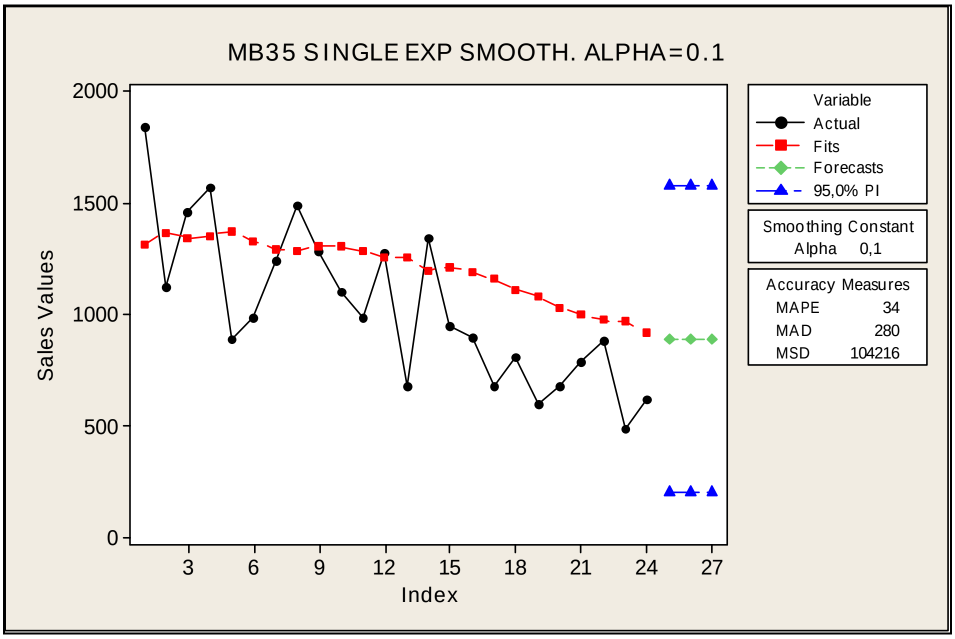

Figure 4.4 Single exp. smooth. (alpha=0.1)

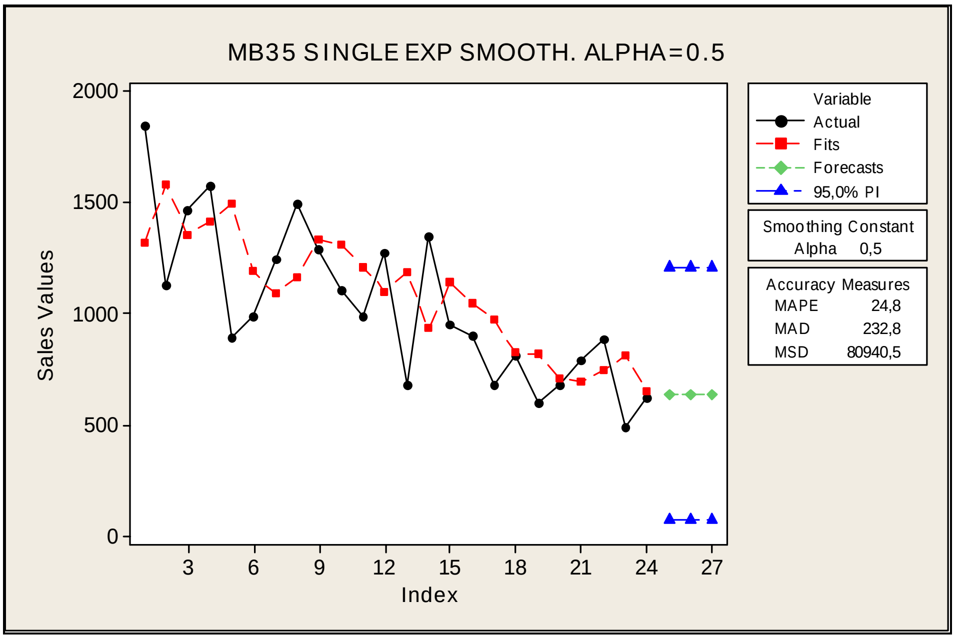

Figure 4.5 Single exp. smooth. (alpha=0.5)

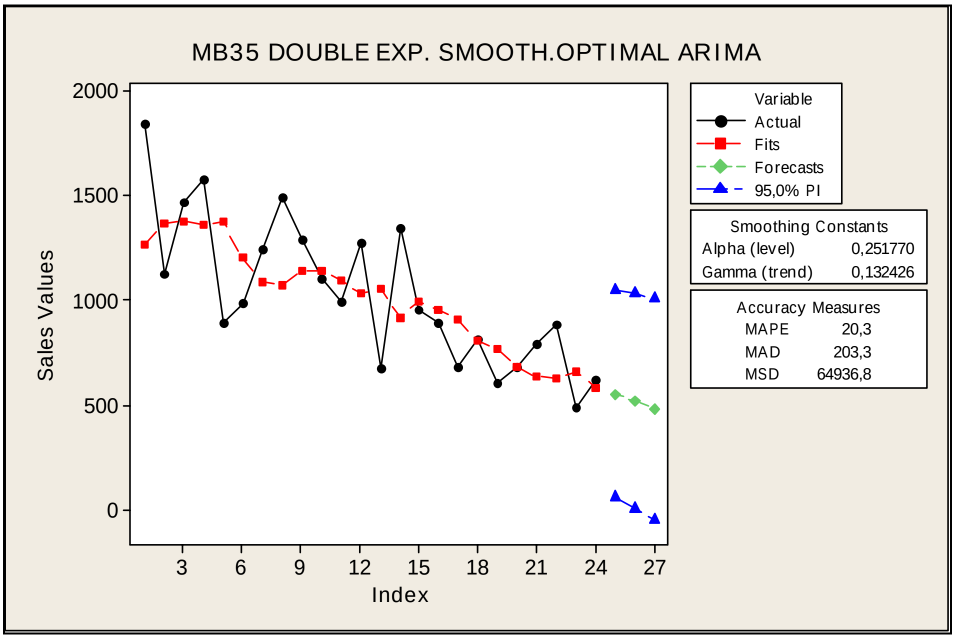

Figure 4.6 Double exp. smooth. optimal ARIMA

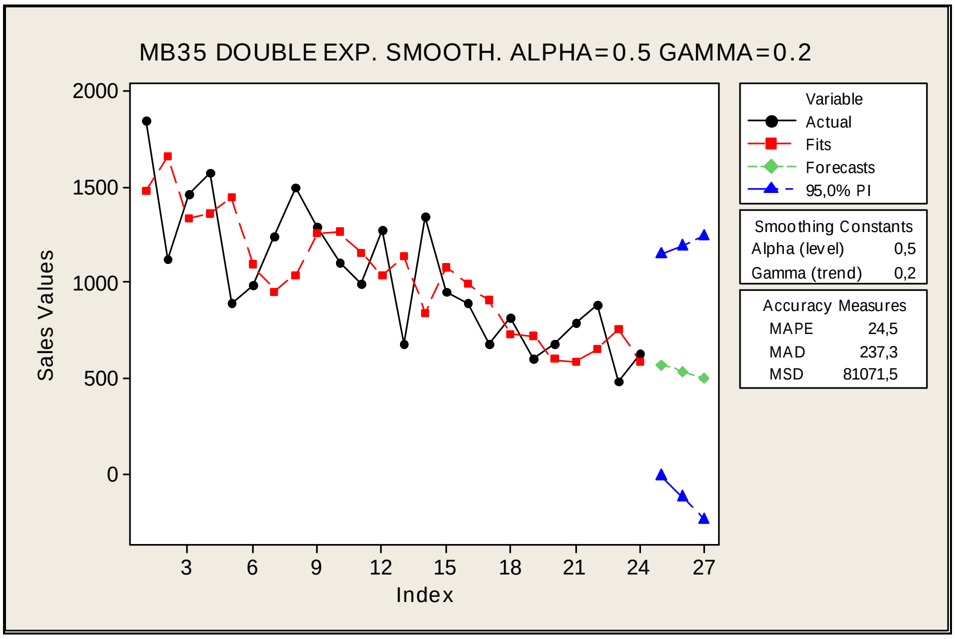

Figure 4.7 Double exp. smooth. (alpha=0.5, gamma=0.2)

The analyses in this study results that no seasonality exists for the product group under concern. Therefore, we do not use Winter's method in the applications.

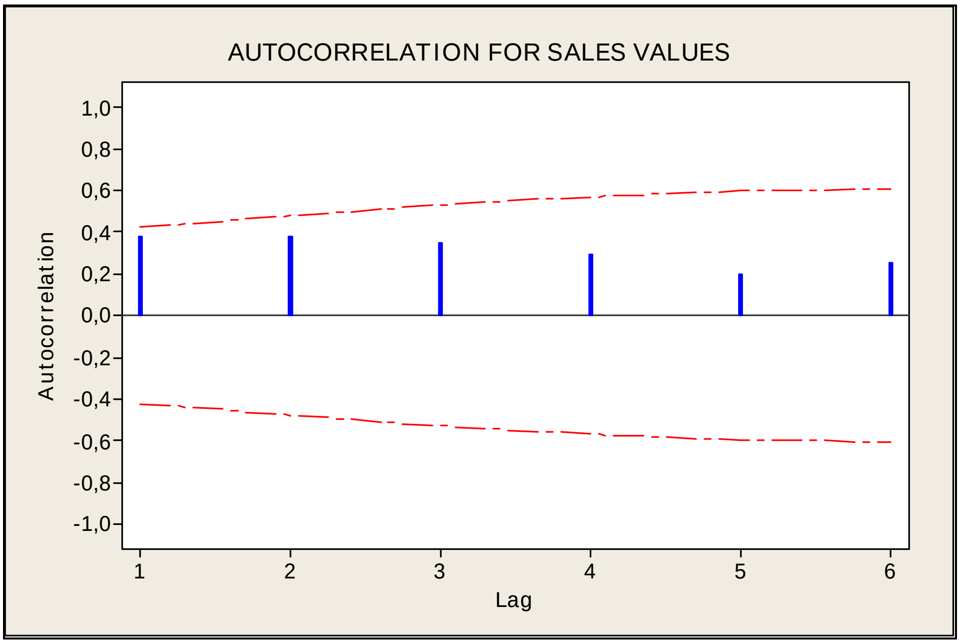

Figure 4.8 Autocorrelation for the sales

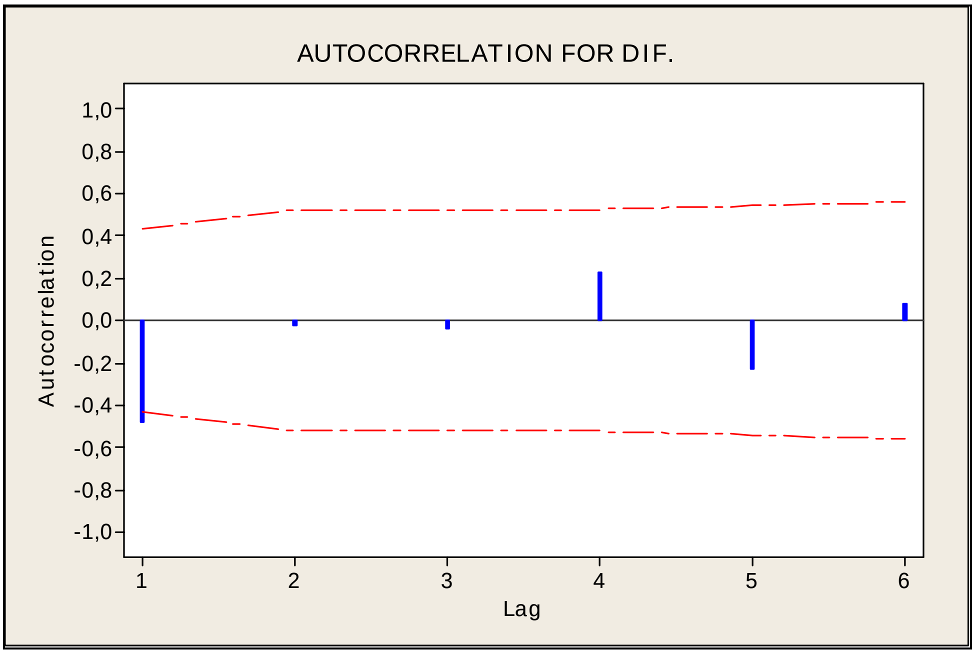

Figure 4.9 Autocorrelation for dif.

MAPE values for the methods employed are reported in Table 4.2.

Table 4.2 MAPE values for the methods employed

Anayse Type	MB70 chas.	Ft	Dt	|(Dt-Ft)/Dt|	MAPE	MB65 chas.	Ft	Dt	|(Dt-Ft)/Dt|	MAPE
Trend Analysis	Jan-12	357	333	0.07	0.22	Jan-12	324	520	0.38	0.34
	Feb-12	390	623	0.37		Feb-12	379	675	0.44	
	Mar-12	423	539	0.22		Mar-12	435	542	0.20	
Single Exp. Smoot. Optimal Arima	Jan-12	639	333	0.92	0.38	Jan-12	356	520	0.32	0.38
	Feb-12	639	623	0.03		Feb-12	356	675	0.47	
	Mar-12	639	539	0.19		Mar-12	356	542	0.34	
Single Exp. Smoot. Alpha=0.1	Jan-12	141	333	0.58	0.70	Jan-12	97	520	0.81	0.83
	Feb-12	141	623	0.77		Feb-12	97	675	0.86	
	Mar-12	141	539	0.74		Mar-12	97	542	0.82	
Single Exp. Smoot. Alpha=0.5	Jan-12	398	333	0.20	0.27	Jan-12	241	520	0.54	0.58
	Feb-12	398	623	0.36		Feb-12	241	675	0.64	
	Mar-12	398	539	0.26		Mar-12	241	542	0.56	
Double Exp. Smoot. Optimal Arima	Jan-12	724	333	1.17	0.83	Jan-12	441	520	0.15	0.20
	Feb-12	878	623	0.41		Feb-12	565	675	0.16	
	Mar-12	1.032	539	0.91		Mar-12	690	542	0.27	
Double Exp. Smoot. Alpha=0.5 Gamma=0.2	Jan-12	488	333	0.47	0.24	Jan-12	351	520	0.32	0.28
	Feb-12	551	623	0.12		Feb-12	413	675	0.39	
	Mar-12	613	539	0.14		Mar-12	475	542	0.12	
Double Exp. Smoot. Alpha=0.5 Gamma=0.4	Jan-12	533	333	0.60	0.33	Jan-12	359	520	0.31	0.25
	Feb-12	635	623	0.02		Feb-12	432	675	0.36	
	Mar-12	737	539	0.37		Mar-12	505	542	0.07	
ARIMA(1,1,0)	Jan-12	685	333	1.06	0.61	Jan-12	323	520	0.38	0.31
	Feb-12	765	623	0.23		Feb-12	426	675	0.37	
	Mar-12	827	539	0.53		Mar-12	447	542	0.18	
ARIMA(0,1,1)	Jan-12	662	333	0.99	0.51	Jan-12	315	520	0.39	0.36
	Feb-12	709	623	0.14		Feb-12	369	675	0.45	
	Mar-12	756	539	0.40		Mar-12	423	542	0.22	
ARIMA(2,1,0)	Jan-12	675	333	1.03	0.56	Jan-12	325	520	0.37	0.27
	Feb-12	738	623	0.18		Feb-12	485	675	0.28	
	Mar-12	788	539	0.46		Mar-12	450	542	0.17	
ARIMA(0,1,2)	Jan-12	669	333	1.01	0.53	Jan-12	367	520	0.29	0.24
	Feb-12	724	623	0.16		Feb-12	451	675	0.33	
	Mar-12	772	539	0.43		Mar-12	498	542	0.08	

Table 4.2 (cont.)

Anayse Type	MB62 chas.	Ft	Dt	|(Dt-Ft)/Dt|	MAPE	MB61 chas.	Ft	Dt	|(Dt-Ft)/Dt|	MAPE
	Jan-12	2.247	1717	0.31		Jan-12	1.161	868	0.34	
Trend Analysis	Feb-12	2.632	3238	0.19	0.17	Feb-12	1.208	762	0.58	0.59
	Mar-12	3.017	3096	0.03		Mar-12	1.254	682	0.84	
	Jan-12	3.262	1717	0.90		Jan-12	903	868	0.04	
Single Exp. Smoot. Optimal Arima	Feb-12	3.262	3238	0.01	0.32	Feb-12	903	762	0.19	0.18
	Mar-12	3.262	3096	0.05		Mar-12	903	682	0.32	
	Jan-12	633	1717	0.63		Jan-12	707	868	0.19	
Single Exp. Smoot. Alpha=0.1	Feb-12	633	3238	0.80	0.74	Feb-12	707	762	0.07	0.10
	Mar-12	633	3096	0.80		Mar-12	707	682	0.04	
	Jan-12	1.736	1717	0.01		Jan-12	874	868	0.01	
Single Exp. Smoot. Alpha=0.5	Feb-12	1.736	3238	0.46	0.30	Feb-12	874	762	0.15	0.15
	Mar-12	1.736	3096	0.44		Mar-12	874	682	0.28	
	Jan-12	3.166	1717	0.84		Jan-12	926	868	0.07	
Double Exp. Smoot. Optimal Arima	Feb-12	4.581	3238	0.41	0.73	Feb-12	948	762	0.24	0.24
	Mar-12	5.996	3096	0.94		Mar-12	970	682	0.42	
	Jan-12	2.500	1717	0.46		Jan-12	881	868	0.01	
Double Exp. Smoot. Alpha=0.5 Gamma=0.2	Feb-12	2.948	3238	0.09	0.21	Feb-12	887	762	0.16	0.16
	Mar-12	3.396	3096	0.10		Mar-12	893	682	0.31	
	Jan-12	2.551	1717	0.49		Jan-12	892	868	0.03	
Double Exp. Smoot. Alpha=0.5 Gamma=0.4	Feb-12	3.100	3238	0.04	0.24	Feb-12	916	762	0.20	0.20
	Mar-12	3.650	3096	0.18		Mar-12	940	682	0.38	
	Jan-12	1.666	1717	0.03		Jan-12	954	868	0.10	
ARIMA(1,1,0)	Feb-12	3.472	3238	0.07	0.11	Feb-12	1.002	762	0.31	0.32
	Mar-12	2.397	3096	0.23		Mar-12	1.049	682	0.54	
	Jan-12	2.242	1717	0.31		Jan-12	954	868	0.10	
ARIMA(0,1,1)	Feb-12	2.625	3238	0.19	0.17	Feb-12	1.001	762	0.31	0.32
	Mar-12	3.008	3096	0.03		Mar-12	1.048	682	0.54	
	Jan-12	2.230	1717	0.30		Jan-12	936	868	0.08	
ARIMA(2,1,0)	Feb-12	3.768	3238	0.16	0.16	Feb-12	987	762	0.30	0.30
	Mar-12	3.119	3096	0.01		Mar-12	1.035	682	0.52	
	Jan-12	1.255	1717	0.27		Jan-12	933	868	0.07	
ARIMA(0,1,2)	Feb-12	2.330	3238	0.28	0.23	Feb-12	994	762	0.30	0.30
	Mar-12	2.681	3096	0.13		Mar-12	1.041	682	0.53	

Table 4.2 (cont.)

Anayse Type	**MB60 chas.**	**Ft**	**Dt**	**|(Dt-Ft)/Dt|**	**MAPE**	**MB46 chas.**	**Ft**	**Dt**	**|(Dt-Ft)/Dt|**	**MAPE**
	Jan-12	2.787	2156	0.29		Jan-12	449	85	4.28	
Trend Analysis	Feb-12	2.949	1889	0.56	0.46	Feb-12	463	699	0.33	2.37
	Mar-12	3.112	2059	0.51		Mar-12	476	136	2.50	
	Jan-12	3.775	2156	0.75		Jan-12	334	85	2.91	
Single Exp. Smoot. Optimal Arima	Feb-12	3.775	1889	1.00	0.86	Feb-12	334	699	0.52	1.63
	Mar-12	3.775	2059	0.83		Mar-12	334	136	1.45	
	Jan-12	1.469	2156	0.32		Jan-12	303	85	2.56	
Single Exp. Smoot. Alpha=0.1	Feb-12	1.469	1889	0.22	0.28	Feb-12	303	699	0.56	1.45
	Mar-12	1.469	2059	0.29		Mar-12	303	136	1.22	
	Jan-12	2.891	2156	0.34		Jan-12	329	85	2.86	
Single Exp. Smoot. Alpha=0.5	Feb-12	2.891	1889	0.53	0.43	Feb-12	329	699	0.52	1.65
	Mar-12	2.891	2059	0.40		Mar-12	329	136	1.41	
	Jan-12	3.397	2156	0.58		Jan-12	378	85	3.44	
Double Exp. Smoot. Optimal Arima	Feb-12	3.617	1889	0.92	0.78	Feb-12	395	699	0.43	1.97
	Mar-12	3.838	2059	0.86		Mar-12	412	136	2.02	
	Jan-12	3.241	2156	0.50		Jan-12	295	85	2.47	
Double Exp. Smoot. Alpha=0.5 Gamma=0.2	Feb-12	3.518	1889	0.86	0.74	Feb-12	289	699	0.58	1.37
	Mar-12	3.794	2059	0.84		Mar-12	283	136	1.07	
	Jan-12	3.385	2156	0.57		Jan-12	289	85	2.39	
Double Exp. Smoot. Alpha=0.5 Gamma=0.4	Feb-12	3.856	1889	1.04	0.90	Feb-12	303	699	0.56	1.43
	Mar-12	4.328	2059	1.10		Mar-12	317	136	1.33	
	Jan-12	3.798	2156	0.76		Jan-12	388	85	3.57	
ARIMA(1,1,0)	Feb-12	4.129	1889	1.19	1.02	Feb-12	419	699	0.40	2.05
	Mar-12	4.320	2059	1,10		Mar-12	435	136	2.19	
	Jan-12	2.774	2156	0.29		Jan-12	363	85	3.27	
ARIMA(0,1,1)	Feb-12	2.936	1889	0.55	0.45	Feb-12	381	699	0.45	1.88
	Mar-12	3.099	2059	0.50		Mar-12	398	136	1.92	
	Jan-12	3.764	2156	0.75		Jan-12	382	85	3.48	
ARIMA(2,1,0)	Feb-12	2.775	1889	0.47	0.66	Feb-12	401	699	0.42	2.03
	Mar-12	3.610	2059	0.75		Mar-12	425	136	2.12	
	Jan-12	3.422	2156	0.59		Jan-12	438	85	4.15	
ARIMA(0,1,2)	Feb-12	3.048	1889	0.61	0.59	Feb-12	439	699	0.37	2.28
	Mar-12	3.219	2059	0.56		Mar-12	452	136	2.32	

Table 4.2 (cont.)

Anayse Type	MB45M chas.	Ft	Dt	|(Dt-Ft)/Dt|	MAPE	MB45 chas.	Ft	Dt	|(Dt-Ft)/Dt|	MAPE
Trend Analysis	Jan-12	1.060	566	0.87	0.81	Jan-12	660	677	0.03	0.28
	Feb-12	1.094	686	0.59		Feb-12	628	509	0.23	
	Mar-12	1.127	578	0.95		Mar-12	597	375	0.59	
Single Exp. Smoot. Optimal Arima	Jan-12	958	566	0.69	0.58	Jan-12	626	677	0.08	0.32
	Feb-12	958	686	0.40		Feb-12	626	509	0.23	
	Mar-12	958	578	0.66		Mar-12	626	375	0.67	
Single Exp. Smoot. Alpha=0.1	Jan-12	741	566	0.31	0.22	Jan-12	899	677	0.33	0.83
	Feb-12	741	686	0.08		Feb-12	899	509	0.77	
	Mar-12	741	578	0.28		Mar-12	899	375	1.39	
Single Exp. Smoot. Alpha=0.5	Jan-12	982	566	0.74	0.62	Jan-12	619	677	0.09	0.32
	Feb-12	982	686	0.43		Feb-12	619	509	0.22	
	Mar-12	982	578	0.70		Mar-12	619	375	0.65	
Double Exp. Smoot. Optimal Arima	Jan-12	1.031	566	0.82	0.76	Jan-12	606	677	0.10	0.23
	Feb-12	1.064	686	0.55		Feb-12	574	509	0.13	
	Mar-12	1.096	578	0.90		Mar-12	542	375	0.44	
Double Exp. Smoot. Alpha=0.5 Gamma=0.2	Jan-12	1.046	566	0.85	0.79	Jan-12	499	677	0.26	0.16
	Feb-12	1.085	686	0.58		Feb-12	460	509	0.10	
	Mar-12	1.124	578	0.94		Mar-12	421	375	0.12	
Double Exp. Smoot. Alpha=0.5 Gamma=0.4	Jan-12	1.077	566	0.90	0.87	Jan-12	530	677	0.22	0.23
	Feb-12	1.133	686	0.65		Feb-12	533	509	0.05	
	Mar-12	1.189	578	1.05		Mar-12	537	375	0.43	
ARIMA(1,1,0)	Jan-12	1.094	566	0.93	0.88	Jan-12	655	677	0.03	0.40
	Feb-12	1.138	686	0.66		Feb-12	686	509	0.35	
	Mar-12	1.178	578	1.04		Mar-12	677	375	0.81	
ARIMA(0,1,1)	Jan-12	989	566	0.75	0.68	Jan-12	585	677	0.14	0.23
	Feb-12	1.015	686	0.48		Feb-12	565	509	0.11	
	Mar-12	1.041	578	0.80		Mar-12	545	375	0.45	
ARIMA(2,1,0)	Jan-12	1.061	566	0.87	0.79	Jan-12	589	677	0.13	0.35
	Feb-12	1.056	686	0.54		Feb-12	630	509	0.24	
	Mar-12	1.133	578	0.96		Mar-12	635	375	0.69	
ARIMA(0,1,2)	Jan-12	914	566	0.62	0.52	Jan-12	629	677	0.07	0.23
	Feb-12	921	686	0.34		Feb-12	584	509	0.15	
	Mar-12	934	578	0.62		Mar-12	553	375	0.47	

Table 4.2 (cont.)

Anayse Type	MB38 chas.	Ft	Dt	|(Dt-Ft)/Dt|	MAPE	MB37 chas.	Ft	Dt	|(Dt-Ft)/Dt|	MAPE
Trend Analysis	Jan-12	100	65	0.54	1.17	Jan-12	151	188	0,20	0.16
	Feb-12	106	67	0.59		Feb-12	153	191	0,20	
	Mar-12	112	33	2.39		Mar-12	155	144	0,08	
Single Exp. Smoot. Optimal Arima	Jan-12	91	65	0.41	0.85	Jan-12	133	188	0,29	0.22
	Feb-12	91	67	0.36		Feb-12	133	191	0,30	
	Mar-12	91	33	1.77		Mar-12	133	144	0,07	
Single Exp. Smoot. Alpha=0.1	Jan-12	53	65	0.19	0.33	Jan-12	124	188	0,34	0.28
	Feb-12	53	67	0.22		Feb-12	124	191	0,35	
	Mar-12	53	33	0.59		Mar-12	124	144	0,14	
Single Exp. Smoot. Alpha=0.5	Jan-12	91	65	0.40	0.84	Jan-12	149	188	0,21	0.15
	Feb-12	91	67	0.36		Feb-12	149	191	0,22	
	Mar-12	91	33	1.76		Mar-12	149	144	0,04	
Double Exp. Smoot. Optimal Arima	Jan-12	122	65	0.88	1.70	Jan-12	139	188	0,26	0.18
	Feb-12	131	67	0.96		Feb-12	140	191	0,27	
	Mar-12	140	33	3.25		Mar-12	142	144	0,01	
Double Exp. Smoot. Alpha=0.5 Gamma=0.2	Jan-12	109	65	0.68	1.36	Jan-12	150	188	0,20	0.17
	Feb-12	115	67	0.72		Feb-12	156	191	0,18	
	Mar-12	122	33	2.69		Mar-12	161	144	0,12	
Double Exp. Smoot. Alpha=0.5 Gamma=0.4	Jan-12	110	65	0.69	1.27	Jan-12	159	188	0,15	0.19
	Feb-12	112	67	0.67		Feb-12	175	191	0,08	
	Mar-12	114	33	2.46		Mar-12	190	144	0,32	
ARIMA(1,1,0)	Jan-12	92	65	0.42	0.89	Jan-12	136	188	0,28	0.15
	Feb-12	89	67	0.32		Feb-12	186	191	0,02	
	Mar-12	96	33	1.91		Mar-12	167	144	0,16	
ARIMA(0,1,1)	Jan-12	103	65	0.59	1.24	Jan-12	146	188	0,22	0.17
	Feb-12	109	67	0.63		Feb-12	150	191	0,22	
	Mar-12	115	33	2.50		Mar-12	153	144	0,06	
ARIMA(2,1,0)	Jan-12	167	65	1.57	1.57	Jan-12	131	188	0,30	0.20
	Feb-12	131	67	0.96		Feb-12	165	191	0,14	
	Mar-12	105	33	2.18		Mar-12	168	144	0,16	
ARIMA(0,1,2)	Jan-12	101	65	0.56	1.21	Jan-12	121	188	0,35	0.21
	Feb-12	108	67	0.62		Feb-12	147	191	0,23	
	Mar-12	114	33	2.46		Mar-12	152	144	0,05	

Table 4.2 (cont.)

Anayse Type	MB36 chas.	Ft	Dt	|(Dt-Ft)/Dt|	MAPE	MB35 chas.	Ft	Dt	|(Dt-Ft)/Dt|	MAPE
Trend Analysis	Jan-12	267	178	0.50		Jan-12	543	551	0.01	
	Feb-12	261	562	0.54	0.96	Feb-12	504	602	0.16	0.12
	Mar-12	255	89	1.86		Mar-12	465	574	0.19	
Single Exp. Smoot. Optimal Arima	Jan-12	325	178	0.83		Jan-12	669	551	0.21	
	Feb-12	325	562	0.42	1.29	Feb-12	669	602	0.11	0.16
	Mar-12	325	89	2.65		Mar-12	669	574	0.17	
Single Exp. Smoot. Alpha=0.1	Jan-12	306	178	0.72		Jan-12	889	551	0.61	
	Feb-12	306	562	0.45	1.20	Feb-12	889	602	0.48	0.55
	Mar-12	306	89	2.44		Mar-12	889	574	0.55	
Single Exp. Smoot. Alpha=0.5	Jan-12	249	178	0.40		Jan-12	635	551	0.15	
	Feb-12	249	562	0.55	0.91	Feb-12	635	602	0.06	0.10
	Mar-12	249	89	1.79		Mar-12	635	574	0.11	
Double Exp. Smoot. Optimal Arima	Jan-12	227	178	0.27		Jan-12	551	551	0.001	
	Feb-12	219	562	0.60	0.75	Feb-12	514	602	0.15	0.11
	Mar-12	211	89	1.37		Mar-12	477	574	0.17	
Double Exp. Smoot. Alpha=0.5 Gamma=0.2	Jan-12	228	178	0.28		Jan-12	568	551	0.03	
	Feb-12	222	562	0.60	0.76	Feb-12	533	602	0.11	0.09
	Mar-12	215	89	1.41		Mar-12	499	574	0.13	
Double Exp. Smoot. Alpha=0.5 Gamma=0.4	Jan-12	255	178	0.43		Jan-12	585	551	0.06	
	Feb-12	263	562	0.53	1.00	Feb-12	554	602	0.08	0.08
	Mar-12	271	89	2.04		Mar-12	523	574	0.09	
ARIMA(1,1,0)	Jan-12	261	178	0.46		Jan-12	469	551	0.15	
	Feb-12	259	562	0.53	1.00	Feb-12	488	602	0.19	0.21
	Mar-12	265	89	1.97		Mar-12	405	574	0.29	
ARIMA(0,1,1)	Jan-12	221	178	0.24		Jan-12	515	551	0.07	
	Feb-12	214	562	0.61	0.73	Feb-12	475	602	0.21	0.17
	Mar-12	207	89	1.33		Mar-12	435	574	0.24	
ARIMA(2,1,0)	Jan-12	262	178	0.47		Jan-12	595	551	0.08	
	Feb-12	258	562	0.54	0.97	Feb-12	465	602	0.23	0.15
	Mar-12	260	89	1.92		Mar-12	487	574	0.15	
ARIMA(0,1,2)	Jan-12	239	178	0.34		Jan-12	556	551	0.01	
	Feb-12	232	562	0.58	0.81	Feb-12	519	602	0.14	0.10
	Mar-12	224	89	1.52		Mar-12	482	574	0.16	

Table 4.2 (cont.)

Anayse Type	**MB30 chas.**	**Ft**	**Dt**	**|(Dt-Ft)/Dt|**	**MAPE**
Trend Analysis	Jan-12	3	2	0.53	0.60
	Feb-12	1	1	0.26	
	Mar-12	0	9	1.00	
Single Exp. Smoot. Optimal Arima	Jan-12	11	2	4.50	4.90
	Feb-12	11	1	10.00	
	Mar-12	11	9	0.22	
Single Exp. Smoot. Alpha=0.1	Jan-12	8	2	2.00	3.37
	Feb-12	8	1	7.00	
	Mar-12	8	9	0.11	
Single Exp. Smoot. Alpha=0.5	Jan-12	6	2	2.23	2.66
	Feb-12	6	1	5.47	
	Mar-12	6	9	0.28	
Double Exp. Smoot. Optimal Arima	Jan-12	2	2	0.001	0.33
	Feb-12	1	1	0.001	
	Mar-12	0	9	1.00	
Double Exp. Smoot. Alpha=0.5 Gamma=0.2	Jan-12	4	2	0.93	1.19
	Feb-12	3	1	1.87	
	Mar-12	2	9	0.79	
Double Exp. Smoot. Alpha=0.5 Gamma=0.4	Jan-12	7	2	2.67	3.10
	Feb-12	7	1	6.49	
	Mar-12	8	9	0.15	
ARIMA(1,1,0)	Jan-12	3	2	0.61	1.34
	Feb-12	4	1	2.57	
	Mar-12	1	9	0.82	
ARIMA(0,1,1)	Jan-12	2	2	0.001	0.29
	Feb-12	1	1	0.001	
	Mar-12	1	9	0.88	
ARIMA(2,1,0)	Jan-12	1	2	0.60	0.92
	Feb-12	2	1	1.23	
	Mar-12	1	9	0.93	
ARIMA(0,1,2)	Jan-12	2	2	0.001	0.33
	Feb-12	1	1	0.001	
	Mar-12	0	9	1.00	

4.1.3 Conclusion of Application I

If we compare the methods in terms of their average MAPE values as the benchmark measure, ARIMA (0,1,1) should be selected as the best performer among the other method (see Table 4.3).

Table 4.3 MAPE values for Analysis Types

Anayse Type	**AVERAGE MAPE**	**RANK**
Trend Analysis	0.63	**4**
Single Exp. Smoot. Optimal Arima	0.93	**11**
Single Exp. Smoot. Alpha=0.1	0.83	**10**
Single Exp. Smoot. Alpha=0.5	0.68	**7**
Double Exp. Smoot. Optimal Arima	0.67	**5**
Double Exp. Smoot. Alpha=0.5 Gamma=0.2	0.58	**2**
Double Exp. Smoot. Alpha=0.5 Gamma=0.4	0.77	**9**
ARIMA(1,1,0)	0.71	**8**
ARIMA(0,1,1)	0.55	**1**
ARIMA(2,1,0)	0.68	**6**
ARIMA(0,1,2)	0.58	**3**

4.2 Application II: Optimization of the Storage Area

4.2.1 Problem Description

As the second problem, we deal with decreasing the inventory transportation cost and picking time in spare parts warehouse of the same company. Previously, the company used walk/ride and pick systems (W/RPSs) from Picker-to-product systems that pickers travel on foot or by motorized trolleys and may visit multiple aisles. It can be stated that a redesign for the layout is obviously needed. Considering this need, KARDEX automation storage system from order-to-picker systems, in which materials can be transported automatically, is used in the spare part warehouse. Figure 4.10 illustrates the KARDEX system in use.

Figure 4.10 The KARDEX system

4.2.2 Methodology of Application II

The application starts with performing a re-design at the warehouse. With this project we aim at removing shelf locations for chassis and power boards. The application reveals that the results obtained by new layout are sufficient. More specifically, total area is reduced from 840 square meters to 500 square meters. In addition, operation time and the number of employees are reduced. Previous layout of the spare parts warehouse is illustrated in Figure 4.11. Figure 4.12 illustrates the new layout. Snapshot of new warehouse can be seen in Figure 4.13.

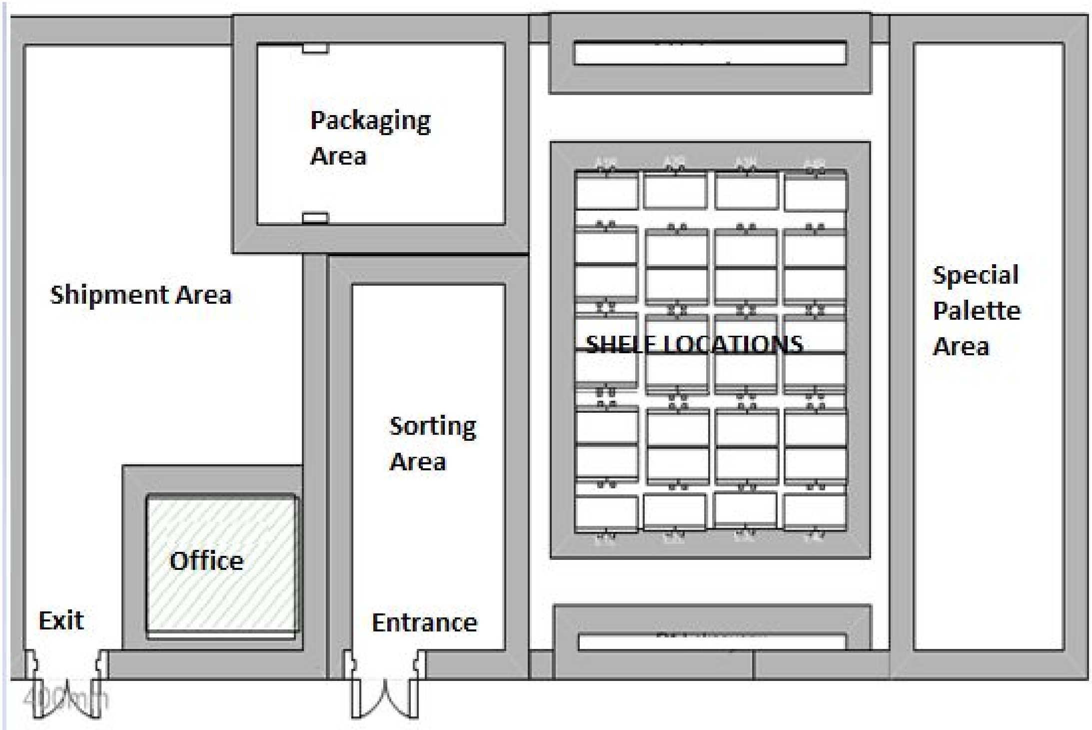

Figure 4.11 Previous layout of the spare parts warehouse

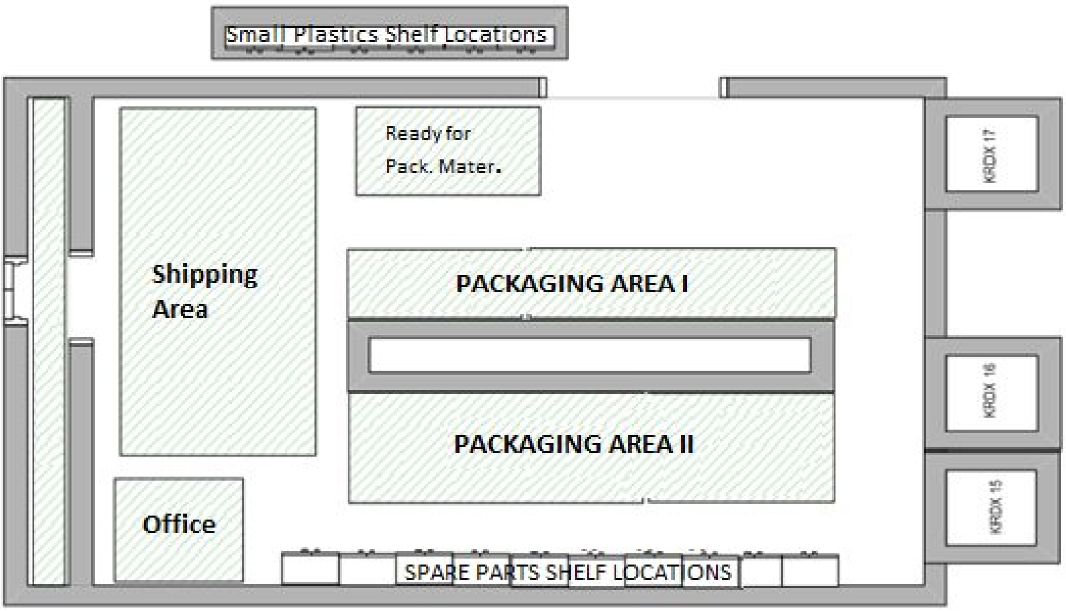

Figure 4.11 New layout of the spare parts warehouse

Figure 4.12 Snapshot of new warehouse

After the layout redesign project, KARDEX optimization is aimed to determine the storage type incurring minimum cost. LINGO 9.0 software package is used to solve the related mathematical model. As recalled, demands for the following two months are estimated in the first application. This data represents the demand and average demand data for the model. Herein, our goal is to minimize the transportation cost. The KARDEX system has 20 floors; each has the capacity of 500. Forecasted demands for the following two months are reported in Table 4.4.

Table 4.4 Forecasted demands for the following two months

SP Type	MB70	MB65	MB62	MB61	MB60	MB46	MB45M	MB45	MB38	MB37	MB36	MB35	MB30
Jan-10	0	0	0	0	0	0	138	633	0	5	90	1845	20
Feb-10	0	0	0	0	0	0	65	447	0	43	354	1123	54
Mar-10	0	0	0	0	0	0	128	917	0	65	349	1465	6
Apr-10	0	0	0	0	0	0	592	1043	0	52	484	1574	14
May-10	0	0	0	8	0	15	311	2751	5	158	538	891	69
Jun-10	0	0	0	57	0	15	306	1481	10	150	222	988	38
Jul-10	0	0	0	53	15	47	486	1544	1	162	469	1240	50
Aug-10	0	0	0	46	15	63	299	1487	2	87	160	1494	8
Sep-10	0	0	0	131	15	149	455	1319	1	142	455	1288	3
Oct-10	0	0	0	173	47	206	851	1103	16	222	571	1105	185
Nov-10	0	0	0	750	360	528	1645	1460	1	150	555	989	23
Dec-10	30	0	0	1457	964	807	862	2098	23	178	708	1275	68
Jan-11	6	0	0	988	381	179	321	370	10	97	120	676	5
Feb-11	0	0	0	1161	1316	484	779	1267	10	130	608	1344	5
Mar-11	18	0	0	1178	2075	290	555	1086	23	171	440	950	0
Apr-11	35	0	0	979	1808	438	545	754	0	204	174	894	23
May-11	89	0	0	750	1572	780	821	958	68	17	250	677	0
Jun-11	72	6	15	695	1317	524	887	1126	53	139	141	810	1
Jul-11	59	0	22	658	1334	357	704	869	71	88	298	600	6
Aug-11	179	2	56	802	1873	267	742	612	61	151	328	680	0
Sep-11	106	25	364	1091	1846	68	1040	357	52	118	132	788	29
Oct-11	162	173	815	681	1710	246	838	385	174	111	261	882	0
Nov-11	331	173	934	883	1682	277	920	583	109	66	262	485	4
Dec-11	562	348	2746	905	4078	404	1072	707	70	207	249	622	7
Jan-12	333	520	1717	868	2156	85	566	677	65	188	178	551	2
Feb-12	623	675	3238	762	1889	699	686	509	67	191	562	602	1
Mar-12	539	542	3096	682	2059	136	578	375	33	144	89	574	9
Apr-12	532	633	3.911	723	1.621	291	706	403	53	162	257	541	2
May-12	572	701	3.953	723	1.621	285	706	362	53	162	252	524	1

Demand values for May 2012 are used as the input for the model. Demands and average daily demands for chassis are reported in Table 4.5.

Table 4.5 Demands and average daily demands for chassis

	MB70	MB65	MB62	MB61	MB60	MB46	MB45M	MB45	MB38	MB37	MB36	MB35	MB30
DEMAND	572	701	3.953	723	1.621	285	706	362	53	162	252	524	1
AVERAGE DAILY DEMAND	19	23	132	24	54	10	24	12	2	5	8	17	0,03

Transportation cost matrix presented in Table 4.6 is calculated by multiplying average demand and floors.

Table 4.6 Transportation cost matrix

19	23	132	24	54	10	24	12	2	5	8	17	0,03
38	46	264	48	108	20	48	24	4	10	16	34	0,06
57	69	396	72	162	30	72	36	6	15	24	51	0,09
76	92	528	96	216	40	96	48	8	20	32	68	0,12
95	115	660	120	270	50	120	60	10	25	40	85	0,15
114	138	792	144	324	60	144	72	12	30	48	102	0,18
133	161	924	168	378	70	168	84	14	35	56	119	0,21
152	184	1056	192	432	80	192	96	16	40	64	136	0,24
171	207	1188	216	486	90	216	108	18	45	72	153	0,27
190	230	1320	240	540	100	240	120	20	50	80	170	0,3
209	253	1452	264	594	110	264	132	22	55	88	187	0,33
228	276	1584	288	648	120	288	144	24	60	96	204	0,36
247	299	1716	312	702	130	312	156	26	65	104	221	0,39
266	322	1848	336	756	140	336	168	28	70	112	238	0,42
285	345	1980	360	810	150	360	180	30	75	120	255	0,45
304	368	2112	384	864	160	384	192	32	80	128	272	0,48
323	391	2244	408	918	170	408	204	34	85	136	289	0,51
342	414	2376	432	972	180	432	216	36	90	144	306	0,54
361	437	2508	456	1026	190	456	228	38	95	152	323	0,57
380	460	2640	480	1080	200	480	240	40	100	160	340	0,6

The mathematical model is as follows:

$$\left.\begin{aligned} & Min \textstyle\sum_{i=1}^{m} \sum_{j=1}^{n} c_{ij}\, x_{ij} \\ & St. \\ & \textstyle\sum_{j=1}^{n} x_{ij} \leq a_i \qquad i=1,\ldots,m \\ & \textstyle\sum_{i=1}^{m} x_{ij} \geq b_j \qquad j=1,\ldots,n \\ & x_{ij} \geq 0 \end{aligned}\right\} \tag{4.1}$$

where;

x_{ij} : amount of transportation of chassis *j* from floor *i*

a_i : capacity of floor *i*

b_j : demand of chassis *j*

c_{ij} : transportation cost of chassis *j* from floor *i*.

LINGO code of the model is as follows.

```
MODEL:
! 20 floors Krdx , 13 Demand point assignment problem;

SETS:
Krdx / 1..20 / : a;
Demand / 1..13 / : b;
Way (Krdx, Demand) : c, x;
ENDSETS

MIN=@SUM (Way: c*x);
!Capacity Constraint;
@FOR (Krdx (I): @SUM (Demand(J): x(I,J)) <= a(I));

!Demand Allocation Constraint;

@FOR (Demand (J): @SUM (Krdx(I): x(I,J)) >= b(J));

DATA:
a=500;
b=572,701,3953,723,1621,285,706,362,53,162,252,524,1;
c=
```

19	23	132	24	54	10	24	12	2	5	8	17	0,03
38	46	264	48	108	20	48	24	4	10	16	34	0,06
57	69	396	72	162	30	72	36	6	15	24	51	0,09
76	92	528	96	216	40	96	48	8	20	32	68	0,12
95	115	660	120	270	50	120	60	10	25	40	85	0,15
114	138	792	144	324	60	144	72	12	30	48	102	0,18
133	161	924	168	378	70	168	84	14	35	56	119	0,21
152	184	1056	192	432	80	192	96	16	40	64	136	0,24
171	207	1188	216	486	90	216	108	18	45	72	153	0,27
190	230	1320	240	540	100	240	120	20	50	80	170	0,3
209	253	1452	264	594	110	264	132	22	55	88	187	0,33
228	276	1584	288	648	120	288	144	24	60	96	204	0,36
247	299	1716	312	702	130	312	156	26	65	104	221	0,39
266	322	1848	336	756	140	336	168	28	70	112	238	0,42

```
285   345   1980   360   810    150   360   180   30   75    120   255   0,45
304   368   2112   384   864    160   384   192   32   80    128   272   0,48
323   391   2244   408   918    170   408   204   34   85    136   289   0,51
342   414   2376   432   972    180   432   216   36   90    144   306   0,54
361   437   2508   456   1026   190   456   228   38   95    152   323   0,57
380   460   2640   480   1080   200   480   240   40   100   160   340   0,6 ;

ENDDATA
END
```

4.2.3 Conclusion of Application II

Optimal solution of the model reveals that total transportation cost is $4,427,100 for May-12. The results of the model are presented in Appendix.

CHAPTER FIVE
CONCLUSION

The criticality of SPM in manufacturing and service operations cannot be understated. Given factors like demand unpredictability, part alternates, parts indigenization and tight control on spare parts inventory coupled with high service levels, the imperative to accurately forecast spare part requirements and to optimize on inventory requires significant decision support. Performing on objectives such as these helps improve profitability and achieve strategic goals such as customer loyalty and lock-in. This study looks at the various facets of spares and service management from primarily a MRO (Maintenance, Repair and Operations) perspective. This study also examines the space from an automation perspective and suggests an automation approach.

SPM has several relationships with other departments. Spare parts management involves several business processes that need application support and data from various classes of applications. The prominent application systems that a SPM system would need to interface with would include manufacturing execution systems – systems that cater to maintenance planning and execution, capture of service history, etc. besides time attendant systems, quality control systems, production scheduling systems, Supply Chain Management systems, ERP systems and PDM Systems (Product Data Management).

The aim of this study is to reduce inventory and transportation costs at the spare parts warehouse of a TV manufacturing company. This aim can be reached by proper forecasting method and optimum storage of the spare parts. In this regard, first, we obtain the forecasts using different methods such as Trend Analysis, Single Exponential Smoothing, Double Exponential Smoothing and Auto-Regressive Integrated Moving Average (ARIMA) methods. Then, the results are evaluated comparatively by using MAPE, and the best forecasts are determined. Finally, using these forecasts, the automated warehouse system, which is called "KARDEX", is optimized by using a linear programming model.

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APPENDIX

A1. LINGO Results for Kardex Optimization Application

Global optimal solution found.
Objective value: 4427100.
Total solver iterations: 68

Variable	Value	Reduced Cost
A(1)	500.0000	0.000000
A(2)	500.0000	0.000000
A(3)	500.0000	0.000000
A(4)	500.0000	0.000000
A(5)	500.0000	0.000000
A(6)	500.0000	0.000000
A(7)	500.0000	0.000000
A(8)	500.0000	0.000000
A(9)	500.0000	0.000000
A(10)	500.0000	0.000000
A(11)	500.0000	0.000000
A(12)	500.0000	0.000000
A(13)	500.0000	0.000000
A(14)	500.0000	0.000000
A(15)	500.0000	0.000000
A(16)	500.0000	0.000000
A(17)	500.0000	0.000000
A(18)	500.0000	0.000000
A(19)	500.0000	0.000000
A(20)	500.0000	0.000000
B(1)	572.0000	0.000000
B(2)	701.0000	0.000000
B(3)	3953.000	0.000000
B(4)	723.0000	0.000000
B(5)	1621.000	0.000000
B(6)	285.0000	0.000000
B(7)	706.0000	0.000000
B(8)	362.0000	0.000000
B(9)	53.00000	0.000000
B(10)	162.0000	0.000000
B(11)	252.0000	0.000000

B(12)	524.0000	0.000000
B(13)	1.000000	0.000000
C(1, 1)	19.00000	0.000000
C(1, 2)	23.00000	0.000000
C(1, 3)	132.0000	0.000000
C(1, 4)	24.00000	0.000000
C(1, 5)	54.00000	0.000000
C(1, 6)	10.00000	0.000000
C(1, 7)	24.00000	0.000000
C(1, 8)	12.00000	0.000000
C(1, 9)	2.000000	0.000000
C(1, 10)	5.000000	0.000000
C(1, 11)	8.000000	0.000000
C(1, 12)	17.00000	0.000000
C(1, 13)	0.3000E-01	0.000000
C(2, 1)	38.00000	0.000000
C(2, 2)	46.00000	0.000000
C(2, 3)	264.0000	0.000000
C(2, 4)	48.00000	0.000000
C(2, 5)	108.0000	0.000000
C(2, 6)	20.00000	0.000000
C(2, 7)	48.00000	0.000000
C(2, 8)	24.00000	0.000000
C(2, 9)	4.000000	0.000000
C(2, 10)	10.00000	0.000000
C(2, 11)	16.00000	0.000000
C(2, 12)	34.00000	0.000000
C(2, 13)	0.6000E-01	0.000000
C(3, 1)	57.00000	0.000000
C(3, 2)	69.00000	0.000000
C(3, 3)	396.0000	0.000000
C(3, 4)	72.00000	0.000000
C(3, 5)	162.0000	0.000000
C(3, 6)	30.00000	0.000000
C(3, 7)	72.00000	0.000000
C(3, 8)	36.00000	0.000000
C(3, 9)	6.000000	0.000000
C(3, 10)	15.00000	0.000000
C(3, 11)	24.00000	0.000000
C(3, 12)	51.00000	0.000000
C(3, 13)	0.9000E-01	0.000000
C(4, 1)	76.00000	0.000000
C(4, 2)	92.00000	0.000000
C(4, 3)	528.0000	0.000000
C(4, 4)	96.00000	0.000000
C(4, 5)	216.0000	0.000000
C(4, 6)	40.00000	0.000000

C(4, 7)	96.00000	0.000000
C(4, 8)	48.00000	0.000000
C(4, 9)	8.000000	0.000000
C(4, 10)	20.00000	0.000000
C(4, 11)	32.00000	0.000000
C(4, 12)	68.00000	0.000000
C(4, 13)	0.1200000	0.000000
C(5, 1)	95.00000	0.000000
C(5, 2)	115.0000	0.000000
C(5, 3)	660.0000	0.000000
C(5, 4)	120.0000	0.000000
C(5, 5)	270.0000	0.000000
C(5, 6)	50.00000	0.000000
C(5, 7)	120.0000	0.000000
C(5, 8)	60.00000	0.000000
C(5, 9)	10.00000	0.000000
C(5, 10)	25.00000	0.000000
C(5, 11)	40.00000	0.000000
C(5, 12)	85.00000	0.000000
C(5, 13)	0.1500000	0.000000
C(6, 1)	114.0000	0.000000
C(6, 2)	138.0000	0.000000
C(6, 3)	792.0000	0.000000
C(6, 4)	144.0000	0.000000
C(6, 5)	324.0000	0.000000
C(6, 6)	60.00000	0.000000
C(6, 7)	144.0000	0.000000
C(6, 8)	72.00000	0.000000
C(6, 9)	12.00000	0.000000
C(6, 10)	30.00000	0.000000
C(6, 11)	48.00000	0.000000
C(6, 12)	102.0000	0.000000
C(6, 13)	0.1800000	0.000000
C(7, 1)	133.0000	0.000000
C(7, 2)	161.0000	0.000000
C(7, 3)	924.0000	0.000000
C(7, 4)	168.0000	0.000000
C(7, 5)	378.0000	0.000000
C(7, 6)	70.00000	0.000000
C(7, 7)	168.0000	0.000000
C(7, 8)	84.00000	0.000000
C(7, 9)	14.00000	0.000000
C(7, 10)	35.00000	0.000000
C(7, 11)	56.00000	0.000000
C(7, 12)	119.0000	0.000000
C(7, 13)	0.2100000	0.000000
C(8, 1)	152.0000	0.000000
C(8, 2)	184.0000	0.000000

C(8, 3)	1056.000	0.000000
C(8, 4)	192.0000	0.000000
C(8, 5)	432.0000	0.000000
C(8, 6)	80.00000	0.000000
C(8, 7)	192.0000	0.000000
C(8, 8)	96.00000	0.000000
C(8, 9)	16.00000	0.000000
C(8, 10)	40.00000	0.000000
C(8, 11)	64.00000	0.000000
C(8, 12)	136.0000	0.000000
C(8, 13)	0.2400000	0.000000
C(9, 1)	171.0000	0.000000
C(9, 2)	207.0000	0.000000
C(9, 3)	1188.000	0.000000
C(9, 4)	216.0000	0.000000
C(9, 5)	486.0000	0.000000
C(9, 6)	90.00000	0.000000
C(9, 7)	216.0000	0.000000
C(9, 8)	108.0000	0.000000
C(9, 9)	18.00000	0.000000
C(9, 10)	45.00000	0.000000
C(9, 11)	72.00000	0.000000
C(9, 12)	153.0000	0.000000
C(9, 13)	0.2700000	0.000000
C(10, 1)	190.0000	0.000000
C(10, 2)	230.0000	0.000000
C(10, 3)	1320.000	0.000000
C(10, 4)	240.0000	0.000000
C(10, 5)	540.0000	0.000000
C(10, 6)	100.0000	0.000000
C(10, 7)	240.0000	0.000000
C(10, 8)	120.0000	0.000000
C(10, 9)	20.00000	0.000000
C(10, 10)	50.00000	0.000000
C(10, 11)	80.00000	0.000000
C(10, 12)	170.0000	0.000000
C(10, 13)	0.3000000	0.000000
C(11, 1)	209.0000	0.000000
C(11, 2)	253.0000	0.000000
C(11, 3)	1452.000	0.000000
C(11, 4)	264.0000	0.000000
C(11, 5)	594.0000	0.000000
C(11, 6)	110.0000	0.000000
C(11, 7)	264.0000	0.000000
C(11, 8)	132.0000	0.000000
C(11, 9)	22.00000	0.000000
C(11, 10)	55.00000	0.000000
C(11, 11)	88.00000	0.000000

C(11, 12)	187.0000	0.000000
C(11, 13)	0.3300000	0.000000
C(12, 1)	228.0000	0.000000
C(12, 2)	276.0000	0.000000
C(12, 3)	1584.000	0.000000
C(12, 4)	288.0000	0.000000
C(12, 5)	648.0000	0.000000
C(12, 6)	120.0000	0.000000
C(12, 7)	288.0000	0.000000
C(12, 8)	144.0000	0.000000
C(12, 9)	24.00000	0.000000
C(12, 10)	60.00000	0.000000
C(12, 11)	96.00000	0.000000
C(12, 12)	204.0000	0.000000
C(12, 13)	0.3600000	0.000000
C(13, 1)	247.0000	0.000000
C(13, 2)	299.0000	0.000000
C(13, 3)	1716.000	0.000000
C(13, 4)	312.0000	0.000000
C(13, 5)	702.0000	0.000000
C(13, 6)	130.0000	0.000000
C(13, 7)	312.0000	0.000000
C(13, 8)	156.0000	0.000000
C(13, 9)	26.00000	0.000000
C(13, 10)	65.00000	0.000000
C(13, 11)	104.0000	0.000000
C(13, 12)	221.0000	0.000000
C(13, 13)	0.3900000	0.000000
C(14, 1)	266.0000	0.000000
C(14, 2)	322.0000	0.000000
C(14, 3)	1848.000	0.000000
C(14, 4)	336.0000	0.000000
C(14, 5)	756.0000	0.000000
C(14, 6)	140.0000	0.000000
C(14, 7)	336.0000	0.000000
C(14, 8)	168.0000	0.000000
C(14, 9)	28.00000	0.000000
C(14, 10)	70.00000	0.000000
C(14, 11)	112.0000	0.000000
C(14, 12)	238.0000	0.000000
C(14, 13)	0.4200000	0.000000
C(15, 1)	285.0000	0.000000
C(15, 2)	345.0000	0.000000
C(15, 3)	1980.000	0.000000
C(15, 4)	360.0000	0.000000
C(15, 5)	810.0000	0.000000
C(15, 6)	150.0000	0.000000
C(15, 7)	360.0000	0.000000

C(15, 8)	180.0000	0.000000
C(15, 9)	30.00000	0.000000
C(15, 10)	75.00000	0.000000
C(15, 11)	120.0000	0.000000
C(15, 12)	255.0000	0.000000
C(15, 13)	0.4500000	0.000000
C(16, 1)	304.0000	0.000000
C(16, 2)	368.0000	0.000000
C(16, 3)	2112.000	0.000000
C(16, 4)	384.0000	0.000000
C(16, 5)	864.0000	0.000000
C(16, 6)	160.0000	0.000000
C(16, 7)	384.0000	0.000000
C(16, 8)	192.0000	0.000000
C(16, 9)	32.00000	0.000000
C(16, 10)	80.00000	0.000000
C(16, 11)	128.0000	0.000000
C(16, 12)	272.0000	0.000000
C(16, 13)	0.4800000	0.000000
C(17, 1)	323.0000	0.000000
C(17, 2)	391.0000	0.000000
C(17, 3)	2244.000	0.000000
C(17, 4)	408.0000	0.000000
C(17, 5)	918.0000	0.000000
C(17, 6)	170.0000	0.000000
C(17, 7)	408.0000	0.000000
C(17, 8)	204.0000	0.000000
C(17, 9)	34.00000	0.000000
C(17, 10)	85.00000	0.000000
C(17, 11)	136.0000	0.000000
C(17, 12)	289.0000	0.000000
C(17, 13)	0.5100000	0.000000
C(18, 1)	342.0000	0.000000
C(18, 2)	414.0000	0.000000
C(18, 3)	2376.000	0.000000
C(18, 4)	432.0000	0.000000
C(18, 5)	972.0000	0.000000
C(18, 6)	180.0000	0.000000
C(18, 7)	432.0000	0.000000
C(18, 8)	216.0000	0.000000
C(18, 9)	36.00000	0.000000
C(18, 10)	90.00000	0.000000
C(18, 11)	144.0000	0.000000
C(18, 12)	306.0000	0.000000
C(18, 13)	0.5400000	0.000000
C(19, 1)	361.0000	0.000000
C(19, 2)	437.0000	0.000000
C(19, 3)	2508.000	0.000000

C(19, 4)	456.0000	0.000000
C(19, 5)	1026.000	0.000000
C(19, 6)	190.0000	0.000000
C(19, 7)	456.0000	0.000000
C(19, 8)	228.0000	0.000000
C(19, 9)	38.00000	0.000000
C(19, 10)	95.00000	0.000000
C(19, 11)	152.0000	0.000000
C(19, 12)	323.0000	0.000000
C(19, 13)	0.5700000	0.000000
C(20, 1)	380.0000	0.000000
C(20, 2)	460.0000	0.000000
C(20, 3)	2640.000	0.000000
C(20, 4)	480.0000	0.000000
C(20, 5)	1080.000	0.000000
C(20, 6)	200.0000	0.000000
C(20, 7)	480.0000	0.000000
C(20, 8)	240.0000	0.000000
C(20, 9)	40.00000	0.000000
C(20, 10)	100.0000	0.000000
C(20, 11)	160.0000	0.000000
C(20, 12)	340.0000	0.000000
C(20, 13)	0.6000000	0.000000
X(1, 1)	0.000000	950.0000
X(1, 2)	0.000000	890.0000
X(1, 3)	500.0000	0.000000
X(1, 4)	0.000000	876.0000
X(1, 5)	0.000000	546.0000
X(1, 6)	0.000000	1103.000
X(1, 7)	0.000000	876.0000
X(1, 8)	0.000000	1067.000
X(1, 9)	0.000000	1253.000
X(1, 10)	0.000000	1196.000
X(1, 11)	0.000000	1139.000
X(1, 12)	0.000000	982.0000
X(1, 13)	0.000000	1290.430
X(2, 1)	0.000000	837.0000
X(2, 2)	0.000000	781.0000
X(2, 3)	500.0000	0.000000
X(2, 4)	0.000000	768.0000
X(2, 5)	0.000000	468.0000
X(2, 6)	0.000000	981.0000
X(2, 7)	0.000000	768.0000
X(2, 8)	0.000000	947.0000
X(2, 9)	0.000000	1123.000
X(2, 10)	0.000000	1069.000
X(2, 11)	0.000000	1015.000
X(2, 12)	0.000000	867.0000

X(2, 13)	0.000000	1158.460
X(3, 1)	0.000000	724.0000
X(3, 2)	0.000000	672.0000
X(3, 3)	500.0000	0.000000
X(3, 4)	0.000000	660.0000
X(3, 5)	0.000000	390.0000
X(3, 6)	0.000000	859.0000
X(3, 7)	0.000000	660.0000
X(3, 8)	0.000000	827.0000
X(3, 9)	0.000000	993.0000
X(3, 10)	0.000000	942.0000
X(3, 11)	0.000000	891.0000
X(3, 12)	0.000000	752.0000
X(3, 13)	0.000000	1026.490
X(4, 1)	0.000000	611.0000
X(4, 2)	0.000000	563.0000
X(4, 3)	500.0000	0.000000
X(4, 4)	0.000000	552.0000
X(4, 5)	0.000000	312.0000
X(4, 6)	0.000000	737.0000
X(4, 7)	0.000000	552.0000
X(4, 8)	0.000000	707.0000
X(4, 9)	0.000000	863.0000
X(4, 10)	0.000000	815.0000
X(4, 11)	0.000000	767.0000
X(4, 12)	0.000000	637.0000
X(4, 13)	0.000000	894.5200
X(5, 1)	0.000000	498.0000
X(5, 2)	0.000000	454.0000
X(5, 3)	500.0000	0.000000
X(5, 4)	0.000000	444.0000
X(5, 5)	0.000000	234.0000
X(5, 6)	0.000000	615.0000
X(5, 7)	0.000000	444.0000
X(5, 8)	0.000000	587.0000
X(5, 9)	0.000000	733.0000
X(5, 10)	0.000000	688.0000
X(5, 11)	0.000000	643.0000
X(5, 12)	0.000000	522.0000
X(5, 13)	0.000000	762.5500
X(6, 1)	0.000000	385.0000
X(6, 2)	0.000000	345.0000
X(6, 3)	500.0000	0.000000
X(6, 4)	0.000000	336.0000
X(6, 5)	0.000000	156.0000
X(6, 6)	0.000000	493.0000
X(6, 7)	0.000000	336.0000
X(6, 8)	0.000000	467.0000

X(6, 9)	0.000000	603.0000
X(6, 10)	0.000000	561.0000
X(6, 11)	0.000000	519.0000
X(6, 12)	0.000000	407.0000
X(6, 13)	0.000000	630.5800
X(7, 1)	0.000000	272.0000
X(7, 2)	0.000000	236.0000
X(7, 3)	500.0000	0.000000
X(7, 4)	0.000000	228.0000
X(7, 5)	0.000000	78.00000
X(7, 6)	0.000000	371.0000
X(7, 7)	0.000000	228.0000
X(7, 8)	0.000000	347.0000
X(7, 9)	0.000000	473.0000
X(7, 10)	0.000000	434.0000
X(7, 11)	0.000000	395.0000
X(7, 12)	0.000000	292.0000
X(7, 13)	0.000000	498.6100
X(8, 1)	0.000000	159.0000
X(8, 2)	0.000000	127.0000
X(8, 3)	453.0000	0.000000
X(8, 4)	0.000000	120.0000
X(8, 5)	47.00000	0.000000
X(8, 6)	0.000000	249.0000
X(8, 7)	0.000000	120.0000
X(8, 8)	0.000000	227.0000
X(8, 9)	0.000000	343.0000
X(8, 10)	0.000000	307.0000
X(8, 11)	0.000000	271.0000
X(8, 12)	0.000000	177.0000
X(8, 13)	0.000000	366.6400
X(9, 1)	0.000000	124.0000
X(9, 2)	0.000000	96.00000
X(9, 3)	0.000000	78.00000
X(9, 4)	0.000000	90.00000
X(9, 5)	500.0000	0.000000
X(9, 6)	0.000000	205.0000
X(9, 7)	0.000000	90.00000
X(9, 8)	0.000000	185.0000
X(9, 9)	0.000000	291.0000
X(9, 10)	0.000000	258.0000
X(9, 11)	0.000000	225.0000
X(9, 12)	0.000000	140.0000
X(9, 13)	0.000000	312.6700
X(10, 1)	0.000000	89.00000
X(10, 2)	0.000000	65.00000
X(10, 3)	0.000000	156.0000
X(10, 4)	0.000000	60.00000

X(10, 5)	500.0000	0.000000
X(10, 6)	0.000000	161.0000
X(10, 7)	0.000000	60.00000
X(10, 8)	0.000000	143.0000
X(10, 9)	0.000000	239.0000
X(10, 10)	0.000000	209.0000
X(10, 11)	0.000000	179.0000
X(10, 12)	0.000000	103.0000
X(10, 13)	0.000000	258.7000
X(11, 1)	0.000000	54.00000
X(11, 2)	0.000000	34.00000
X(11, 3)	0.000000	234.0000
X(11, 4)	0.000000	30.00000
X(11, 5)	500.0000	0.000000
X(11, 6)	0.000000	117.0000
X(11, 7)	0.000000	30.00000
X(11, 8)	0.000000	101.0000
X(11, 9)	0.000000	187.0000
X(11, 10)	0.000000	160.0000
X(11, 11)	0.000000	133.0000
X(11, 12)	0.000000	66.00000
X(11, 13)	0.000000	204.7300
X(12, 1)	0.000000	19.00000
X(12, 2)	0.000000	3.000000
X(12, 3)	0.000000	312.0000
X(12, 4)	223.0000	0.000000
X(12, 5)	74.00000	0.000000
X(12, 6)	0.000000	73.00000
X(12, 7)	203.0000	0.000000
X(12, 8)	0.000000	59.00000
X(12, 9)	0.000000	135.0000
X(12, 10)	0.000000	111.0000
X(12, 11)	0.000000	87.00000
X(12, 12)	0.000000	29.00000
X(12, 13)	0.000000	150.7600
X(13, 1)	0.000000	14.00000
X(13, 2)	0.000000	2.000000
X(13, 3)	0.000000	420.0000
X(13, 4)	500.0000	0.000000
X(13, 5)	0.000000	30.00000
X(13, 6)	0.000000	59.00000
X(13, 7)	0.000000	0.000000
X(13, 8)	0.000000	47.00000
X(13, 9)	0.000000	113.0000
X(13, 10)	0.000000	92.00000
X(13, 11)	0.000000	71.00000
X(13, 12)	0.000000	22.00000
X(13, 13)	0.000000	126.7900

X(14, 1)	0.000000	9.000000
X(14, 2)	0.000000	1.000000
X(14, 3)	0.000000	528.0000
X(14, 4)	0.000000	0.000000
X(14, 5)	0.000000	60.00000
X(14, 6)	0.000000	45.00000
X(14, 7)	500.0000	0.000000
X(14, 8)	0.000000	35.00000
X(14, 9)	0.000000	91.00000
X(14, 10)	0.000000	73.00000
X(14, 11)	0.000000	55.00000
X(14, 12)	0.000000	15.00000
X(14, 13)	0.000000	102.8200
X(15, 1)	0.000000	4.000000
X(15, 2)	497.0000	0.000000
X(15, 3)	0.000000	636.0000
X(15, 4)	0.000000	0.000000
X(15, 5)	0.000000	90.00000
X(15, 6)	0.000000	31.00000
X(15, 7)	3.000000	0.000000
X(15, 8)	0.000000	23.00000
X(15, 9)	0.000000	69.00000
X(15, 10)	0.000000	54.00000
X(15, 11)	0.000000	39.00000
X(15, 12)	0.000000	8.000000
X(15, 13)	0.000000	78.85000
X(16, 1)	296.0000	0.000000
X(16, 2)	204.0000	0.000000
X(16, 3)	0.000000	745.0000
X(16, 4)	0.000000	1.000000
X(16, 5)	0.000000	121.0000
X(16, 6)	0.000000	18.00000
X(16, 7)	0.000000	1.000000
X(16, 8)	0.000000	12.00000
X(16, 9)	0.000000	48.00000
X(16, 10)	0.000000	36.00000
X(16, 11)	0.000000	24.00000
X(16, 12)	0.000000	2.000000
X(16, 13)	0.000000	55.88000
X(17, 1)	276.0000	0.000000
X(17, 2)	0.000000	4.000000
X(17, 3)	0.000000	858.0000
X(17, 4)	0.000000	6.000000
X(17, 5)	0.000000	156.0000
X(17, 6)	0.000000	9.000000
X(17, 7)	0.000000	6.000000
X(17, 8)	0.000000	5.000000
X(17, 9)	0.000000	31.00000

X(17, 10)	0.000000	22.00000
X(17, 11)	0.000000	13.00000
X(17, 12)	224.0000	0.000000
X(17, 13)	0.000000	36.91000
X(18, 1)	0.000000	2.000000
X(18, 2)	0.000000	10.00000
X(18, 3)	0.000000	973.0000
X(18, 4)	0.000000	13.00000
X(18, 5)	0.000000	193.0000
X(18, 6)	0.000000	2.000000
X(18, 7)	0.000000	13.00000
X(18, 8)	200.0000	0.000000
X(18, 9)	0.000000	16.00000
X(18, 10)	0.000000	10.00000
X(18, 11)	0.000000	4.000000
X(18, 12)	300.0000	0.000000
X(18, 13)	0.000000	19.94000
X(19, 1)	0.000000	9.000000
X(19, 2)	0.000000	21.00000
X(19, 3)	0.000000	1093.000
X(19, 4)	0.000000	25.00000
X(19, 5)	0.000000	235.0000
X(19, 6)	285.0000	0.000000
X(19, 7)	0.000000	25.00000
X(19, 8)	162.0000	0.000000
X(19, 9)	0.000000	6.000000
X(19, 10)	0.000000	3.000000
X(19, 11)	53.00000	0.000000
X(19, 12)	0.000000	5.000000
X(19, 13)	0.000000	7.970000
X(20, 1)	0.000000	20.00000
X(20, 2)	0.000000	36.00000
X(20, 3)	0.000000	1217.000
X(20, 4)	0.000000	41.00000
X(20, 5)	0.000000	281.0000
X(20, 6)	0.000000	2.000000
X(20, 7)	0.000000	41.00000
X(20, 8)	0.000000	4.000000
X(20, 9)	53.00000	0.000000
X(20, 10)	162.0000	0.000000
X(20, 11)	199.0000	0.000000
X(20, 12)	0.000000	14.00000
X(20, 13)	1.000000	0.000000

Row	Slack or Surplus	Dual Price
1	4427100.	-1.000000
2	0.000000	1291.000
3	0.000000	1159.000
4	0.000000	1027.000
5	0.000000	895.0000
6	0.000000	763.0000
7	0.000000	631.0000
8	0.000000	499.0000
9	0.000000	367.0000
10	0.000000	313.0000
11	0.000000	259.0000
12	0.000000	205.0000
13	0.000000	151.0000
14	0.000000	127.0000
15	0.000000	103.0000
16	0.000000	79.00000
17	0.000000	56.00000
18	0.000000	37.00000
19	0.000000	20.00000
20	0.000000	8.000000
21	85.00000	0.000000
22	0.000000	-360.0000
23	0.000000	-424.0000
24	0.000000	-1423.000
25	0.000000	-439.0000
26	0.000000	-799.0000
27	0.000000	-198.0000
28	0.000000	-439.0000
29	0.000000	-236.0000
30	0.000000	-40.00000
31	0.000000	-100.0000
32	0.000000	-160.0000
33	0.000000	-326.0000
34	0.000000	-0.6000000