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SPARE PARTS INVENTORY MANAGEMENT

MERVE ŞAHİN

PhD THESIS

DEPARTMENT OF INDUSTRIAL ENGINEERING
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SPARE PARTS INVENTORY MANAGEMENT

A thesis submitted by Merve ŞAHİN in partial fulfillment of the requirements for the degree of **DOCTORATE OF SCIENCE** is approved by the committee on 13.11.2017 in Department of Industrial Engineering.

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Merve ŞAHİN

TABLE OF CONTENTS

Page

LIST OF SYMBOLS

α	Smoothing constant between 0 and 1.
β	Inflated rate between 0 and ADI
γ	Gradually ordering rate
$\phi(z)$	Cumulative normal distribution
r	Reorder point
F $(t+1)$	Forecast for period t+1
Q	Order quantity
S	Order-up-to level

LIST OF ABBREVIATIONS

ADI	Average Demand Interval
AERNJ	Average the Error Ratio of the Occurrence of Nonzero Demand Judgments
ARIMA	Auto Regressive Integrated Moving Average
ARTA	Autoregressive to Any Algorithm
CAPM	Capital Asset Pricing Model
CSL	Cycle Service Level
CV	Coefficient of Variation
EOQ	Economic Order Quantity
EWMA	Exponentially Weighted Moving Average
FR	Fill Rate
GMAE	Geometric Mean Absolute Error
GMAMAE	Geometric Mean of the Arithmetic Mean of the Absolute Errors
GMAMIC	Geometric Mean of the Arithmetic Means of the Inventory Costs
GRMSE	Geometric Root Mean Square Error
IFM	Integrated Forecasting Method
LTD	Lead Time Demand
MAD/A	Mean Absolute Deviation to Average
MAPE	Mean Absolute Percentage Error
MASE	Mean Absolute Scaled Error
MRO	Maintenance, Repair and Overhaul
MSE	Mean Square Error
OUL	Order Up to Level
PB	Percentage Better
RGRMSE	Relative Geometric Root Mean Square Error
RMSE	Root Mean Square Error
SKU	Stock Keeping Unit
SL	Service Level
SMA	Simple Moving Average
sMAPE	Symmetric Mean Absolute Percentage Error
SES	Simple Exponential Smoothing
THY	Turkish Airlines
YTU	Yıldız Technical University

LIST OF FIGURES

LIST OF TABLES

ABSTRACT

SPARE PARTS INVENTORY MANAGEMENT

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Since there is a high competition in the aviation industry, reducing costs comes into prominence and is becoming more critical each day. In the aviation industry, maintenance and inventory holding costs of spare parts give the opportunity to managers to decrease their operational costs. Therefore, demand forecasting with high accuracy is indispensable matter in spare parts inventory management. In the literature, traditional demand forecasting methods and measures are claimed to be insufficient due to the variability in demand size and the uncertainty in demand occurrence. While comparing traditional forecasting methods with non-traditional methods; classical performance measures are usually preferred and these measures often give misleading results when inventory cost minimization is selected as a primary objective for service parts. The main reason is the nature of demand that contains a large percentage of zero values with less non-zero demand.

In this thesis, cost-based performances are measured employing different inventory policies and ordering approaches that are proposed to compare the traditional forecasting methods with the non-parametric and parametric forecasting methods generated for non-smooth demand. In order to compare these non-smooth demand forecasting methods, 535 different items are selected from the inventory of Turkish Airlines Technic MRO. A methodology is presented that is consisting of data classification, initial parameter estimation, parameter search with optimization and evaluation. Although in the literature it is claimed that traditional methods may fail in forecasting non-smooth demand, it has been observed that non-traditional methods are not performing better than the traditional alternatives when the inventory cost is taken into account as the performance measure.

In this thesis, it is also claimed that applying different inventory policies and newly proposed ordering approaches with optimized parameters can reduce inventory costs more than the existing methods. Generated outputs of this study may provide a framework that will guide the inventory planners to make their decisions on which forecasting method, replenishment policy and ordering approach give the minimum inventory cost based on demand data type.

Keywords: Spare Parts, Inventory Cost, Intermittent Data, Bootstrapping, (Q, R) Policy, Base Stock

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ÖZET

YEDEK PARÇALARIN ENVANTER YÖNETİMİ

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Doktora Tezi

Tez Danışmanı: Yrd. Doç. Dr. Fahrettin ELDEMİR

Havacılık endüstrisinde yüksek rekabet olması sebebiyle maliyetlerin düşürülmesi ön plana çıkmakta ve her geçen gün daha kritik hale gelmektedir. Havacılık endüstrisinde, yedek parçaların bakımı ve stok tutma maliyetleri, yöneticilere işletme maliyetlerini düşürme olanağı verir. Bu nedenle yedek parça stok yönetiminde yüksek doğrulukta talep tahmini vazgeçilmez bir konudur. Literatürde, talep miktarının değişkenliği ve belirsizliği nedeniyle geleneksel talep tahmin yöntemlerinin ve de performans ölçüm metotlarının yeterli olmadığı iddia edilmektedir. Bu yöntemleri karşılaştırırken; klasik performans ölçütleri genellikle tercih edilir. Ancak bu karşılaştırma sonuçları, envanter maliyeti minimizasyonu düşünüldüğünde genellikle yanıltıcı sonuçlar verir. Bu çalışmada, geleneksel tahmin yöntemleri ve de kesikli talep için üretilen tahmin yöntemlerini karşılaştırmada maliyet esaslı performans ölçütü dikkate alınarak farklı envanter politikaları ve geliştirilmiş farklı sipariş verme yaklaşımları kullanılmıştır. Talep tahmini yöntemlerini ve geliştirilen sipariş verme yaklaşımlarını karşılaştırmak için THY Teknik MRO envanterinden 535 farklı madde seçilmiştir. Veri sınıflandırması, başlangıç değerleri atama, optimizasyon kullanılarak parametrelerin minimum maliyeti verecek şekilde araştırılması ve performans ölçümünden oluşan bir metodoloji sunulmuştur. Literatürde düzenli olmayan talep verisi için geleneksel yöntemlerin gelecekteki talebi tahmin etmede başarısız olabileceği iddia edilmesine rağmen, performans ölçütü olarak stok maliyeti dikkate alındığında geleneksel olmayan yöntemlerin geleneksel alternatiflerden önemli oranda iyi performans göstermediği görülmüştür.

Bu çalışmada, havacılık yedek parça tedariğini karşılamak için farklı envanter politikaları ve geliştirilmiş sipariş verme yaklaşımları optimize edilmiş parametrelerle uygulanarak mevcut yöntemlerden daha fazla envanter maliyetlerini azaltabileceği iddia edilmektedir. Bu çalışmadan üretilen çıktılar, envanter planlayıcılarının hangi yedek parça talep verisi için hangi tahmin yöntemi ve yenileme politikası kullanarak minimum stok maliyeti elde edebileceğine ilişkin kararlarını vermelerinde bir çerçeve sağlayabilir.

Anahtar Kelimeler: Yedek Parça, Envanter Maliyetleri, Kesikli Veri, Bootstrapping, (Q,R) Politikası, Base Stok

CHAPTER 1

INTRODUCTION

1.1 Literature Summary

Aviation is a substantial sector in the transportation industry. Due to the highly competitive environment and regulations in this industry, lowering costs comes into prominence. The most applicable approach to lower costs is to minimize inventory using the accurate forecasting methods with appropriate inventory policies together. Demand forecasting of spare parts with high accuracy is crucial for aircraft maintenance because of the high aircraft and spare part downtime costs. Spare parts in aviation industry mostly have many time periods with zero demand that is characterized as intermittent demand. Accurate forecasting and updating inventory parameters with the appropriate methods for intermittent demand can result in considerable cost savings. The parts that present intermittent demand structure can have a value of up to 60% of the total stock value in the industry [1, 2]. However, the traditional methods fail to achieve high accuracy due to the variability in demand quantity and occurrence of these parts. The demand for intermittent structure needs to be handled in a different way. Current intermittent demand forecasting methods in literature are not satisfactorily responsive. They might give misleading results when the inventory cost minimization comes into the consideration.

Good decisions such as determining how many items should be ordered in which intervals and how can set target inventory levels to minimize inventory costs are given by employing appropriate forecasting methods and inventory policies. Forecasting of spare parts demand with high accuracy in order to sustain continuous maintenance operations entails keeping the inventory at some safe level to reduce the undesirable effect of demand variations. There is a dilemma between make-to-stock and make-to-order decisions since make-to-order decision may interrupt the maintenance operations as lead time. Stock out costs could be seen in make-to-order decisions although holding costs could be seen in the make to stock decisions. Inventory planners have the aim of reducing inventory costs with high levels of customer service by using proper and applicable forecasting methods. What the inventory cost performance of a stock keeping unit (SKU) depends on the accurateness of the forecasting method and inventory policy that employed. The non-smooth demand pattern requires forecasting demand with the optimum potential degree of accuracy and establishing the inventory policy parameters based on that information, which is a common problem. The typical feature of demand data has a close relationship with the accuracy of forecasting methods [3]. Innovative approaches have been brought in literature for intermittent demand, since that the requirement of producing more accurate forecasts keeps up being a matter in both computing area and aviation industry. Exponential smoothing methods and variations are typically used for both smooth demand pattern and prediction of spare parts demand [4]. Nevertheless, in the case that traditional forecasting methods are employed, variability and uncertainty of occurrence of these parts rise difficulties in forecasting with high accuracy. More weight on the most recent data, however, is placed by exponential smoothing methods. In this respect, by its occurrence, it underestimates the size of the demand while overestimating the long-term average demand. Moreover, methods of biased forecasting lead to excessively high stocks. There is the need of different methods for non-smooth demand pattern which does not appear any demand in most of the periods.

1.2 Objective

It is possible to control the inventory level and minimize the inventory cost in the place where the order is received because the cost of the parts used for maintenance can reach over million dollars. In addition, since the parts used might be large abruptly, the inventory requires additional cost to keep them. On the other hand, the absence of some spare parts used for aircraft maintenance can even cause the aircraft not to fly at the scheduled time, which causes an additional high amount of cost.

In this study, what was applied to selected non-smooth demand data from airline industry were forecasting methods which are specially developed for non-smooth demand data and employ different inventory policies and approaches. Inaccurate estimation of the demand of spare parts may cause exorbitant interruption costs, for this reason, when compared to the smooth and continuous occurrence of demand, it is significant to adopt particular methods to forecast with high accuracy because of that spare parts have irregular demand attribute. Therefore, it is a critical operational issue to manage spare parts in manufacturing and service industry. Small improvements, which might be turned into considerable cost savings, could be the reason of that. There has arisen interest about the issue of decreasing stock out and holding costs in the academic literature for decades and people have paid attention to forecasting methods which increase forecast accuracy for non-smooth demand types in the area of inventory management. Computerized forecasting solutions, additionally, which consider different performance measures can help companies to control their inventories by decreasing costs. Companies that attach importance to supplies and operational continuity, such as Turkish Airlines, tend to provide minimum inventory costs and improve processes using strong demand forecasting techniques that provide less inventory and better customer service level.

As inventory management needs to be more systematic, it is essential to understand the relationship between coherent forecasting and stock policy. The most effective method of predicting demand for intermittent demand and intermittent inventory decision has an effect on inventory costs and therefore on the performance of the system. Industry inventory planners need to overcome the problems arise while handling this kind of irregular demand data to increase the performance of inventory planning systems, and modifications are required for the interaction between forecasting and stock control. In this study, our aim is to provide a framework to practitioners in the aviation industry for best inventory strategy regarding demand data type considering inventory costs.

One of the key objectives of any inventory management problem is to balance the requirement of having stock on hand to keep operation continuous against the cost of maintaining that stock. The exact estimates of total demand during the lead time, historical demand data, and stock policy that company adopted are needed in inventory control to manage this balance efficiently. Building simple cost optimization procedure could help managers and planners to comprehend which costs are important and how critical the stock-outs can be. When considering inventory cost minimization of the non-smooth demand data type to decrease stock holding costs and stockout costs depending on the target service level is a tradeoff for companies to be handled it in a proper way while building an optimum balance between stock out and holding stock costs.

1.3 Hypothesis

The following research questions are elucidated in this research in general;

1. Which forecasting method can be chosen to impact on the decisions of inventory that decreases costs and thus increase the performance of the system?
2. How can we develop a cost-based inventory ordering decision and investigate inventory implications of forecasting methods for chosen different real data sets and compare them applying different inventory policies?
3. Which inventory policy and which developed inventory control approaches in this study can provide minimum costs for each demand data category by keeping customer service level as high as possible?
4. Is there any difference between parametric and non-parametric forecasting methods considering inventory costs?

In this study, inventory cost based comparisons are given considering different inventory policies and different forecasting methods with the optimization of the forecast parameters and generated ordering approach parameters. In order to meet the aviation industry needs some improvements are employed to the stock replenishment methods. These improvements are made by inflated demand forecasting parameter and by applying gradually ordering approach. The parameters for inflated demand forecast and gradually ordering are searched to minimize inventory costs. Turkish Airlines spare parts data are employed in this study and it is observed that the considerable cost reductions can be realized. This study also aims to provide guidance to the airline practitioners in determining the appropriate forecasting techniques for different demand characteristics in the light of inventory costs minimization. Overall advantages of efficient spare parts inventory management as follows;

1. Costs associated with long maintenance operations will be reduced as such airplanes spend more time in the air yielding profits.
2. Investment in inventory will be turned into cash.
3. Availability of parts will be increased so that better and faster service will be provided to external customers.
4. Maintenance operations will take shorter times that ensure efficient personnel, procurement and production/operation planning.

Items in demand data set are classified to determine the most accurate forecasting method and inventory policy for each demand data type. Traditional and non-traditional forecasting methods are employed with base stock policy and total cost results of methods are compared in Chapter 3. Non-parametric methods inventory cost results are given in Chapter 4. Parametric forecasting methods cost results are compared in Chapter 5 by applying (Q, R) inventory policy. Newly generated ordering approaches (gradually ordering and inflated forecasting) are employed in Chapter 6 in order to compare cost results of the forecasting methods. Upon simulating inventory levels and ordering quantities on real data set, inventory costs of the forecasting methods are compared using different inventory policies and ordering approaches. It will draw insights into which methods and replenishment policies are better for each demand category. In Chapter 7, all findings are summarized and possible implications of these results are discussed along with future research.

CHAPTER 2

LITERATURE REVIEW

2.1 Spare Parts

Spare parts inventory management is a sophisticated business in the aviation industry. In most studies, it is claimed that companies need faster and highly satisfied service to provide a competitive advantage. For this reason, forecasting based activities are getting more attention in order to increase the availability of spare parts and control the inventory in aviation maintenance industry and other manufacturing systems. Most of the spare parts demand shows irregular patterns that have many time period presents zero demand and the remaining time periods have non-zero demand with high variability. Estimating the cost of inventory of these items is critical to invest the required spare parts. There is the will of keeping stocks low to decrease holding costs and at the same time high to ensure availability. Accurate demand forecasts could resolve that common inventory management dilemma. Even as demand forecasting is not easy mostly, forecasting demand for service parts could be particularly more challenging. Traditional forecasting methods usually could not meet the demand requests when there is non-smooth demand type.

Spare parts are items that have non-smooth demand type and they are generally known as ‘slow moving’. Lumpy demand type which is subcategory of non-smooth demand data, referring to include extra diverse amongst the non-zero demand values [5]. This type of data mostly could be seen in aircraft maintenance spare parts, long-lasting spare parts, textile machines, petrochemical, defense and automotive industries [6, 7, 8]. The success of the operations in these industries is influenced by the availability of spare parts which is subject to accurately forecasting demand and planning inventory.

Traditional forecasting methods assume that the probability distribution of demand data could fit normal distribution for smooth demand type since smooth has known patterns such as trend, seasonality, cycle and random [9]. However, there is a problem with non-smooth demand type as it could not fit normal demand distribution that causes forecasting such demand type requires more specific methods than smooth demand type [10]. In the following sections, this type of data is investigated from categorization to inventory cost implications.

2.2 Demand Categorization

Employing forecasting method that gives the highest accuracy on demand data is a key subject in operational management of the spare parts [11]. Historical demand data can be categorized in order to select the best forecasting method for each demand type. Categorization of demand is an important part of the inventory system that provides which forecasting method and stock control method might be beneficial for the specific type of data [3, 12]. Demand categorization methods, schemes and demand characteristics are analyzed in the following.

2.2.1 ABC Classification Scheme

Demand data can be classified based on different parameters. ABC classification can be employed to put in order SKUs according to demand frequency, demand volumes or demand profit [13]. After arranging these parts Category A, B and C items can be identified. Category A items are handled as the most important SKUs, Category B is moderate and Category C items have less importance [14]. Even though Category C items are not important that much, decision makers should consider their efficient management in inventory if costs related to those items are high.

2.2.2 Demand Categorization Schemes

The accuracy of forecasting method may be related to the characteristic of demand data [3]. Categorization schemes are employed to develop a general idea of the number of stock keeping units [15].

These schemes were followed for classifying the data according to the selected method. The idea of classifying demand patterns is introduced by Williams and he worked on the categorization of products based on the demand type, and proper demand forecasting methods for different types of products [16].

2.2.2.1 Williams Categorization Scheme (1984)

Williams categorized demand with defined two parameters: Lumpiness degree and Intermittency degree of demand data [16]. Lumpiness is related to variability and intermittency is related to demand occurrence and number of lead times between consecutive demands. Lead time variance of the parts might be a variance of the order sizes, transaction variability, and variance of the lead-times with the assumption of constant lead times [15].

$\frac{CV^2(x)}{\lambda \bar{L}}$ is the lumpiness degree of the data that indicates how the squared coefficient of variation of demand during lead time.

$\frac{1}{\lambda \bar{L}}$ is the intermittency of the data that represents the number of lead times between successive demands.

$\bar{L}$: Mean lead time

λ: Mean demand arrival rate

CV^2: Squared coefficient of demand sizes

Demand data categorization is given in Figure 2.1 with cut-off values that are selected empirically.

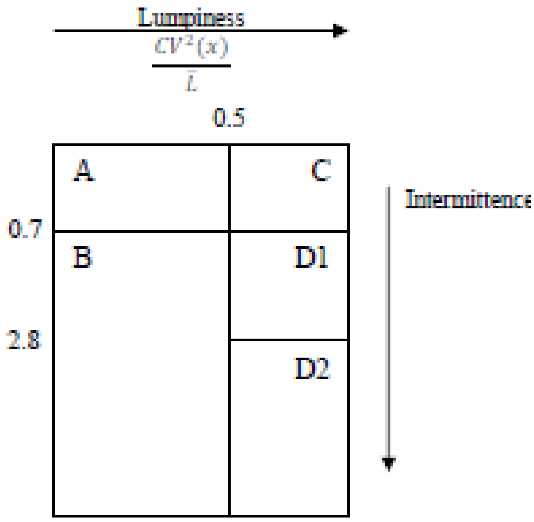

Figure 2.1 Williams categorization scheme [16]

Category A and C represent smooth demand, Category B shows slow-moving, Category D1 shows sporadic and Category D2 shows highly sporadic demand.

2.2.2.2 Johnston and Boylan Categorization Scheme (1996)

There is a categorization scheme that considers Exponentially Weighted Moving Average (EWMA) and Croston methods comparison [1]. If the average inter-demand interval is greater than 1.25 forecasting periods Croston method might give more accurate results than EWMA method.

2.2.2.3 Eaves Categorization Scheme (2002)

Transaction variability, demand size variability, and lead time variability are considered in Eaves categorization scheme [17]. Data set from Royal Air Force identifies the cut off values for classification. Since these values are dependent on data set they used, it might not be valid for all data sets. Category A represents smooth demand, Category B represents slow-moving, Category C represents irregular, Category D1 represents erratic and Category D2 represents highly erratic demand data as given in Figure 2.2.

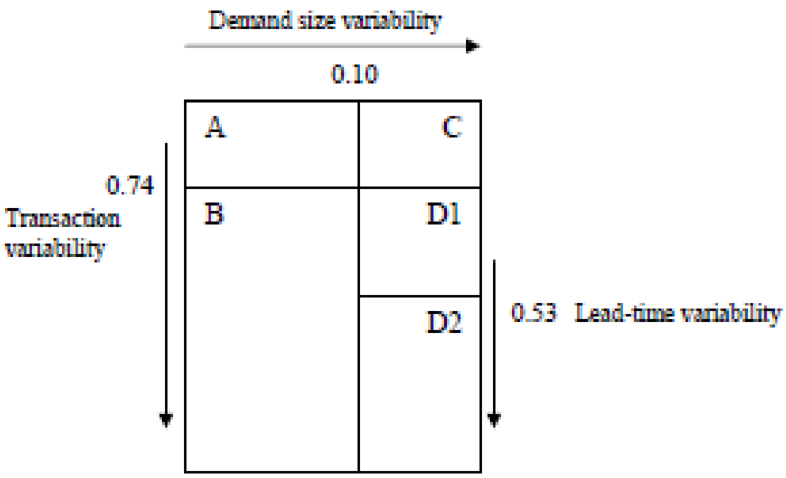

Figure 2.2 Eaves' categorization scheme [17]

2.2.2.4 Syntetos and Boylan Categorization Scheme (2005)

Mean square error measure is employed to determine the demand categories by comparing forecasting methods [18]. Croston's method bias can be reduced by Syntetos Boylan method and they generated four categories of demand, namely: erratic, lumpy, smooth, and intermittent. Categorization scheme considers the mean inter-demand interval and the squared coefficient of variation of demand sizes when demand occurs. Their comparison between the mean standard error performances of Croston's method, EWMA and the Syntetos Boylan methods are compared by using mean square error measure and cut-off values are suggested as the average inter-demand interval (ADI)= 1.32 and the squared coefficient of variation (CV^2)= 0.49 [19]. 3000 SKU from the automotive industry is employed to test validity and results give that Syntetos Boylan method is better in non-smooth demand while Croston method is better in smooth demand.

The categorization is based on the characteristics of demand data that are derived from two parameters: ADI and CV^2. ADI is defined as the average number of time periods between two consecutive demands.

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

where N indicates the number of periods with non-zero demand and t_i is the interval between two successive demands. The CV^2 is defined as the squared of the ratio of the standard deviation of the demand data divided by the average demand which shows the variability of demand.

$$\mathrm{CV}^2 = \frac{\sum_{i=1}^{n}(D_i - \bar{D})^2}{(n-1)\bar{D}^2} \tag{2.2}$$

where n is the number of periods, D_i and $\overline{D}$ are the actual demand in period i and average demand, correspondingly. Cut off values and Syntetos and Boylan categorization scheme are given in Figure 2.3 [18].

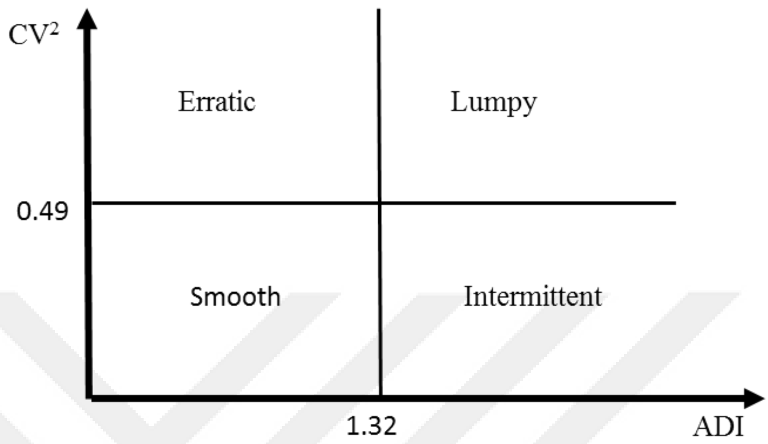

Figure 2.3 Syntetos and Boylan data categorization scheme

If the average number of time periods between two successive demands is higher than ADI cut off value which is 1.32 and the coefficient variation of non-zero demand sizes is higher than the corresponding value which is 0.49 demand data is categorized as lumpy. Other demand categories are identified in the same way as given in Syntetos and Boylan categorization scheme. There are four categories based on demand size variation and average non-zero demand interval in this scheme.

Demand patterns are classified according to the results by comparing forecasting methods to build superior performance areas [1]. Each demand categories can be described in the following section as they are in literature.

Smooth Demand

If the square of the coefficient of variation is lower than 0.49 and the average inter-demand interval is lower than 1.32 cut off values this demand data is classified as smooth demand. If time is considered as a discrete and Poisson process, this type of demand data can be modeled as a Bernoulli process [20].

Intermittent Demand

If the square of the coefficient of variation is lower than 0.49 however the average inter-demand interval is greater than 1.32, this demand data is classified as intermittent demand. This demand type has not highly variable demand however it has many time periods having no demand. The definition of intermittent demand according to Silver (1998) is that ‘infrequent in the sense that the average time between consecutive transactions is considerably larger than the unit time period, the latter being the interval of forecast updating’ [13]. Intermittent demand is also defined in the literature as the inter-demand interval greater than 1.25 inventory review periods [1].

Lumpy Demand

If ADI is greater than 1.32 and also CV^2 is greater than 0.49; the demand data is classified as lumpy that has larger inter-demand interval and the variation of demand. Lumpy demand is defined as “items whose demand frequency is less than 4 times a year” [21]. Lumpy demand is the most problematic demand type for spare parts in forecasting and inventory management since it induces excessive stocks and low customer service levels [15].

Erratic Demand

If ADI is lower than 1.32 but CV^2 is greater than 0.49; the demand data is classified as erratic that has a higher variation of demand when demand occurs. Erratic demand is defined as “one having primarily small demand transactions with occasional very large transactions” [22].

2.2.2.5 Boylan, Syntetos and Karakostas Categorization Scheme (2008)

Syntetos et al. provided the categorization scheme; in comparison to it, two changes were made considering the criteria that are used of. After examining the group of the data in their case study, Boylan et al. made the decision of resetting the cut-off value of CV^2 from 0.49 to 0.32, since the demand size of nearly fifty percent of the first group of data had zero diversity [3]. Hence, while another group is named lumpy, this group is called slow differing from Syntetos et al. (2005)’s intermittent definition [18]. A criterion that the manufacturer was using took the place of the inter-arrival interval which Syntetos et al. (2005) applied [18].

The number of zero demand periods collected in the last 13 periods, along with the cut-off value that is 3 periods, is the criterion. In the separation of the normal demand from intermittent demand, this criterion plays a role. 16,000 SKUs from the automotive, aerospace and chemical industry are employed in this categorization scheme in that the Croston method, the Syntetos and Boylan for the non-smooth demand categories and Simple Exponential Smoothing (SES) and Simple Moving Average (SMA) for the smooth categories are compared for varies of cut-off values of zero demand periods in the last 13 months. Geometric root mean squared error (GRMSE) and the average mean absolute error (MAE) reveals less sensitivity through the selection of the cut-off values from 2 to 6 while the estimated accuracy is quite sensitive to the cut-off value from 7 to 13 with the fast increase prediction error.

2.2.2.6 Rossetti and Varghese Categorization Scheme (2009)

Non-smooth demands, which are present in very few units, mostly identified as slow demand [20, 16]. Slow demands usually stand for intermittent demands. Syntetos, by the way, defines erratic (or irregular) demand as having patterns with high variability in non-zero demands. The size of the demand is the basis of the description of both Syntetos and Silver et al.; on the contrary, there is not included demand occurrence in their definition [20, 13]. Varghese identified a bursty demand in their categorization scheme that successive periods of non-zero demand is taken into account. In literature, Rossetti and Varghese categorization scheme presents several demand scenarios that have intersection with intermittent demand and that are often used interchangeably: bursty demand, lumpy demand, slow demand, sporadic demand, erratic demand, intermittent demand which are illustrated in Figure 2.4 [23]. Lag 1 correlation between consecutive non-zero demands is considered in the intermittency examination for categorization [24].

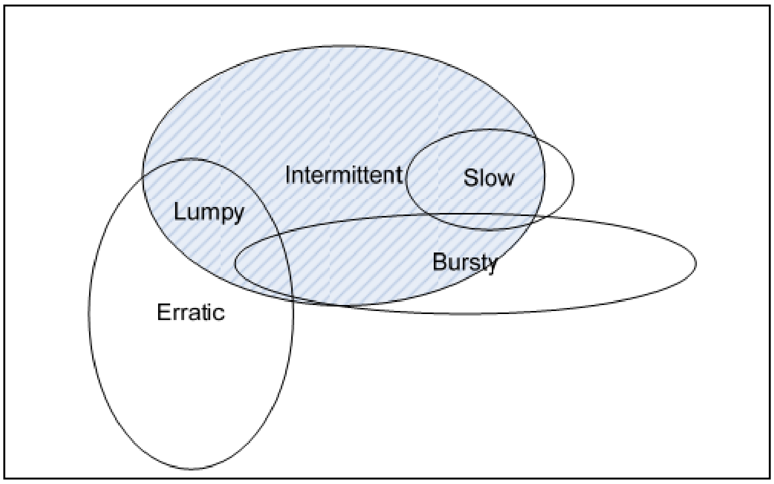

Figure 2.4 Rossetti and Varghese categorization scheme (2009) [23]

Series length, the seasonal period length, and the forecasting horizon are considered besides ADI and CV^2 of demand data when building up a forecasting strategy to select the best forecasting method [25, 26]. These studies aim the minimization of the forecasting error and classify demand data based on that comparisons. Inventory performance is considered in a study that is related to the Kolmogorov Smirnov (K-S) goodness-of-fit test to find the best-fitting distribution to data set they employed and compare the inventory implications of these distributions [27]. Syntetos et al. develop a categorization scheme to reveal which distribution fits the data set considering average inter demand interval (p) and coefficient of variation of demand sizes. In Figure 2.5, best fit distributions are classified. If CV^2 low and p is low then the best fit distribution is normal. If CV^2 is low and p is high then Poisson distribution fits. If p and CV^2 is slightly high then the negative binomial distribution or stuttering Poisson may fit. If p and CV^2 is high then Gamma distribution fits.

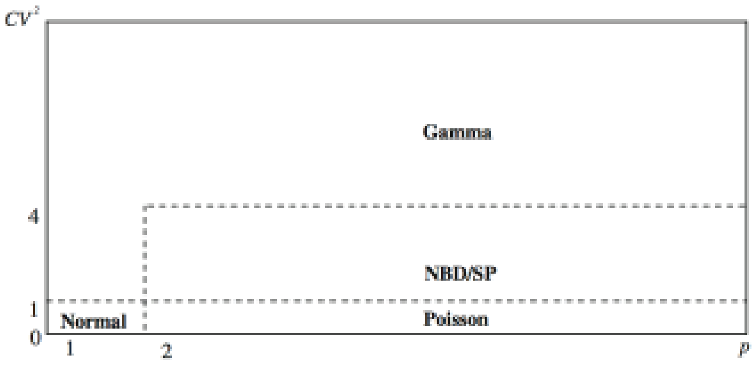

Figure 2.5 Syntetos et al. distributional assumptions (2011) [28]

Syntetos et al. examined if there is a linkage between the goodness-of-fit of a distribution and the inventory performance of it when it applied to inventory policy. However, the best distribution fit into data set could not mean it will give high inventory performance [28].

An alternative classification scheme based on the mode and CV^2 of demand is proposed by Lengu et al. Based on these two parameters, different types of compound Poisson might be used [29]. In order to increase forecasting accuracy, another scheme is proposed by Kostenko and Hyndman. They compared forecasting methods by investigating the implication of CV^2 and employing mean squared error [30]. In another study, classification results are investigated by empirically on more than 10.000 SKUs from different industries. This comparison results give the advantages of the methods [31].

So as to classify and plan spare parts inventory, demand classification procedure is developed by employing real data set. Laplace model reveals that the best inventory performance when it is compared to a normal distribution. Laplace and Gamma models give better results considering the service level and inventory cost measures [32]. Since inventory cost calculations are difficult and unclear, dynamic re-order policies are investigated using non-smooth demand data and management approaches are compared based on average inventory level, average and maximum stock out situation [33].

2.3 Demand Forecasting

Demand forecasting is fundamental for planning, control and managerial activities of the inventory to establish ordering decisions and meet customer satisfaction [34, 35]. Inaccurate demand forecasting may cause high inventory levels, storage costs, backorder costs and low customer service levels [36, 37, 38, 39]. As the demand history is getting longer, quantitative forecasting might be effective. If the demand history is short, quantitative forecasting with the combination of judgmental forecasting might increase the performance of forecasting [40]. Since the demand nature of most of the parts in inventories is non-smooth, forecasting them is getting complicated [41].

Forecasting methods accuracy is closely related to the demand pattern, inventory planning and spare parts availability. In order to increase the availability of spare parts and decrease inventory costs, forecasting methods with the highest accuracy could be employed in the system. Ever since Croston's study of intermittent demand forecasting in 1972, forecasting guidance in inventory planning systems are investigated rarely in literature even intermittent demand data can be seen in most of the spare parts in inventory [42, 43]. In this regard, there are two approaches suggested by some researchers to the issue: one is the proposed methods to forecast non-smooth demand, and the other is the focus on the management of the industrial resources when faced with an irregular demand to provide a competitive advantage [5]. It can be claimed that the control of inventories of non-smooth demand SKUs is the focus of the most studies in this field, with the assumption of a proper estimator to forecast future demand [44, 45]. Companies have the aim of demand forecasting with high accuracy to reduce inventory costs and satisfy customers. Forecasting methods can be divided into three categories in general as the following:

1. Causal methods
2. Time-series methods
3. Judgmentally methods

2.3.1 Causal Methods

Causal methods are employed to find out the relationship between independent and dependent variables. These methods are applicable when there are not many historical data available. Defining most effective factor and the relation between the factors could help to forecast demand. For instance, spare parts demand has a relationship with the past usage such as flying hours, aircraft age. Spare part need can be determined by some factors or variables such as variance, average demand interval, and usage [25].

2.3.2 Time Series Based Forecasting

Time series forecasting methods are assumed that future values of demand data can be estimated using the historical data, as demand may represent the same pattern in future as well [46]. These methods are generally employed to forecast spare parts if there is sufficient historical demand data [47]. If there is a relationship in specific time periods and can be explained statistically, using these methods is reasonable. Moving Averages, Exponential Smoothing, Holt’s method and Winter’s method are traditional forecasting methods that are developed for smooth demand data in the literature. For non-smooth demand data, different forecasting methods are needed which will be discussed in sub-sections.

2.3.2.1 Moving Averages

The average of a group of the data within a particular time period is called as simple moving average. With the passing of time, the earliest data is excluded from the moving average calculation and leaves its place to the most recent data. What enables the moving average to "move" is that procedure by which it keeps progress. Each value has the same effect and the number of time periods in past is taken between 2 to 12. If the period length is taken as small, results might be sensitive than the large time periods for average calculations. By giving more weight to last observations results might be obtained as responsive to provide a competitive advantage. This modified moving average is named as weighted moving average.

2.3.2.2 Exponential Smoothing

Exponential smoothing method is a special sort of method that is applied to smooth data to forecast demand using time series data. Also, in the estimation of intermittent demand, this method might be applicable. When there is the need for well direct forecasts in the short term, exponential smoothing methods are appealing. More emphasis is placed on the demand by this method in more recent periods and less in earlier periods incrementally. Exponential smoothing, or infrequently, the exponentially weighted moving average is a favored way for taking the benefits of the weighted moving average approach in which the forecasting procedure is simple and easy to use. In its straightforward computational version, α is defined as a parameter, the name of which is the smoothing coefficient, smoothing factor or smoothing constant, in the forecast of the next period of time which forms a weighted combination of the last experience and the last prediction.

The expert opinion and the nature of the demand data are the parameters that determine the choice of an appropriate value. It would mean the relative importance placed on the recent data in the series. For instance, if α of 0.2 is used, each successive forecast consists of 20% of the most recent data and 80% former data. In the formulation of the exponential smoothing is given by, where F_t denotes the smoothed estimate, X_t the actual value at time t and α is the smoothing factor, which has a value between 0 and 1.

$$F_{t+1} = \alpha X_t + (1-\alpha) F_t \tag{2.3}$$

2.3.2.3 Double Exponential Smoothing

If demand data has a trend, forecasting method considers the effect of trend and in order to avoid to overestimate it, there is one parameter related to a trend that is added to forecasting method. Double exponential smoothing has two smoothing constants, α and β: α is for the size of series and β for the trend seen in demand.

S_t is the value of intercept at time t and G_t is the value of trend at time t. Formulations are given as the following:

$$S_t = \alpha X_t + (1-\alpha)(S_{t-1} + G_{t-1}) \tag{2.4}$$

$$G_t = \beta(S_t - S_{t-1}) + (1-\beta) G_{t-1} \tag{2.5}$$

The τ-step forecast made in period t is:

$$F_{t,t+\tau} = S_t + \tau G_t \tag{2.6}$$

2.3.2.4 Box-Jenkins Methods

In 1970, George Box and Gwilym Jenkins have developed the Box and Jenkins methodology. In the process of finding the optimal representation of these series, the ARMA or ARIMA (autoregressive integrated moving average) models are made use of. In other words, an ARIMA model is used to forecast by depending on a proper ARIMA procedure which fits the data. This methodology is able to propose flexible models, which makes ARIMA model the leading way in the identification of the data. Model selection, parameter estimation, and model checking are the three-stage process of Box-Jenkins modeling technique. There is also a prior stage of data preparation and a final stage of model application with the new enhancements of the process [48]. The notation of the ARIMA model is ARIMA (p, q) in which p represents the number of autoregressive parameters and q represents the moving average parameters.

Traditional time series methods are generally used for a smooth data type with the variety of methods based on data characteristics. Appropriate variants for trended, damped trended and seasonal data generally accompany traditional time series methods for estimating these types of demand. On the other hand, inaccurate forecasts cause these variants to be mostly inapplicable for the non-smooth demand type. The method that will be used to forecast non-smooth demand should be chosen by considering the characteristics of the demand pattern. Hence, when it comes to forecasting non-smooth demand, the nature of data pattern need some special methods. The following sub-section give the details of the fundamental forecasting methods that are developed for non-smooth demand type.

2.3.2.5 Croston's method

The first method that is developed for low size and infrequent demand forecasting is Croston; especially it is claimed that Croston's method can be more appropriate for non-smooth demand type and application of this method is preferable than exponential smoothing or traditional time series methods when there is irregular and problematic demand data. The non-zero demand size and the inter-arrival time between sequential demands, by the application of exponential smoothing individually, are forecasted with predictions that are refreshed right after demand occurrences in Croston's method. The inter-arrival time refers to the period between two successive non-zero demands [49]. The notation for Croston method as follows:

Y(t) is the estimation of the demand size of a nonzero demand at time t,

P(t) is the estimation of the interval between nonzero demands at time t,

α is the smoothing parameter,

X(t) is the demand data at time t,

Q is time interval from the last nonzero demand.

Croston forecasting method procedure is given in Figure 2.6.

$$\begin{array}{l}
\text{If } X(t) = 0 \text{ then} \\
\quad Y(t) = Y(t-1) \\
\quad P(t) = P(t-1) \\
\quad Q = Q + 1 \\
\text{Else} \\
\quad Y(t) = \alpha X(t) + (1-\alpha)Y(t-1) \\
\quad P(t) = \alpha Q + (1-\alpha)P(t-1) \\
\quad Q = 1
\end{array}$$

Figure 2.6 Croston's methodology

The forecast of mean demand per period;

$$F(t) = \frac{Y(t)}{P(t)} \tag{2.7}$$

Croston method updates Y(t) and P(t) estimations if nonzero demand occurs. If zero demand occurs, only Q parameter is updated. The assumption made in this method that the demand occurrence is Bernoulli process and intervals between successive non-zero demands are distributed independently and identically [49].

2.3.2.6 Syntetos and Boylan Variation of Croston's Method

Croston's method's estimation of demand per period is not giving accurate results and it is found as positively biased [15]. Croston method is also not suitable to overcome stock out cases since the method is not updating after zero demand [50]. Syntetos and Boylan modified the Croston's method to avoid bias effect by adding a parameter. Croston's per period estimation is given;

$$E(X_t) = E\left[\frac{Y_t}{P_t}\right] = \frac{E(Y_t)}{E(P_t)} \tag{2.8}$$

If estimators of demand size and demand interval are independent as assumed in Croston paper, bias rises as given;

$$E\left[\frac{Y_t}{P_t}\right] = E(Y_t)E\left[\frac{1}{P_t}\right] \tag{2.9}$$

$$E\left[\frac{1}{P_t}\right] \neq \frac{1}{E(P_t)} \tag{2.10}$$

Syntetos and Boylan suggested a new forecaster given as:

$$SB_t = \left(1 - \frac{\alpha}{2}\right)\frac{\hat{Y}_t}{\hat{p}_t} \tag{2.11}$$

where α is the smoothing constant employed to update the inter-demand intervals.

2.3.2.7 Leven-Segerstedt Variation of Croston's Method

Croston's method is revised in a way that aims to create a method which would work for both slow and fast moving items by Levén and Segerstedt. Their method is updated by this revision as follows:

$$LS_t = \alpha\frac{Y_t}{p_t} + (1-\alpha)LS_{t-1} \tag{2.12}$$

Yt demand size at time t when demand occurs and Pt is the interval between nonzero demands and α is the smoothing parameter.

Leven's method is found that have high mean square forecast error than the original Croston method besides the bias of the Leven is higher than the Croston method [51].

2.3.2.8 Size Interval Method

The Size-Interval method (SI) was offered to satisfy intermittent demand requirements by Johnston and Boylan [1]. Croston's demand estimates from fundamental elements are the base of this method. The demand arrival process is presumed Poisson distribution rather than Bernoulli and eventually, the exponential distribution was better than the geometric one in the inter-demand intervals. About theoretically produced demand data over a great variety of possible occurrences, the comparison is made between their method and EWMA (Exponentially Weighted Moving Average). These potential occurrences can be specified as different average inter-demand intervals (negative exponential distribution), smoothing constant values and sizes of demand [1]. With the inter-demand intervals which are greater than 1.25 forecast revision periods, SI method seems to be preferable comparing to EWMA.

2.3.2.9 Snyder's Method

Snyder suggested a forecasting and inventory control method that considers smooth and non-smooth demand data [4]. Parameters can be defined as;

$\widehat{Y}_t$: The forecasted demand,

X_t : Binary random variable from Bernoulli distribution,

ε_t : Error of normal distribution with mean 0 and variance σ^2,

μ_t : Actual demand at time t,

Smoothing equations are given as below;

$$\widehat{Y}_t = x_t\mu_{t-1} + \varepsilon_t \tag{2.13}$$

$$\mu_t = \mu_{t-1} + \alpha\varepsilon_t \tag{2.14}$$

ε_t and x_t are generated employing the parametric bootstrapping approach to determine $\widehat{Y}_t$ for each time index. Though, it allows the occurrence of negative forecasted values. Snyder recommended to apply logarithms to the data in order to change the negative values to zero.

2.3.2.10 MCARTA

Time periods with zero demands make traditional methods inadequate for the modeling of the non-smooth type of demand. For this problem, Varghese came up with two algorithm stages which generate demand, demand occurrence and determine nonzero demand sizes [20].

Y_t is modeled as a function of the squared coefficient of variation CV^2 ($Y_{t,NZ}$), lag 1 correlation coefficient of nonzero demand $\emptyset_{1,NZ}$ and probability of zero demand π_z at time *t*. To integrate the probability of zero demand, $X_t \in \{0,1\}$ and $\{X_t: t \in I^t\}$ is a stochastic process to the occurrence of demand in period *t* and I^t is the set of times that demand is occurred. The demand occurrence process was modeled as the two state Markov chain process, where, $p_{ij} = P\{X_t = j|X_{t-1} = i\}$ denotes the transition probabilities. Autoregressive to Any Algorithm (ARTA) is applied that generates correlated demands $Y_{t,NZ} \sim \text{ARTA}\,(G(Y_{NZ}), \emptyset_{1,NZ})$ with correlation coefficient $\emptyset_{1,NZ}$ and geometric distribution [20].

Traditional statistical forecasting methods presumed that the probability distribution of total demand is corresponding to the normal distribution for smooth demand type. Unfortunately, according to some, it doesn't correspond to any basic distribution completely. Thus choosing which distribution model corresponds in the best way to the aforementioned type of demand is mandatory.

Despite the fact that any parametric forecasting approach considers distributional fitting assumptions, this does not satisfy the need. The obscurity of demand distribution leads to modeling free approach. The succeeding section focuses on the details of the relationship between nonparametric method and intermittent demand forecasting.

2.3.2.11 Non-Parametric Forecasting by Bootstrapping

The effectiveness of any parametric approach becomes compelling to fit the standard theoretical distribution as the data becomes more irregular. A debatable notion on this topic is that using non-parametric bootstrapping approaches would let the further developments be reached when there is lumpy demand. Non-parametric bootstrapping approaches, which depend on a random sampling of individual observations from the demand history with an aim of creating a histogram of the lead time demand distribution. The most important assumption in non-parametric bootstrapping approaches is that the demand seen in the past will most probably be seen in the future as well [52]. Notable literature, which concerns with bootstrapping approaches for forecasting intermittent demand items [4, 53, 54], are followed the stimulating work of Efron [55]. The work of Willemain et al. that was published in 2004 became the most noteworthy work of that time, in that work the authors defended that forecasting accuracy contributions were reached over parametric approaches [53]. However, calculations of non-parametric bootstrapping are complicated and not to easily applicable in industry. Additionally, advantages of this method over the other classical methods are doubtful [56].

2.3.2.12 Willemain's Method

Willemain et al. apply bootstrapping and jittering as a model-free method in intermittent demand forecasting by simulating of a whole distribution for lead-time demand rather than a point forecast. This is also a combination of the Markov process. Markov model provides transition probabilities for two states after receiving historical demand data.

Following, Markov equations which rely on the last demand produce a sequence of zero and nonzero values. This process continues with selecting random non zero demand values from historical data and using them for non-zero states. Non-zero demand's neighborhood values ensure more instability abiding by demand data. Jittering is a way of obtaining non zero demand values which have not appeared before. The sum of the predicted values over the forecast horizon is needed for getting the lead time demand (LTD) forecasts. The related distribution that fits the data could be found by sorting the LTD values [53].

2.3.2.13 Hua's Method

Hua et al. established an integrated forecasting method (IFM) by integrating autocorrelated demand process over lead time and the relationship between explanatory variables and nonzero demand in order to forecast non-zero demand during lead time. Hua et al. also offered two methods to evaluate forecasting methods. In their forecasting method, they applied the first order of Markov process. In this process, the first thing to do is determining the nonzero demand and then the distribution of the lead time. The user determines a variable for modifying the nonzero demand, and then the lead time distribution is predicted by bootstrapping. They compared the integrated method with Exponential Smoothing, Croston and Modified Bootstrap (MB), which is similar to the Willemain's bootstrap method except for jittering method. Over an eight-month time span, the MB performed dramatically worse than IFM when employed newly developed average the error ratio of occurrences of nonzero demand judgments over lead time (AERNJ) measure, data set was selected based on 40 sorts of spare parts from a petrochemical company in China. Further, MB was less competent at forecasting occurrences of nonzero demand than IFM. It turned out that IFM was superior at forecasting LTD when compared with the three other forecasting methods that were aforementioned [57].

2.3.2.14 Neural Networks

One of the areas that neural networks is also used in recent years is the spare parts forecasting. Linking inputs and outputs adaptively in quantitative models during a learning process is a common feature in both neural networks and the human brain. The parts of a network are basically units, labeled neurons, joined by a set of rules and weights.

The process of analyzing the data takes place along different layers, while learning occurs with the modification of the weights linking the existing units in layers. The final iteration is the phase, in which the connection between the input and output layers is constituted. In that context, the study conducted by statisticians, engineers, and mathematicians in the field remains dynamic.

Carmo and Rodrigues employed a Radial Basis Function (RBF) network and elliptical basis function networks with the aim of practicing ANN modeling in their implementation of Gaussian radial in the former and producing better predictive performance than alternative models for the latter [58]. A multilayer perceptron (MLP) which was developed by a back-propagation (BP) algorithm was the most widely used method. Gutierrez et al. followed that method and suggested an estimation of if the ANN-based approach is a preferable alternative for traditional approaches to model and forecast lumpy demand [59].

There is made a comparison between traditional methods and neural networks by Amin-Naseri and Rostami Tabar [60]. They put into practice both generalized regression neural network (GRNN) and Elman recurrent neural network (RNN) to predict the lumpy demand of spare parts. It is indicated in their study that accurate forecasting might be obtained by applying neural networks.

A hybrid forecasting approach, which includes a multi-layered perceptron neural network and a traditional recursive method to predict future demands, is one of the latest research in the field by Nasiri Pour et al [61]. It takes the characteristic of lumpy demand patterns of spare parts as its basis. In the forecast of the existence of non-zero demands, Nasiri Pour et al. prefer the multi-layered perceptron neural network, while in the prediction of the volume of non-zero demands they use a traditional recursive method. Their combined technique was compared to Syntetos and Boylan method. The comparison is also made between that technique and recently developed neural network models, which are as follows: multi-layered perceptron neural network, generalized regression neural network, and Elman recurrent neural network. More accurate forecasts were indicated in the study of Nasiri Pour et al. even there were traditional methods.

In one of the recent studies, ANN forecasting techniques were employed by defining different types of inputs based on the characteristic of spare parts demand patterns. Their study compared the performance of ANN to exponential smoothing, Croston, Syntetos&Boylan and Leven&Segersted methods. Their models were applied to different types of real data that are from a major airline company in Turkey. After evaluating the performance of models based on MSE criteria their proposed method gave better results than other forecasting methods [62].

2.3.2.15 Teunter-Syntetos-Babai (TSB) method

Another modified forecasting method is developed by Teunter et al. for non-smooth demand data considering inventory obsolescence [50]. In this method, instead of updating demand interval as Croston method, demand probability is updated. TSB method applies exponential smoothing to demand size and demand probability. This method is found unbiased and can be employed for inventory calculations since method updates parameters that are used in every period. Application of different demand size and probability parameters can provide a variety of calculations for forecasting and inventory management.

2.3.3 Judgmentally Forecasting

Demand forecasts can be adjusted by employing judgmental influences to reflect features of historical demand data that could not be considered. Manager's know-how can be used in judgmental forecasting of spare parts. In the first phase of the historical data (during initialization period), there is the need of expert's view. At this stage, judgmental forecasting comes into prominence beside the cases need judgmental adjustments where demand is forecasted by other time series methods.

Judgmental forecasting is commonly beneficial for strategic decisions while other quantitative methods are beneficial for operational decisions. If the quantitative methods are integrated with judgmental forecasting, inventory service level performance of forecasting methods can increase [63].

Recent studies in the literature on spare parts intermittent demand forecasting methods are given as; neural networks [64, 65, 66], support vector machines [67] and Bayesian method [68]. Modification of Holt's double exponential smoothing for intermittent demand is developed by Altay et al. compared the modified Croston method with the Wright's method and results show that Wright's method gives better service levels [69]. There is also two-step method that employs time series data with part consumption and repair information from aviation industry and method is found that significantly better than the Croston method [70]. Clint et al. developed a robust method that is involving preventive maintenance to conduct a relation between demand size and inter-arrival time of demand and they compared with current forecasting and bootstrapping methods [71].

2.4 Forecasting Performance Measures

If the demand shows an irregular pattern it is needed to be forecasted with high accuracy and interpreted the forecast error results reasonably which is challenging task. The difficulty of describing it leads to a requirement for relative performance measures which refers to the forecast errors on a comparative basis [72].

Conventional performance measures report that traditional forecasting methods fall behind the Croston-type methods. The ascertainment of consistently superior performance in Croston-type and traditional methods has rarely taken place in literature considering inventory performance. The performance of Croston-type methods are found better on average in many research studies [73, 72, 74]; yet still, the better results could be obtained by the traditional methods [75]. In the measurement of the accuracy of forecasting techniques, traditional performance measures or performance measures that are developed for non-smooth demand are employed by researchers regardless of the forecasting method. These forecasting accuracy measures in literature are given in sub-section.

2.4.1 The Mean Deviation (MD)

The calculation of the arithmetic average of forecast errors gives a simple error statistic, the mean deviation is an example of which. In the characterization of the bias of a forecasting method, it is applied. The value that the mean deviation will take depends on two factors. When the forecast underestimates the actual, it takes a negative value; on the other hand, it takes a positive value when the forecast overestimates the actual. Small mean deviation stands for the bias; it does not mean the dimension of the errors.

Mean deviation can be defined as;

$$MD = (1/n)\sum_{i=1}^{n} e_t \tag{2.15}$$

e_1, e_2 . . . e_n are the forecast errors observed over n periods.

2.4.2 The Mean Absolute Deviation (MAD)

Canceling out the problem by averaging the exact value of the errors is the concern of the mean absolute deviation. In this way, disregarding whether the status of the estimation is under or over, the MAD represents the average size of the errors. Since it is straightforward to calculate, it is widely held error measure in forecasting methods and inventory systems. MAD calculation is given as the following;

$$MAD = (1/n)\sum_{i=1}^{n}|e_i| \tag{2.16}$$

$e_1, e_2 \ldots e_n$ are the forecast errors observed over n periods.

2.4.3 The Mean Squared Error (MSE)

Averaging the squares of the forecast errors is the method that employed to calculate the Mean Squared Error. Similar to MAD, that method gets rid of canceling out the problem. The MSE equals to the variance of the forecast errors and it is suitable for measuring errors in terms of statistics. For a given item, that method is mostly used in the comparison of the accuracy of various forecasting methods, the aim of it is finding the best method that minimizes the MSE. It can be defined as;

$$MSE = (1/n)\sum_{i=1}^{n}e_i^2 \tag{2.17}$$

$e_1, e_2 \ldots e_n$ are the forecast errors observed over n periods.

2.4.4 The Root Mean Squared Error (RMSE)

The Root Mean Squared Error is basically the square root of the MSE. RMSE denotes the standard deviation of the forecast errors. It is more utilizable to comprehend variations in error. RMSE is defined as the following;

$$RMSE = \sqrt{(1/n)\sum_{i=1}^{n}e_i^2} \tag{2.18}$$

$e_1, e_2 \ldots e_n$ are the forecast errors observed over n periods.

2.4.5 Mean Absolute Percentage Error (MAPE)

The absolute size of each forecast error can be indicated as a percentage of the actual demand and then, in MAPE calculation, these data are averaged. When any pattern is observed in a time series, the noise influences the forecasts in the long term. Thus, calculating the noise to be accurate is a requirement in the long term. Time series which contains any pattern is specifically suitable for the application of MAPE. It is represented as follows;

$$MAPE = \left[(1/n) \sum_{i=1}^{n} \left| e_i / D_i \right| \right] \times 100 \tag{2.19}$$

e_1, e_2 . . . e_n are the forecast errors observed over n periods and D_t is the demand data at time *t*.

2.4.6 Modification of MAPE

Mean absolute percentage error states that accuracy as a percentage of the errors. Since non-smooth demand has many time period zero value this equation is unsuitable that need some modification. Makridakis proposed a substitute accuracy measure to avoid zero division error given as; Symmetric MAPE (sMAPE) [76]:

$$sMAPE = \frac{1}{n} \sum_{t=1}^{n} \frac{|Y_t - \hat{Y}_t|}{|Y_t + \hat{Y}_t|/2} \tag{2.20}$$

where n is the number of forecasts in the error measure, Y_t is the actual demand and $\hat{Y}_t$ is the forecast of demand at time *t*.

The sMAPE is estimated as 200 percentages for any period by Boylan and Syntetos, on the condition that the actual demand is zero, disregarding the error size. The sMAPE could be discussed for its lacking of providing a reasonable comparison of forecasting methods. This makes it unfitting for non-smooth demand [72].

2.4.7 Mean Absolute Deviation to Average (MAD/A)

Mean absolute deviation is straightforward accuracy measure that is applicable to any data type. General equation of the mean absolute deviation (MAD) measure given as;

$$MAD = \frac{1}{n} \sum_{t=1}^{n} \left| Y_t - \hat{Y}_t \right| \tag{2.21}$$

The division by zero problem occurs in this measure, as well. There are four alternatives suggested to overcome this problem, they are as follows: the MAD/Average ratio, the geometric mean absolute error, percentage better method, and the mean absolute scaled error. MAD/A calculation is given as the following;

$$\frac{\mathrm{MAD}}{\mathrm{Average}} = \frac{\frac{1}{n}\sum_{t=1}^{n}|Y_t - \hat{Y}_t|}{\frac{\sum_{t=1}^{n} Y_t}{n}} \tag{2.22}$$

where Y_t represents the demand at period t and $\hat{Y}_t$ represents the forecast made for the period t, n is the number of the demand periods.

The assumption of the MAD/A that the data is constant over time was acknowledged by Hyndman. Lack of consideration of seasonality might cause this measure to be unreliable for seasonal non-smooth data [77].

2.4.8 Geometric Mean Absolute Error (GMAE)

Boylan and Syntetos emphasize that GMAE is tender to zero errors and robust to outliers [72]. One absolute accurate forecast is the result of the zero value of the GMAE without considering the size of the other errors. GMAE is given as below;

$$GMAE = \left(\prod_{t=1}^{n}|Y_t - \hat{Y}_t|\right)^{1/n} \tag{2.23}$$

where Y_t represents the demand at period t and $\hat{Y}_t$ represents the forecast made for the period t, n is the number of the demand periods.

2.4.9 Geometric Mean of the Arithmetic Mean of the Absolute Errors (GMAMAE)

No matter how the problem size, the geometric mean (based on series) of the arithmetic mean (based on time) can be applied by the use of the forecast errors. GMAMAE provides the error calculation of the multiple series as the following:

$$GMAMAE = \left(\prod_{i=1}^{N}\left(\frac{1}{n_i}\sum_{t=1}^{n_i}|Y_{it} - \hat{Y}_{it}|\right)\right)^{1/N} \tag{2.24}$$

where Y_{it} represents the demand of i^{th} data series at period t and $\hat{Y}_{it}$ represents the forecast made for the demand of i^{th} data series at period t, n is the number of the demand periods, N is the number of data series that is evaluated.

This measure is robust for high forecast errors provided that the remaining errors are steady. It measures the performance of the multiple series at once and also it is not severely affected by trend or seasonality [72].

2.4.10 Percentage Better (PB)

In the measurement of the non-smooth demand data, percentage better method acts as an alternative which is convenient. One forecasting method and another can be compared to find out the method which gives the least error by employing any performance measure [7].

2.4.11 Mean Absolute Scaled Error (MASE)

MASE (mean absolute scaled error), a new error measure for non-smooth demand, was suggested by Hyndman [77]. He scaled the errors based on the MAD from the naive forecasting method in that measure. MASE is the robust measure for outliers and applicable for all different types of data series. It is formulated as below;

$$\text{MASE}=\text{mean}(|q_t|) \tag{2.25}$$

$$q_t = \frac{Y_t - \hat{Y}_t}{\frac{1}{n-1}\sum_{i=2}^{n}|Y_t - Y_{t-1}|} \tag{2.26}$$

where Y_t represents the demand at period t and $\hat{Y}_t$ represents the forecast made for the period t, n is the number of the demand periods.

Teunter and Duncan claim that inappropriateness of the traditional forecast error measures. In their study, Croston's method and bootstrapping give better inventory performance results than the Moving Average and Exponential Smoothing [78]. In order to avoid the negative effect of zero demand, aggregating demand method is employed by some of the authors in literature. 5000 SKUs from Royal Air Force is used to decide the optimum aggregation level and moreover the possible effects of aggregating demand during the lead time and review period [79]. Aggregating demand estimates during lead time might be used in periodic inventory management system. Traditional forecasting error measurements (mean absolute deviation and mean square error) are evaluated as well as newly generated error measurements such as periods in stock and number of shortages in their study. It is found that forecasting method's performance is closely related to the error measurement that is employed [80].

Snyder and et al. generated a performance measure which is related to the whole estimate distribution instead of the point estimation. They compared three models on 1046 automobile parts and results indicate that inventory planning should use dynamic models that are handling distributions in a more flexible way rather than Poisson [81]. Spare parts demand gives a skewed lead-time distribution for reasonably short lead-times while the distribution is getting symmetric for long lead times [26].

2.5 Inventory Management for Spare Parts

The dilemma of determining the amount of the order that will be placed on a regular principle or the consistency of the order stems from the inventory policy that employed. There are various scenarios applied in order to obtain optimal solutions [82]. Regarding the spare parts inventory basis, forecasting the demand becomes essential because of the relation of developing an estimation of spare parts demand [83]. At this point, it is important to realize that demand forecasting and stock control, each of them, are often analyzed independently. There are little theoretical and experimental studies concentrating on the relation between them in the academic literature until now from Croston's work, no matter how much it has been emphasized. The control of inventories is the focus of many studies, which adopt the idea that a convenient method of forecasting is in the position of estimating future demand [84, 85]. The relations between forecasting and inventory decisions have been the studied in a few research studies. In this regard, [49], [86] and [85] illustrated that errors in forecasting could misguide customer service estimates. The idea of forecast accuracy splitting from the inventory control performance of the estimators applied [75, 42] is accepted by the minority of scholars. Boylan and Syntetos claimed the standpoint of the inventory planner to be the service level based inventory performance or inventory costs based performance [72].

There are also works in which empirical investigations have been studied regarding the performance of various intermittent demand forecasting methods [53] and [7] conducted by some researchers. On the other hand, there are not many studies carried out about the effect of adjusting intermittent demand forecasts, the aim of which is to incorporate qualitative information. This feature of that qualitative information is not being apprehended by the computerized application at issue. The measures for the results of the comparison are linked with forecast accuracy. However, they just disregarded the implications of that accuracy to inventory costs.

Boylan and Syntetos also claimed that the aforementioned naive method is sensitive regarding large demands and therefore results in high forecasts, which will surely lead to over-stocking and obsolescence in the case that is applied [72]. The risk of depending on statistical error measures merely is emphasized in that instance. Hence, considering the stock-holding and service implications of different forecasting methods is always necessary. It is also important to note that improved stock control performance is not transformed by the improvements in forecasting accuracy, but the forecast error measures are often used in the analysis of problems regarding forecasting methods and stock control performance.

Over the period of six years, Teunter and Duncan operated on UK Royal Air Force data for 5000 items with the aim of comparing forecasting methods specified for spare parts [78]. The intention of their study is to meet service-level expectations and minimizing stock levels at the same time. They conducted a study comparing six different methods of forecasting demand. The relative geometric root mean square error (RGRMSE) which is for calculating the performances of two methods is used for the first five methods. The zero forecast method gave the most accurate results when the RGRMSE was applied, though the scholars claimed that it is not possible to measure forecasting methods performance firmly considering such error measures. Teunter and Duncan showed that the original Croston's method is identical to the Syntetos & Boylan and the Leven & Segerstedt variants by using a new performance measure that is based on the comparison of the achieved service level to target [78].

2.5.1 Inventory Policies

Inventory policies include ordering and review procedures to meet demand needs in the management of the inventory (at which time and how much orders should be placed). The most frequently used policies are the following [9];

Periodic-Review Policy

Equal intervals of time are counted under this policy. *T* is the interval that indicates the review period length. No action is taken if the inventory level exceeds a predetermined reorder level at the end of period t. An order is placed to bring the inventory to the target, which is the maximum level in the case that inventory level is less than the reorder level.

There is a special type of periodic review policy. After setting the reorder level to equal the maximum level, an order is placed at the end of period *t*.

Continuous Review Policy

When the inventory level decreases to the reorder level or below, continuous observation of the inventory level and the placement of size order occur. What differentiates this policy form the periodic review policy is the fact that under this policy, orders are placed when the inventory decreases to the reorder point or below of it. However, under the periodic review policy, the placement of the order at the end of the period is dependent on the inventory level.

Fixed-Reorder Quantity Policy

The difference between fixed-reorder and continuous review policy is that under this policy, the units are taken out from the inventory one by one. Thus, if the inventory level declines to the reorder point, it can be easily monitored. As a result, when there is equivalence between the inventory and reorder point, a fixed order size is ever placed.

Base Stock Policy

The reorder level is equalized to the maximum inventory and orders are placed following the withdrawals from the inventory within this policy. Hence, the base stock level means the maximum level of inventory. The difference between base stock level and inventory on hand is ordered.

2.5.2 Inventory System Performance Measure

Studies regarding the accurate demand forecasting are worked in order to bring efficient supply chain management. Gupta and Maranas claim that demand forecasting and supply network planning model could be used to minimize costs of the chemical industry when dealing with the demand uncertainty [87]. Each department in the firm would eventually get affected when accurate demand forecasting methods could not be applied by an organization for upcoming demands. Efficient system control is inhibited by also inaccurate forecasts, which lead to the very high amount of inventory costs and low service level. On the other hand, accurate demand forecasting increases the cash flow within the company, since it eliminates redundant costs. That makes it easier for the firm to allocate the aforementioned cash into other areas that might be needed and make investments to high technologies. High service level and low inventory costs are provided by accurate demand forecasting along with the minimum error. Thus, the first thing that should be done is minimizing inventory cost along with keeping forecast accuracy as high as possible.

It is of vital importance to consider the fact that stock control is not a determinant of the results of specific estimators when non-smooth demand forecasting is taken into account. Forecast accuracy was cleared up by few researchers. They explained that it needs to be distinguished from the employed estimators' stock control performance [88]. Even some researchers claim that such separation should be done, Boylan and Syntetos asserted that forecasting stock control process might be integrated with the measures associated with the inventory costs. They illustrated such relationship in Figure 2.7.

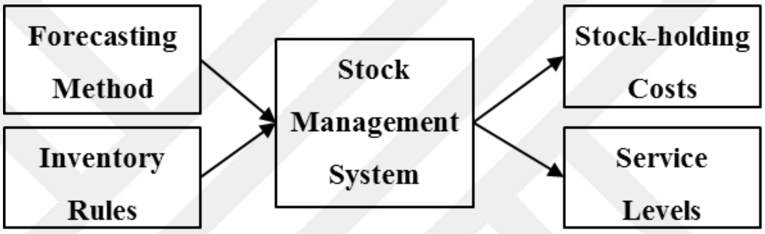

Figure 2.7 Inventory management for spare parts [89]

The interactions in demand forecasting and stock control systems are assessed in a simulation test environment employing real data set from different suppliers [90]. They reveal that forecasting error measures should not be evaluated to determine the best forecasting method. They need to be compared considering inventory performance measures as well.

Willemain et al. and Syntetos and Boylan carried out empirical studies using different intermittent demand forecasting performances [53, 7]. Boylan and Syntetos claimed that regardless of the inventory system that is used, the accuracy-implication metrics concerning the costs of stock-holding, stock-out and service levels need to be adopted because of the fact that this is the most important part of the organization [72]. Also, it is important to note that these measures would also be used when there is not the difficulty of assessing forecast error directly. "By keeping an inventory method fixed, accuracy-implication metrics offer a direct comparison of the effects of using different forecasting methods." [63]. The most important aspects of calculating inventory management system performances are stock-holding cost and service level measures. When calculating inventory costs, companies need more information [91]. Inventory costs can be divided three measures. First one is ordering costs arises if there is order. There might be a decrease in ordering costs if ordering amount is high and consolidated. The second measure is holding costs that increase by possessing the parts in inventory. Costs related to holding inventory might arise with the running warehouse, space that part locates and keeping parts in inventory in safe conditions. Perishables carrying risk need to be considered since it increases along with the inventory [92]. The third measure is stock out costs that arise if the part is not available even there is a need for the regarding item. If one practitioner would like to take advantage of high order quantities it appears to decrease stock out costs, on the other hand, this perspective can increase the holding costs. There should be a balance between holding, ordering and stock out costs that leads to inventory planners develop ordering strategy.

The two measures of part availability can be described as fill rate and cycle service level. The first one can be simplified as the fraction of the demand for an item which is successfully fulfilled in the form of item to item. The second one is basically the fraction of replenishment cycles that are satisfied and stock-outs are not present.

2.5.3 Spare Parts Inventory Planning Applications

Spare parts inventory planning concept has some drawbacks so that the requirement of holding service level in satisfied level with decreasing excessive stock in inventory. This requirement entails efficient inventory management with appropriate replenishment policy. Efficient inventory management is provided with demand forecasting and stock control interaction. Efficiency and inventory performance can be evaluated by employing different forecasting methods. In literature, some of the researchers acknowledged that inventory performance of forecasting methods should be different from the accuracy of these methods [93, 94]. It is essential to capture the forecasting and stock control interaction considering service level and inventory cost performance measures for non-smooth demand [72, 95]. Empirical performance of the forecasting methods with newly proposed Teunter Syntetos Boylan method (which rely on updating demand probability) considering different smoothing constants to investigate its effect on the inventory and forecasting accuracy performance is studied employing datasets from the military and automotive sector [96]. In another study, judgmentally adjusted forecasting methods' accuracy and inventory performance are evaluated by employing dataset from pharmaceutical industry considering different inventory measures [97]. Some of the studies take into account failure distribution of parts in inventory to estimate the need of those parts. Two non-linear models are applied to estimate the future demand considering the failure distribution of parts such that total cost is minimized by obtaining optimum ordering time and quantity [98]. Re-order point control policy is searched dynamically and the parameters for this policy is calculated based on target service level and its performance is measured employing data set from pharmaceutical sector [99]. Optimum order points are investigated with lead time demand modeling by applying different methods for non-smooth demand data type [100].

Lumpy demand is modeled as a negative binomial and worst case non-parametric model under the base stock inventory policy and these approaches are investigated for inventory control of non-smooth demand types [101]. The spare parts inventory control topic is reviewed in a study considering demand forecasting methods and inventory management combination by enquiring the parts need to be stocked and ordering amounts on real data set [102]. Inventory items are distributed based on the precedence of the customers and criticality level is set dynamically considering target service levels and backorder costs and the suggested policies are compared in one of the recent studies [103].

Saidane et al. established a model that is used base stock policy, claiming that base stock policy is commonly employed in spare parts inventory control. Their model assumed that demand intervals and sizes follow Erlang distribution and Gamma distribution respectively. They managed to decrease the optimal base stock level [104]. In one of the recent studies, lead time demand is calculated with extreme value theory considering expected waiting time and cycle service level measures and it increases inventory performance [105]. Lead time demand variance and re-order levels are adjusted by Prak and et al. and forecasting methods safety stock calculations are set and service level is decreased [106]. There is also new aggregation approach generated for non-smooth demand type and it reduces the variability in demand sizes and inventory performance is compared in defense and automotive industry [107]. Croston and non-smooth demand forecasting methods are employed to calculate order-up-to levels and other inventory parameters that achieve the target service level [108, 109]. In order to determine the inventory policy that is the most suitable and applicable to each spare part category, a simulation study is conducted by Jose and Marco. They employed three forecasting methods (Moving Average, SBA and newly generated bootstrapping method) and six lead time demand distributions under (s,nQ) inventory policy and four target fill rates. These combinations are investigated considering the measure of cost and realized fill rates [110]. Instead of selecting one target fill rate for all SKU's, it is proposed to give different fill rates for each SKU that meet the system target service level and decrease inventory investments [111].

Inventory cost is reduced by the generated nonlinear stochastic model and it aims to define the reorder points and increase the availability of parts in inventory employing ABC analysis and heuristic method [112]. Inventory cost is minimized in another study by applying the genetic algorithm for inventory control in supply chain [113]. Continuous tabu search metaheuristic is established to find out demand forecasting and inventory management policy that is most applicable and optimum [114]. Newly generated bootstrapping method by Wingerden et al. performs well for the demand type that has high demand interval and low demand variation considering inventory costs and fill rates [115]. Forecasting methods for spare parts, judgmentally adjustments to those methods and recent research including forecasting support system is reviewed by Boylan and Syntetos [116]. In another study, spare parts management is enquired in a theoretical and practical manner for spare parts from classification to stock control exploring the drawbacks of the models in literature and practical complement need to theoretical findings [117].

Some of the recent studies overview is given in Table 2.1.

Table 2.1 Literature of spare parts inventory management

Literature	**Year**	**Methodology**	**Contribution Overview**
Kumar and Knezevic [118]	1998	Mathematical Programming	Maximization of availability of component that need many spares subject to cost constraint
Kalchschmidt et al. [119]	2003	Order-up-to level	Decrease inventory level
Leven and Segerstedt [120]	2004	Croston forecast is employed in Periodic review model with the Erlang distribution.	Stock-outs are decreased with lower inventory levels

Table 2.1 (cont'd)

Syntetos and Boylan [121]	2006	Periodic order-up-to level	SBA method gives better stock control performance
Teunter and Duncan [78]	2009	Order-up-to level	Modification of the OUL that improves performance of forecasting methods
Bijvank, Koole, and Vis [122]	2010	Establishing new service level	Generating new algorithm that includes new service level
Nenes et al. [123]	2010	Periodic review inventory policy with order-up-to	Decrease inventory costs
Syntetos et al. [124]	2010	Reorder point, Economic Order Quantity	Reduce inventory costs, advance the operational efficiency
Teunter et al. [125]	2010	Order-up-to level	Reduce average inventory level
Zhou and Viswanathan [126]	2011	Order-up-to level under CSL constraint	New Bootstrapping Method
Babai et al. [127]	2011	Order-up-to level	Develop a method to decide optimal order-up-to level under compound Poisson process demand.
Saidane et al. [104]	2013	Base-stock policy	Decreasing optimal base stock level assuming demand distribution for demand interval and demand sizes are Erlang and Gamma respectively.
Digiesi, Mossa, and Rubino [128]	2015	Improved Economic order quantity (EOQ) model	Develop new cost function that includes economic and environmental factors
Van Ooijen, and Bertrand [129]	2015	Inventory level under capacity constraint	Combined optimization of spare parts inventory level and maintenance capacity
Jin, Tian, and Xie [130]	2015	Game theory approach	Combined optimization of spare parts inventory and maintenance

Cavalieri et al. are developed the decision making framework from classification to stock control for spare parts management [131]. Their decision-making framework shed light on inventory management for spare parts from beginning to end in a couple of phases. These phases include classification, demand forecasting, and inventory replenishment policy. Another study related with framework generation for spare parts aims that propose a framework to integrate classification of spare parts, demand forecasting, and stock replenishment policies by employing multi-criteria analysis, three forecasting models and different stock policies [132]. They applied their suggested framework and analysis to data set from the service industry. Qualitative strategies are proposed in some of the studies besides decision-making framework [133]. One another study targets to develop efficient inventory control of spare parts for different industries [134]. Their study reviews the literature concerning the effectiveness of the forecasting methods and spare parts inventory management based on the requirements of the company.

CHAPTER 3

INVENTORY COST COMPARISONS USING BASE STOCK POLICY

Service parts inventory is a challenging subject in the aviation industry, where the parts holding costs and the stock out costs are extremely high. Classical time series forecasting methods usually cannot meet the expectations when they are employed to handle intermittent demand. The problems that arise while handling this kind of data are to be solved by increasing the performance of inventory. There are many benefits of accurate demand forecasting in inventory planning to gain competitive advantage. In this study, one of our goals is to provide a framework which considers inventory costs of non-smooth demand by applying different forecasting methods for inventory practitioners in the aviation industry. A common problem for non-smooth demand pattern is the difficulty of forecasting demand with an acceptable degree of accuracy and setting the inventory policy parameters based on the 'real-time' forecasted demand over the lead time.

Intermittent demand can be observed for the items of engineering spares and stock keeping units (SKUs) at the level of a warehouse or various products at different stages in a supply chain. For such organizations, the dedicated amount of intermittent items can be a significant amount of opportunity cost since even small improvements in their inventory management may result in a great amount of cost savings. The most important concern is to determine whether inventory control models can achieve the high service levels with minimum inventory costs so that an inventory manager is able to run the underlying inventory model, reach the planned service level and determine the optimal policy levels. The decision of the most appropriate inventory control models by employing different forecasting methods in the face of intermittent and highly variable demand provide efficient management of spare parts.

An inventory performance does not necessarily demonstrate the improvements of predicted forecasting accuracy. Moreover, the extent of the improvement remains unknown, even though an improvement is obtained with the most accurate estimation method. Advancement of an appropriate inventory control simulation is crucial in that it enables the assessment of the empirical utility of academic findings. This chapter will discuss that whether periodic review order-up-to-level (OUL) is the preferable policy considering inventory cost minimization which serves to the goal of this research from the theoretical, computational and practical aspects by the application of real data set.
Exponential smoothing methods give more weight to the latest data. For this reason, when demand arises, it underestimates of demand size and overestimates the average demand. Thus, biased methods cause higher stocks, as such, forecasting methods that are developed for non-smooth demand are more reasonable to apply for spare parts demand data. In this chapter, forecasting methods for non-smooth demand are employed besides traditional methods on the selected data set from a Maintenance, Repair and Overhaul (MRO) industry.

3.1 Employed Forecasting Methods

How many stock to be held in inventory is set by the demand forecasting and inventory levels are adjusted based on that forecasted demand information [135]. In order to keep operational sustainability of the companies in the aviation industry, availability of spare parts that are associated with the operational performance have great importance. Availability of spare parts is subject to forecasting with high accuracy and efficient inventory planning. Since demand data for spare parts appear generally non-smooth pattern that needs to be given more credit on the estimation of them and planning. When one considers the minimization of inventory costs of spare parts, forecasting with high accuracy and implementing the appropriate inventory policy is the fundamental task. Naïve method, Exponential Smoothing, Croston method and Syntetos' method are employed in this study in order to give comparisons considering inventory costs.

3.1.1 Naïve Method

Naïve method basically gives the last observation of demand. There is no need to adjust the demand with choosing a parameter, it just gives the latest demand and mostly employed for comparison with other forecasting methods. This method is employed to make comparisons with other intermittent demand forecasting methods.

$$F(t)=X(t-1) \tag{3.1}$$

X(t) is the actual demand at time t

F(t) is the estimate of demand at time t.

3.1.2 Exponential Smoothing

Exponential smoothing methods are employed to time series data and they are based on the forecasting for the next period. It is generally used for demand data that has no trend and seasonality with smoothing the last observation and the last forecast as below:

$$\mathrm{F(t)} = \alpha.\,\mathrm{X(t)} + (1-\alpha).\,\mathrm{F(t-1)} \tag{3.2}$$

where α is a parameter called the smoothing parameter. *Ft* represents the smoothed estimate, *Xt* the actual value at time t.
The selection of the smoothing constant can denote the forecasting methods responsiveness in that if it closes to 1, the forecast will be more responsive to the recent observations means that have adjust capability to any enormous changings while if it closes to 0, the forecast will not be responsive to last demand data and could not reflect the changing in demand and cause high errors [136, 137, 138].

3.1.3 Croston's Method

In forecasting of non-smooth demand, the most common application is Croston method. The historical demand is separated into two by Croston, representing inter-arrival time and non-zero demand. The period between two consecutive non-zero demands is described as the inter-arrival time in the algorithm. The method is practical in the case of forecasting the inter-arrival time of the successive demands and non-zero demand size, with the help of individual exponential smoothing. The following notation is used in the algorithm:

Y(t) is the estimate of nonzero demand size at time *t*,

P(t) is the estimate of the mean interval between nonzero demands at time *t*,

X(t) is the actual demand at time *t*, Q is the time interval since the last nonzero demand

α is the smoothing constant and F(t) is the estimate of demand per period at time *t*.

Croston forecasting method updates values of Y(t) and P(t) according to the procedure shown in Figure 3.1.

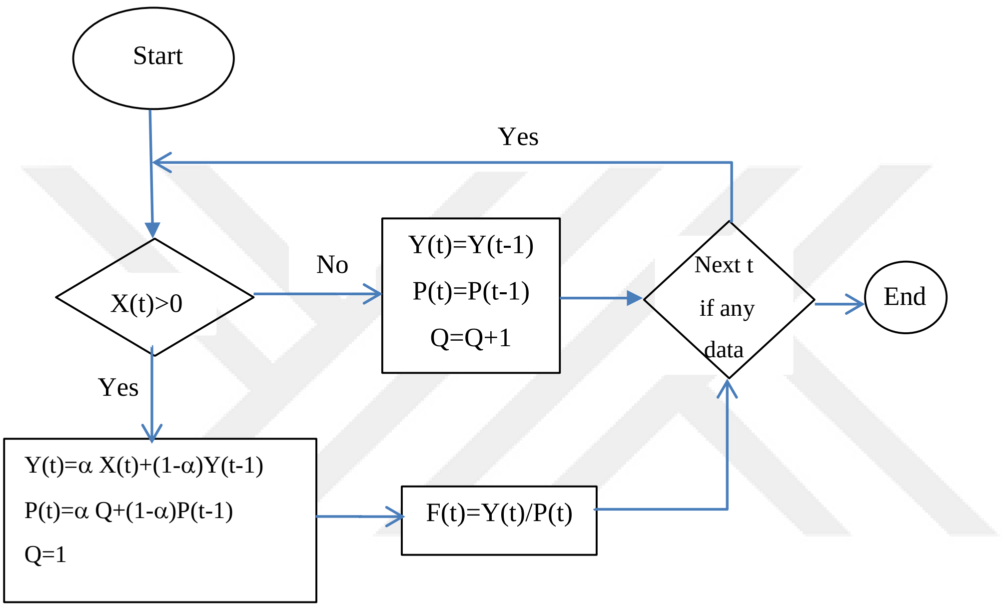

Figure 3.1 Croston's algorithm

Croston method finds the forecast of the demand for the period *t* as follows:

$$F(t) = \frac{Y(t)}{P(t)} \tag{3.3}$$

3.1.4 Syntetos Method

Syntetos and Boylan have revealed that the Croston technique is biased [15]. They have corrected the bias effect by multiplying the forecast for the demand per period with $(1 - \alpha/2)$ which is defined as the correction factor. If the demand occurs, estimates are updated as the Croston's method. Otherwise, estimates remain same. Their forecast of the demand per period is given at time t is:

$$F(t) = \left(1 - \frac{\alpha}{2}\right)\frac{Y(t)}{P(t)} \tag{3.4}$$

Y(t) is the estimate of nonzero demand size and P(t) is the estimate of the mean interval between nonzero demands at time t.

3.2 Methodology

The inventory level is determined by balancing the stock on hand and stock out amount that is faced. Reducing inventory levels considering this balance have to be handled to build effective inventory control. Demand data has high variability in this study and this feature makes it nondeterministic, which would let it be defined as stochastic demand. Also, it is important to keep in mind the continuous and periodic review policy, which are the two inventory review policies. There would be the continuous track of inventory level in the continuous review policy. On any occasion that the inventory level reduces below or to the reorder point, it is necessary to place an order up to the point [36, 139]. The inventory level is recurrently examined in the periodic review. The review period is considered as the aforementioned period of time [36]. The amount and the occurrence time of the order are the fundamental questions in inventory control. These are what the inventory costs involve [140];

- Stock holding Costs
- Stock-out Costs
- Ordering Costs

The decision of inventory policies through the investigation of the time and amount of the order ought to be made by supply chain practitioners. In a periodic inventory model, the inventory policies are assigned a reorder point (ROP) and order quantity in a continuous review and the order is determined by the order up to level (OUL). In this section, inventory performance is calculated for each selected forecasting method by adopting periodic review policy monitoring the inventory at certain intervals (T) and ordering an amount to bring the inventory level to a planned order level. The order level in each period is changed according to the real-time demand forecasting values. When the inventory position is lower than the OUT level in the comparison, an order should be placed to increase to the OUL level.

Despite the fact that the application of the periodic review system in the context of an intermittent demand is rationalized and also promoted with many instances in the literature, the sort of the data presented for simulation provokes this decision, as well as supporting [13, 121]. In this case, data was obtained and analyzed per month in order to review the stock status and determine the replenishment order levels. It is also important to note that one month was taken as the inventory review interval period (T=1). Specifically, in this work, the order-up-to-level (T, OUL) is established, which can be computationally more practical than the other systems. This has already been addressed in many real cases. In this system, the S value is calculated in the process of the simulation by the help of forecasting methods and the inventory position is increased up to the replenishment level S, decisions are taken regarding the replenishment order levels, and the stock status is evaluated at the end of every period. The implementation of the periodic control policy and, to be specific, the OUL, by regarding any backorders which might occur, ends up with the development of a stochastic model, which was aforementioned. Each month the input data are collected and one month of the review interval period is predicted for this process. The forecast is revised, the stock levels are reviewed and the OUL is measured whenever a review period (T) terminates. The formula of an order is that the expectation of receiving orders is added to stock on hand, and backorders referring to debt is subtracted, then the new replenishment order is added to indicate the OUL level that is the addition of the received orders to stock on hand, and from that result the subtraction of backorders gives the inventory position.

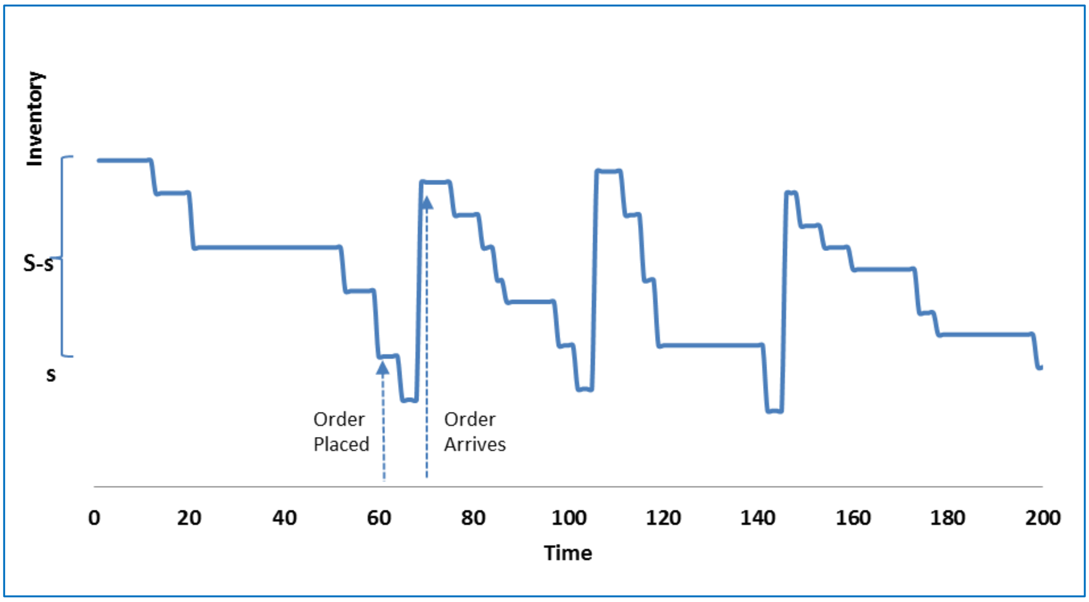

Figure 3.2 Periodic Review (T, OUL) inventory system

In Figure 3.2 periodic review inventory system, ordering and arrival times are given. In reality, the OUL level (S) is fluctuating at each review interval period. However, in the graph, the aforementioned level is constant. If the inventory position is less than the OUL level (S), an order is placed in order to increase it to the OUL level (S). The continuous review policy has been neglected because of the maintenance of the continuous track of inventory might be costly [13, 121, 141]. In the periodic inventory review, the amount of time an inventory planner devotes to calculating inventory is greatly reduced, which results in more time for the other aspects of the business.

The following procedures have been performed while establishing efficient spare parts management model;

- Analyzing historical data set provided by the aviation industry
- Categorization of the data to understand the spare parts pattern in aviation industry
- Optimization of inventory costs for spare parts considering forecasting methods and demand category

The following steps are taken while determining the best strategy to lower inventory costs:

1. Categorize spare parts demand data
2. Use some data for initialization
3. Hide some of the latest data for validation purposes

4. Select intermittent demand forecasting methods (Naïve, Exponential Smoothing, Croston and Syntetos)
5. Use constant smoothing factor (α= 0.2) as recommended in literature [20]
6. Forecast the future (hidden) demand to measure the performance
7. Calculate order up to levels (feed by forecasted values)
8. Determine ordering times and amounts
9. Calculate inventory holding costs, ordering costs and stockout costs
10. Compare results of Naïve method, Exponential Smoothing, Croston and Syntetos
11. If the results are not satisfactory then optimize smoothing factor α during the optimization period
12. For performance measurements; calculate the inventory costs using optimum smoothing factor to the data that are reserved for validation
13. Compare the cost performance results in order to select the most appropriate method for each demand category

Assumptions for holding and stock out costs are given as below;

1. Holding cost= Part Price*0.2 (Holding cost rate is defined considering opportunity costs and interest rates that are given in the literature. Capital Asset Pricing Model (CAPM) is applied for the estimation of opportunity costs of capital for a couple of industries [142]. Interest rates for each sector are given in his study and 0.2 interest rate which is the approximate value given for construction & materials sector is found suitable for holding inventory rate in the aviation industry.
2. Stock out cost=Part Price*5 (multiplication by 5 is the company application in stockout cases. MRO companies might have agreements with vendors for urgent situations to fulfill the demand of spare parts, they accept paying approximately 5 times of part price to not to interrupt operations).
3. Ordering costs and part prices are real market values.
4. Optimum smoothing factor that gives minimum inventory cost is exhaustively searched by using spreadsheet. α is searched within 0 to 1 range by 0.01 increments.

3.3 Application in THY

In this section, spare parts demand data set is employed to make comparisons of forecasting methods considering inventory costs in Turkish Airlines Technic MRO. Accurate demand forecasting for stock keeping units has a high degree of importance in the aviation industry that nonexistence of any small part can cause significantly high downtime costs. Minimization inventory costs by keeping service parts availability as high as possible is a fundamental dilemma that needs to be investigated with new approaches.

3.3.1 Thy Technic MRO

TURKISH TECHNIC is the notable aircraft maintenance, repair, and overhaul (MRO) services company in the region. TURKISH TECHNIC MRO is certified by EASA 145, JAA 145, FAA and Turkish DGCA for the operation of maintenance services. These maintenance services include airframe heavy maintenance, engine and APU overhaul, LDG overhaul, scheduled maintenance of aircrafts etc. TURKISH TECHNIC serves maintenance operations to its customers (business partners, airlines, etc.) for approximately all aircraft components (4,000 Boeing and 4,000 Airbus parts) from two wide & narrow-body hangars and one VIP & light aircrafts hangar in Istanbul. Maintenance operations include scheduled maintenance of the aircrafts, repair and overhaul operations with over 80 years of experience and more than 5,500 qualified employees.

3.3.2 Data Set

In this study, real data set from Turkish Airlines spare parts inventory are employed. These spare parts were selected randomly and it has been observed that majority of the data have ADIs greater than 1.32 and CV^2 values are higher than 0.49. Data set include 510 items that have non-smooth data type and 25 items have smooth pattern. Each item has the historical data that covers 106 monthly periods from 2005 to 2013. Descriptive statistics of the demand data set is given in Table 3.1.

Table 3.1 Descriptive statistics of spare parts demand data

	Num of Occurence	Average Demand	ADI	Demand Per Period	Standart Dev	CV^2
Mean	49,439	9,377	2,787	6,513	9,457	0,7782
Minimum	12	1,042	1	0,142	0,204	0,0384
1st Quart	27	1,792	1,515	0,557	1,076	0,3209
Median	44	2,950	2,372	1,236	2,418	0,5353
3rd Quart	69	6,047	3,786	3,642	5,651	0,8933
Maximum	106	934,009	8	934,009	880,645	10,3276
Count	535	535	535	535	535	535

Non-smooth demand data example from each demand category is given in the Figures 3.3-3.6 as monthly. 106 monthly demand data of service parts from Turkish Airlines MRO inventory is randomly selected to represent the data in each category.

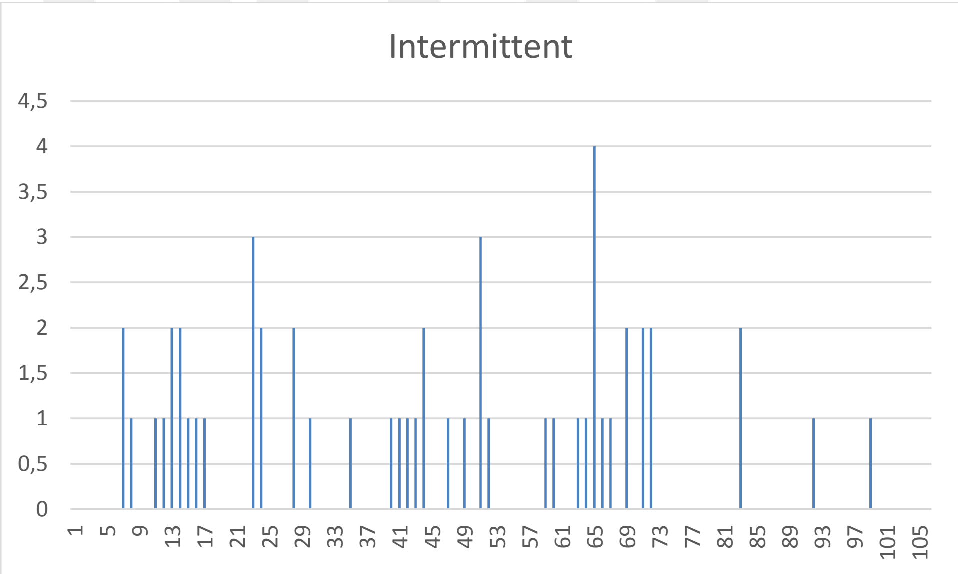

Figure 3.3 An example of intermittent data

Intermittent data displays very discrete form and has ADI values greater than 1.32 in Figure 3.3.

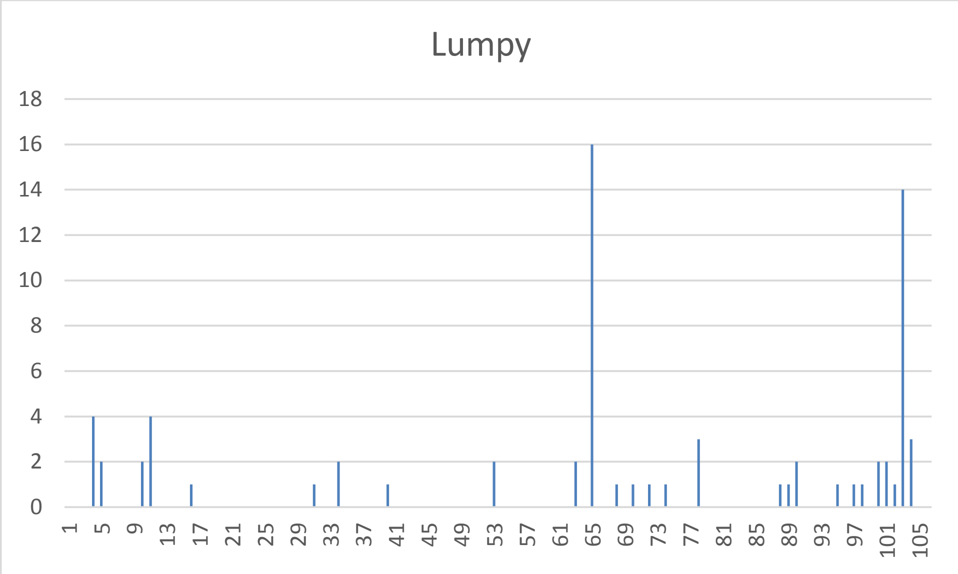

Figure 3.4 An example of lumpy data

Lumpy data has high ADI values (greater than 1.32 cut-off value) and high CV^2 values which can be seen in Figure 3.4 that data has high variation and large demand interval.

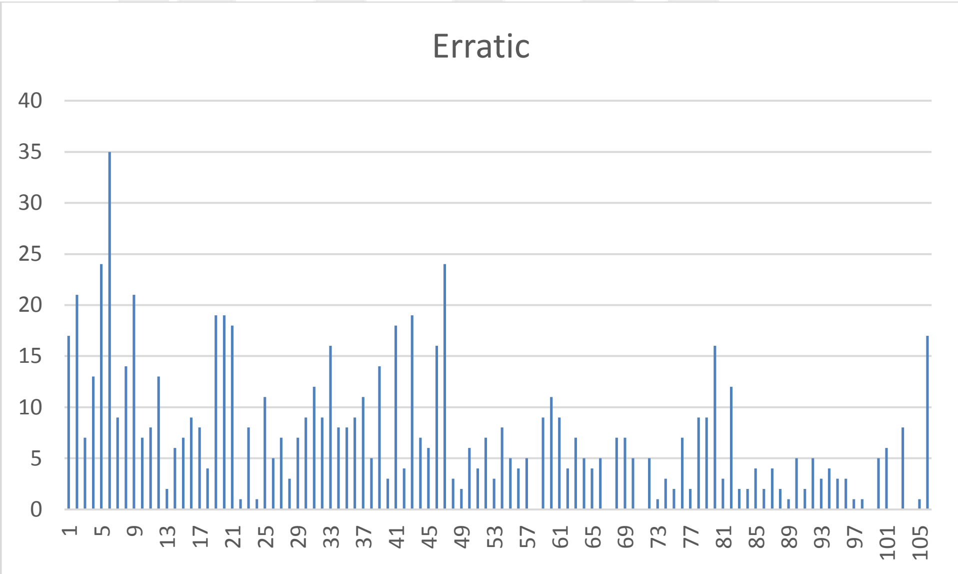

Figure 3.5 An example of erratic data

Erratic data category has high variations in demand volumes (greater than 0.49) that can be seen in Figure 3.5.

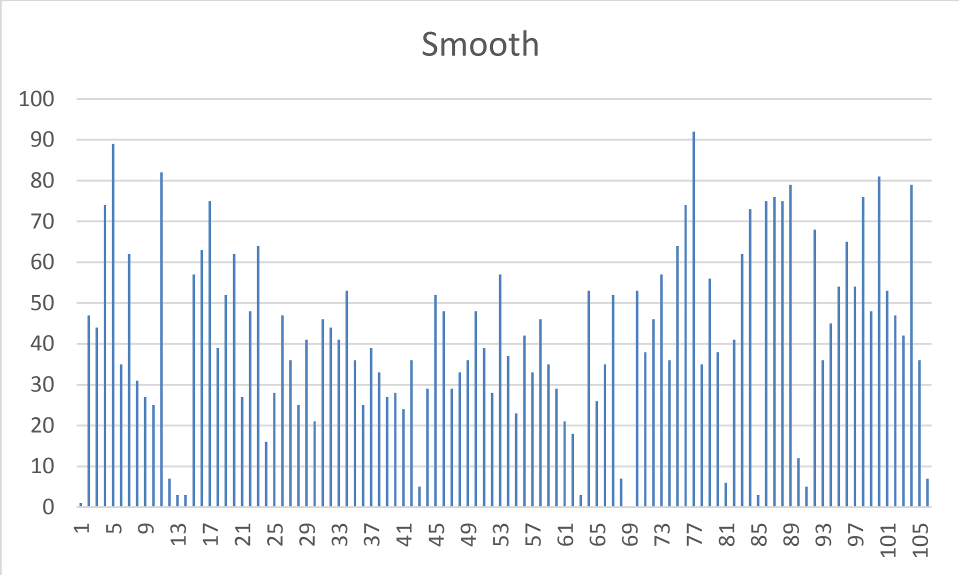

Figure 3.6 An example of smooth data

Smooth demand data has no high variations in demand volumes and ADI either as represented in Figure 3.6. That type of data has more stable and regular pattern comparing to non-smooth data.

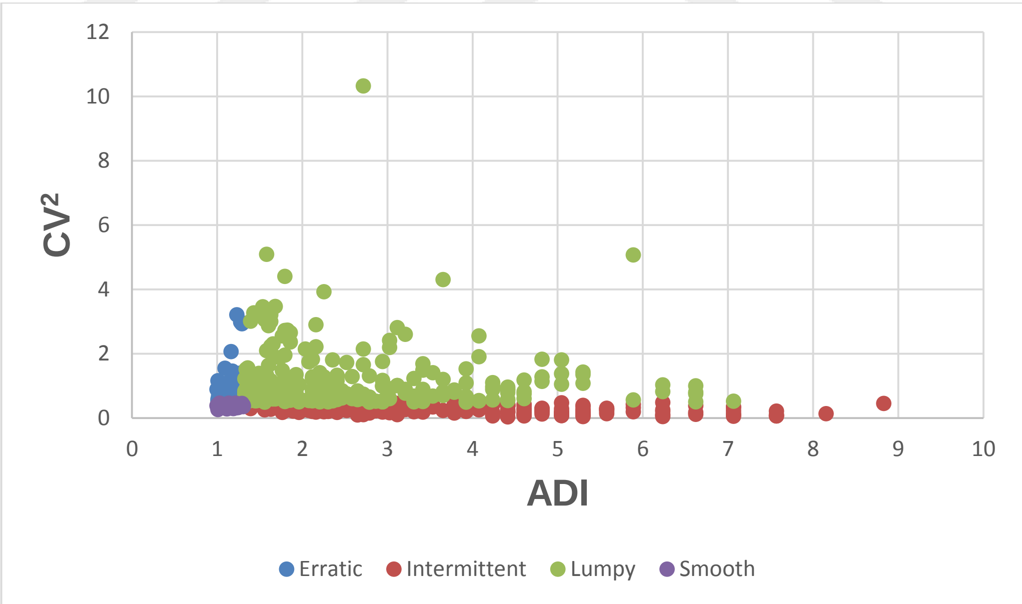

Figure 3.7 Demand Categories ADI vs CV^2

ADI and CV^2 values of data set with the specification of data categories are given in Figure 3.7. Number of items in each data categories in the data set is given in Table 3.2.

Table 3.2 Number of spare parts in each category

Demand Pattern Condition	Demand Type	Number of Data Series
ADI≤1.32; CV^2>0.49	Erratic	59
ADI>1.32; CV^2>0.49	Lumpy	234
ADI≤1.32; CV^2≤0.49	Smooth	25
ADI>1,32; CV^2≤0.49	Intermittent	217

3.3.3 Comparison of Forecasting Methods with Traditional Performance Measure

In this study, the performance of the forecasting methods is investigated considering most common accuracy measure. The Root Mean Squared Error (RMSE) is generally used to compare the accuracy of time series demand forecasting methods. RMSE gives variance of forecasting errors and it is calculated as follows;

$$RMSE = \sqrt{(1/n)\sum_{i=1}^{n}(Y-X)_i^2} \tag{3.5}$$

Considering the RMSE as a performance measure, four forecasting methods are applied and results are compared for the given demand data set. Each forecasting method that gives the minimum RMSE results is counted for each demand series. Comparison results are given for each data category in Table 3.3.

Table 3.3 RMSE comparisons of forecasting methods vs data types with constant smoothing parameter

Data Category	**Erratic**	**Intermittent**	**Lumpy**	**Smooth**	**Grand Total**
Croston	38	78	113	14	243
Exp. Smoothing	5	27	34		66
Naive		9	9	1	19
Syntetos	16	103	78	10	207
Grand Total	**59**	**217**	**234**	**25**	**535**

In order to compare forecasting methods smoothing parameter is selected as 0.2. Smoothing parameter is optimized in order to increase performances of forecasting methods. Between 0 and 1, the optimum parameter that gives the minimum error during optimization period is searched and after finding optimum smoothing parameter, it is used in the performance period that will be explained in detail in next section. Results of the comparisons of optimized forecasting methods are given in Table 3.4. RMSE results of the forecasting methods for 200 data series are given with constant α and optimum α in Appendix A.1 and Appendix A.2 respectively.

Table 3.4 RMSE comparisons of forecasting methods vs data types with optimum smoothing parameter

Data Category	Erratic	Intermittent	Lumpy	Smooth	Grand Total
Croston	55	77	108	22	262
Exp. Smoothing	2	47	23	1	73
Naive		7	9		16
Syntetos	2	86	94	2	184
Grand Total	**59**	**217**	**234**	**25**	**535**

3.3.4 Statistical Testing of RMSE Comparison Results

One tail statistical testing is applied to the forecasting methods RMSE results to compare the differences significance. Constant smoothing parameter results firstly compared as the following;

H0: Croston and Syntetos have same performance for smooth data

H1: Syntetos is worse than Croston method

Significance level α= 0.05

$$Zstat = \frac{X - nPo}{\sqrt{nPo(1 - Po)}} \tag{3.6}$$

If one tail testing is applied with below parameters;

n=25 X=14 and $Po = 0.5$

Table 3.5 Syntetos vs Croston in smooth series with constant parameter

	Smooth
Croston	14
Syntetos	11
	25

ZStat = 0.6; p-value= 0.27>0.05

The proportion test indicates that there is not sufficient evidence that the Syntetos method is worse than the Croston method for the smooth data when constant smoothing parameter is applied.

H0: Croston and Syntetos have same performance for non-smooth data

H1: Croston is better than Syntetos method.

Table 3.6 Syntetos vs Croston in non-smooth series with constant parameter

	Non-smooth
Croston	251
Syntetos	259
	510

Z Stat = 0.97; p-value=0.36>0.05

The proportion test indicates that there is not sufficient evidence that the Syntetos Method is better than the Croston method for the non-smooth data when constant smoothing parameter is applied.

RMSE results are optimized by setting smoothing parameter that comparison results are given in Table 3.4. The statistical testing for the differences significance between Croston and Syntetos is given as below;

H0: Croston and Syntetos have same performance for smooth data

H1: Syntetos is worse that Croston method

Table 3.7 Syntetos vs Croston in smooth series with optimum parameter

	Smooth
Croston	22
Syntetos	3
	25

ZStat = 3.8; p-value= 0.00007<0.05

The proportion test indicates that there is sufficient evidence that the Croston method is better than the Syntetos method for the smooth data when optimum smoothing parameter is applied.

H0: Croston and Syntetos have same performance for non-smooth data

H1: Syntetos is worse than Croston method.

Table 3.8 Syntetos vs Croston in non-smooth series with optimum parameter

	Non-smooth
Croston	265
Syntetos	245
	510

Z Stat = 0.88; p-value=0.18>0.05

The proportion test indicates that there is not sufficient evidence that the Syntetos method is worse than the Croston method for the non-smooth data when optimum smoothing parameter is applied.

Chi-square statistics results are given in Table 3.9-3.10 to find out the whether there is statistically significant difference between forecasting methods for non-smooth and smooth demand data when RMSE is applied as performance measure.

Table 3.9 Chi-square testing of forecasting methods optimized RMSE results for smooth data

Methods	**Smooth**	**Expected**	**(Oi-Ei)^2/Ei**
Croston	22	6,25	39,69
Exp.Smoothing	1	6,25	4,41
Naive Method	0	6,25	6,25
Syntetos	2	6,25	2,89
Total	**25**		**53,24**

Chi-Square Statistics=53.24, Critical Value for 0.05 is 7.81

There is statistically evidence that forecasting methods optimized RMSE results for smooth data are different.

Table 3.10 Chi-square testing of forecasting methods optimized RMSE results for non-smooth data

Methods	**Non-Smooth**	**Expected**	**(Oi-Ei)^2/Ei**
Croston	240	127,5	99,265
Exp.Smoothing	72	127,5	24,159
Naive Method	16	127,5	97,508
Syntetos	182	127,5	23,296
Total	510		244,23

Chi-Square Statistics=244.23 Critical Value for 0.05 is 7.81

There is statistically evidence that forecasting methods optimized RMSE results for non-smooth data are different.

3.3.5 Cost Based Comparison of Intermittent Demand Forecasting Methods

Forecasting methods comparison results using RMSE performance measure is given in previous section that represents the non-smooth demand forecasting methods are better than traditional methods as many of studies in literature confirm that superiority of these methods in non-smooth demand data. Accuracy of these methods can be evaluated by traditional measures such as RMSE. However, inventory performance of these methods have more importance to plan inventories and give order decisions based on the most applicable method. Two smoothing parameter selected to compare inventory costs of the forecasting methods to reveal the inventory performances of the methods.

1. **Forecasting Using Constant Parameter**

Forecasting methods that are selected for comparisons applied using constant parameter α=0.2 given in literature as recommended value [20]. Application steps and assumptions are given in methodology section. Base stock policy is adopted and comparisons are made considering this policy replenishment decisions.

2. **Forecasting Using Optimum Parameter**

Data set (each spare parts has 106 months demand data) is divided into three parts with overlapping as follows;

Initialization: The first 24 months of data are used to initialize the model. During that period of time smoothing parameter α is obtained as 0.2.

Optimization: Between 12^{th} month and 96^{th} month of the data is used for the minimization of total inventory costs. The smoothing parameters are searched between 0 and 1 using EXCEL VBA to give minimum total inventory costs. The smoothing parameter that give the minimum inventory cost is selected to be used in validation period.

Validation: Last 36 month of data set is used to measure the performances of the forecasting methods by applying base stock policy.

3. **Comparison Results**

Considering the inventory costs as performance measure, four forecasting methods are applied and results are compared for the given demand data set. Each forecasting method that give the minimum cost results are counted for each demand series. Comparison results of forecasting methods are given for each data category when smoothing parameter is constant (α=0.2) in Table 3.11.

Table 3.11 Cost based comparison of forecasting methods versus data types (α=0.2)

Forecasting Method	Erratic	Intermittent	Lumpy	Smooth	Grand Total
Croston	5	22	16	3	46
Exp.Smoothing	12	61	50	3	126
Naive	41	122	143	17	323
Syntetos	1	12	25	2	40
Grand Total	59	217	234	25	535

In Figure 3.8, best forecasting methods for each demand category results are given when α is 0.2.

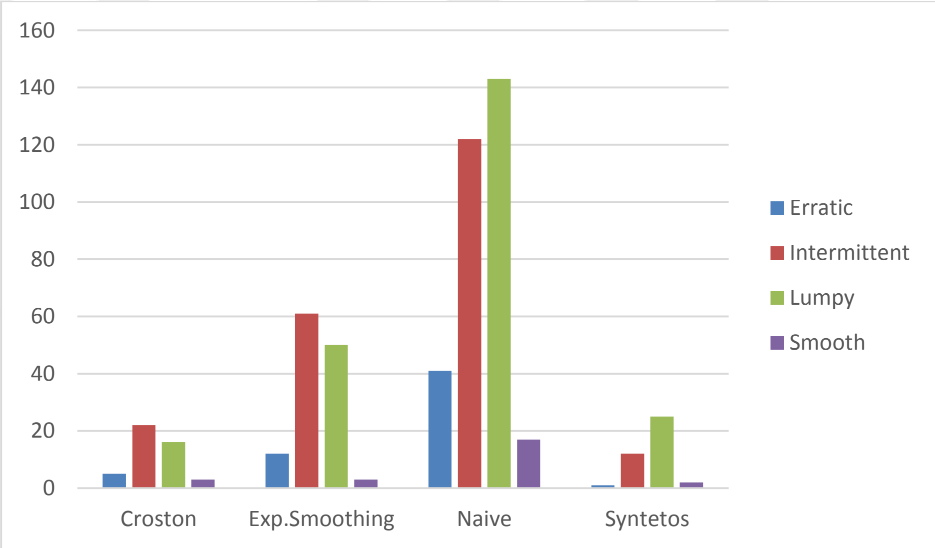

Figure 3.8 Forecasting methods vs data types (α=0.2)

Inventory cost results of each forecasting methods versus data types when smoothing parameter is constant (α=0.2) are given in Table 3.12. The results of these methods for the remaining data set are given in Appendix-A.

Table 3.12 Inventory cost results of each forecasting methods versus data types (α=0.2)

	Naive	Exp.Smoothing	Croston	Syntetos	Best Method	Data Type
1	54.90	64.84	67.48	69.84	Naive	Lumpy
2	1897.68	3121.62	2505.92	2519.58	Naive	Lumpy
3	1074.26	1175.21	1190.15	1195.97	Naive	Lumpy
4	353.35	705.63	527.15	539.41	Croston	Lumpy
5	376.11	534.46	541.47	541.47	Naive	Intermittent
6	849.46	1002.92	1075.83	913.40	Naive	Lumpy
7	100.38	108.01	106.32	107.74	Naive	Lumpy
8	520.95	654.14	634.04	834.17	Naive	Erratic
9	1384.96	1820.94	2395.91	1944.83	Exp.Smoothing	Lumpy
10	326.08	368.83	356.48	388.94	Croston	Lumpy
11	158.34	197.51	199.60	202.59	Naive	Lumpy
12	44.98	60.18	57.91	59.40	Syntetos	Lumpy
13	2182.47	2210.87	2808.73	2808.73	Naive	Lumpy
14	6.31	5.82	6.88	6.09	Exp.Smoothing	Lumpy
15	458.72	1314.98	1108.80	5935.72	Naive	Lumpy
16	5.73	8.67	9.90	8.70	Naive	Lumpy
17	59.00	91.82	79.45	125.88	Syntetos	Lumpy
18	539.97	673.64	818.28	811.55	Naive	Intermittent
19	12.04	221.48	323.92	303.04	Naive	Lumpy
20	3903.07	1974.46	1974.46	1974.46	Exp.Smoothing	Intermittent

Considering the optimized inventory costs as performance measure, four forecasting methods are applied and results are compared for the given demand data set when smoothing parameter is optimized. Each forecasting method that give the minimum cost results are counted for each demand series. Comparison results of forecasting methods are given for each data category in Table 3.13.

Table 3.13 Cost based comparison of forecasting methods versus data types ($\alpha_{optimum}$)

Forecasting Method	Erratic	Intermittent	Lumpy	Smooth	Grand Total
Croston	13	26	54	5	98
Exp.Smoothing	24	138	107	10	279
Naive	17	33	59	8	117
Syntetos	5	20	14	2	41
Grand Total	59	217	234	25	535

In Figure 3.9, best forecasting methods for each demand category results are given when α is optimum.

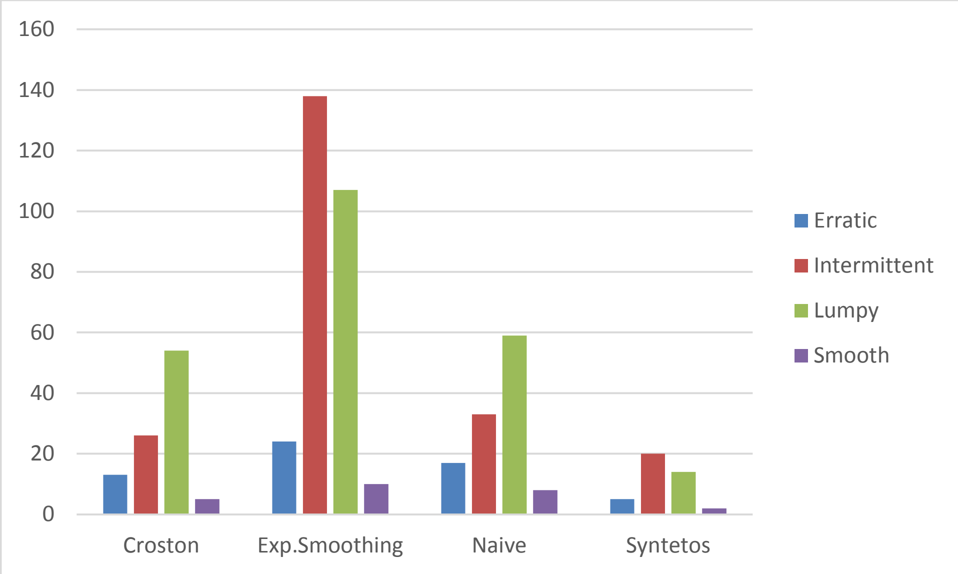

Figure 3.9 Forecasting methods vs data types ($\alpha_{optimum}$)

Inventory cost results of each forecasting methods versus data types when smoothing parameter is optimum are given in Table 3.14. Inventory cost results of the forecasting methods for 200 data series are given with constant α and optimum α in Appendix A.3 and Appendix A.4 respectively.

Table 3.14 Inventory cost results of each forecasting methods versus data types ($\alpha_{optimum}$)

No	Naive	Exp.Smoothing	Croston	Syntetos	Best Method	Data Type
1	49.70	36.25	31.82	33.53	Croston	Lumpy
2	94.84	118.54	114.87	159.44	Naive	Erratic
3	39.93	39.97	42.34	51.21	Naive	Erratic
4	352.63	325.80	300.89	319.99	Naive	Lumpy
5	1139.38	1140.02	1419.43	1330.07	Exp.Smoothing	Lumpy
6	2.75	3.00	3.29	3.44	Exp.Smoothing	Lumpy
7	1189.78	997.72	1299.48	1328.01	Naive	Lumpy
8	555.18	458.62	801.99	663.30	Exp.Smoothing	Intermittent
9	251.93	200.74	167.56	218.74	Croston	Intermittent
10	14.85	21.68	11.85	23.06	Naive	Intermittent
11	31.82	31.40	32.40	43.78	Exp.Smoothing	Intermittent
12	77.21	69.42	79.34	70.23	Exp.Smoothing	Lumpy
13	4193.58	1550.59	1465.35	966.80	Croston	Intermittent
14	306.20	255.98	287.79	304.52	Exp.Smoothing	Erratic
15	7.62	6.64	9.02	9.75	Exp.Smoothing	Lumpy
16	1549.19	1454.58	1644.91	1649.72	Exp.Smoothing	Lumpy
17	138.70	140.53	144.21	154.08	Exp.Smoothing	Lumpy
18	54.90	56.59	53.01	60.55	Naive	Lumpy
19	1897.68	1907.11	703.40	2217.32	Naive	Lumpy
20	1074.26	965.65	899.39	1098.74	Naive	Lumpy

3.3.6 Geometric Mean of the Arithmetic Mean of the Inventory Costs (GMAMIC)

Since there are multiple items in the stock, a performance measure that collectively calculate the performances of the forecasting methods. Regardless of the variability of the items in the stock, the geometric mean (based on SKUs) of the expected inventory costs (based on time) can be employed to compare forecasting methods inventory costs as the following:

$$GMAMIC = \left(\prod_{j=1}^{N}\left(h_j\left(\frac{Q_j^*}{2} + R_j^* - \lambda_j \tau j\right) + \frac{K_j\lambda_j}{Q_j^*} + \mathrm{p}_j\lambda_j \mathrm{n}(R_j^*)/Q_j^*\right)\right)^{1/N} \tag{3.7}$$

Geometric mean of the inventory cost results of the forecasting methods are given in Table 3.15.

Table 3.15 GMAMIC results of forecasting methods

	Naive	**Exp. Smoothing**	**Croston**	**Syntetos**
Constant α	624.5575	678.6236	723.6885	752.6664
Optimized α	624.5575	534.9307	578.4342	676.5540

3.3.7 Statistical Testing of Inventory Cost Comparisons

Chi-square statistics results are given in Table 3.16 to find out the whether there is statistically significant difference between forecasting methods for non-smooth and smooth demand data.

Table 3.16 Chi-square testing of forecasting methods for smooth data

	Smooth	**Expected**	**(Oi-Ei)^2/Ei**
Croston	5	6.25	0.81
Exp.Smoothing	10	6.25	0.49
Naive Method	8	6.25	0.81
Syntetos	2	6.25	1.21
Total	**25**		**3.32**

Chi-Square Statistics=5.88; Critical Value for 0.05 is 7.81

There is no evidence that forecasting methods cost results are statistically different for smooth data.

Table 3.17 Chi-square testing of forecasting methods for non-smooth data

Row Labels	**Non-Smooth**	**Expected**	**(Oi-Ei)^2/Ei**
Croston	93	6,25	1204,09
Exp. Smoothing	269	6,25	11046,01
Naive Method	109	6,25	1689,21
Syntetos	39	6,25	171,61
Total	**510**		**14110,92**

Chi-Square Statistics= 14110.92; Critical Value for 0.05 is 7.8.

There is statistically evidence that forecasting methods for non-smooth data is different when inventory cost is considered.

One tail statistical testing is applied to the forecasting methods inventory cost results to compare the differences significance. One method from non-smooth demand forecasting methods and one method from traditional forecasting methods that have close results are selected to test the difference significance. Comparison results of these methods when optimum smoothing parameter is used given as the following;

H0: Croston and Naive have same performance for smooth data (P1=P2=0.5)

H1: Croston is better than Naive method for smooth data (P1>P2 or P1>0.5 the methods will be significantly different)

Zstat is given in 3.6

Significance level α= 0.05

If one tail testing is applied with below parameters;

n=25 X=14 and $Po = 0.5$

Table 3.18 Naive vs Croston in smooth series

	Smooth
Naive	12
Croston	13
	25

ZStat = 0.2; p-value= 0.42>0.05

The proportion test indicates that there is not sufficient evidence that the Croston Method is better than the Naïve method for the smooth data.

H0: Croston and Naive have same performance for non-smooth data

H1: Croston is worse than Naive method for non-smooth data

Table 3.19 Naive vs Croston in non-smooth series

	Non-smooth
Naive	266
Croston	244
	510

Z Stat = 0.97; p-value=0.83>0.05

The proportion test indicates that there is not sufficient evidence that the Croston Method is worse than the Naïve method for the non-smooth data.

CHAPTER 4

INVENTORY COST COMPARISONS USING BOOTSTRAPPING AND MARKOV MODELS

Traditional accuracy measures are often used in the literature in order to compare the performance of forecasting methods; however, the application of such measures becomes problematic in the context of interval estimation methods for intermittent demand that contain many zero values. In this chapter, the inventory implications of a non-parametric method developed by Willemain et al. [53] is investigated in a simulated environment and compared it with results obtained from the previous chapter using a real data set of aircraft spare parts demand. Arguably, a most realistic formulation of the forecasting and inventory control problem in an intermittent demand context is related to an inventory cost minimization approach (that aims at balancing the holding and stock out costs). Such an inventory system is considered in this study and the effects and implications of non-parametric forecasting method is assessed in detail. The choice of the forecasting method has an impact on the inventory costs achieved and thus on the performance of the system.

Classical statistical forecasting methods presume that probability distribution of demand for SKU or an item in inventory over a lead time look like a normal distribution. Their approach disregards features of spare parts demand data in inventory and they cannot estimate accurately the entire distribution of lead time demand. Instead of the estimate of demand per period, forecasting the entire distribution for intermittent demand data have great importance to provide initial values to inventory control models. In order to keep service level as high as possible one needs to apply a different method that considers to fulfill lead time demand with high accuracy and expected customer service level.

Bootstrapping forecasting method is an empirical method of computational statistics that increase service parts availability and customer service with the minimization of inventory costs. It provides accurate forecasts for demand per period besides high service level. Historical demand data is employed to simulate lead time demand scenarios as much as practitioner need in order to represent the total demand over lead time and build a distribution of lead time demand. It can be either analyzed employing statistical methods or estimating inventory control parameters to decrease inventory costs and meet customer service level.

4.1 Methodology

Bootstrapping method includes following steps;

1. Obtain historical demand data in chosen time buckets.
2. Estimate transition probabilities for two-state (zero vs. non-zero) Markov model
3. Conditional on last observed demand, use Markov model to generate a sequence of zero/non-zero values over forecast horizon.
4. Replace every non-zero state marker with a numerical value sampled at random, with replacement, from the set of observed non-zero demands.
5. 'Jitter' the non-zero demand values – this is efficiently an ad hoc procedure designed to allow greater variation than that already observed. The process enables the sampling of demand size values that have not been observed in the demand history.
6. Sum the forecast values over the horizon to get one predicted value of lead time demand (LTD).
7. Repeat steps from 3 to 6 many times (as much as the practitioner need).
8. Sort and use the resulting distribution of LTD values to input inventory control system; Order the lead time demand values and get the percentile of interest to us. The percentile that is chosen is the Target Cycle Service Level. Order-up-to-level is directly related with this cycle service level. In this study target service level is obtained as %95 and inventory parameters are updated with this input.

Forecasting method for intermittent demand based on a combination of Markov modeling and statistical bootstrapping is applied to current data set. The Markov model captures the serial correlation observed in company data and generates scenarios about the mixture of zero and nonzero values in future demand. The bootstrap then resamples observed nonzero demand values. Repeating this process many thousands of times rapidly provides an estimate of the entire distribution of demand over a lead time. Willemain et al. have worked on bootstrapping and Markov modeling of the spare parts and they introduced a patent study includes jittering procedure [143]. In our case their flow diagram which is given in their study is modified according to our case needs and employed in our study. The flow diagram is given in Figure 4.1;

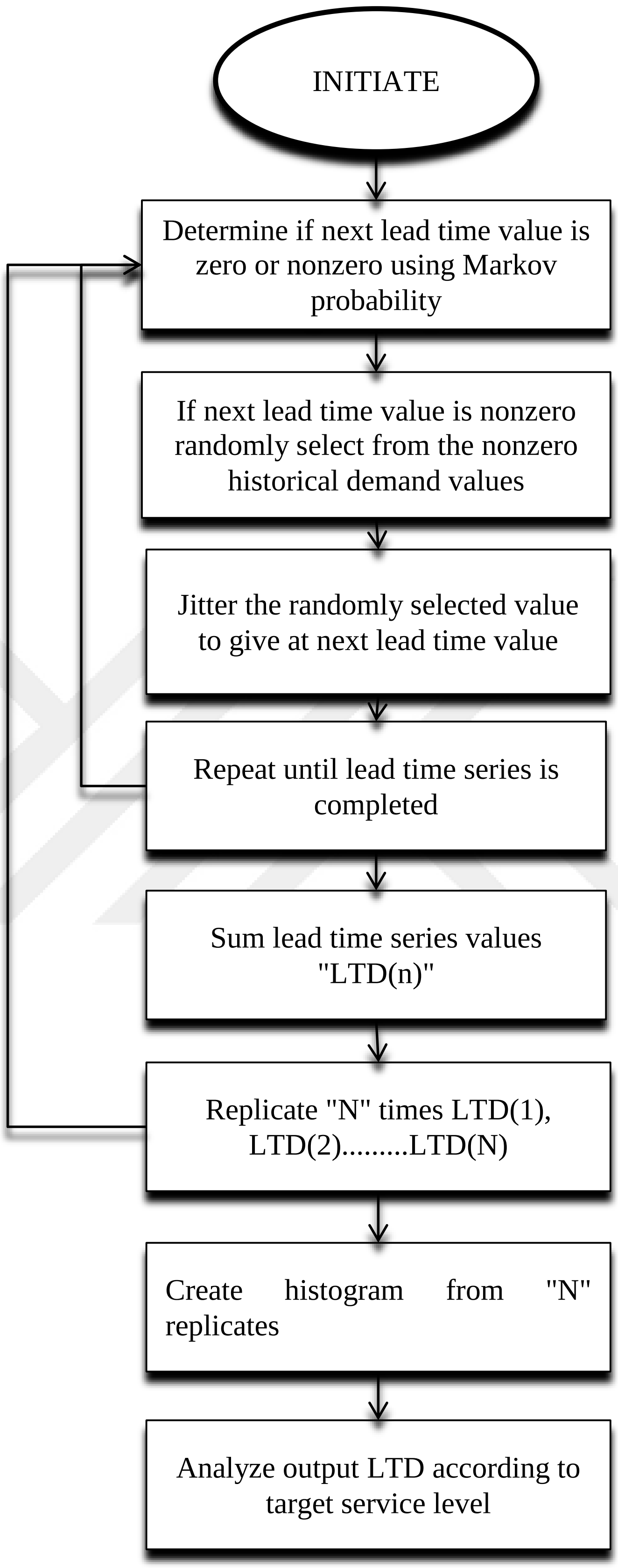

Figure 4.1 Bootstrapping method and Markov Model application steps

The methods should be evaluated directly on service level or inventory costs and not using forecast error measures. In inventory system, a customer service level is specified as the probability ($P1$) of no stock-out during the active demand period. To determine the customer service level, holding costs and stock out costs are key factors. It is necessary to find achieved service level when the optimum point is captured in cost service level graph. And the other aspect is finding 100% fill rate point and it can be seen on the fill rate-service level point. Then corresponding of this point on the cost-customer service level graph can give an idea about the comparison between decisions related to achieved service level at minimum cost and cost that is providing maximum satisfaction ratio or fill rate balancing between these costs is crucial in these graphs and performance evaluation depends on the company perspective. In this stage coefficients of shortage cost and holding cost are significant to make a wise decision. In Figure 4.2 inventory cost corresponding to service level that achieved is given as an example from data set.

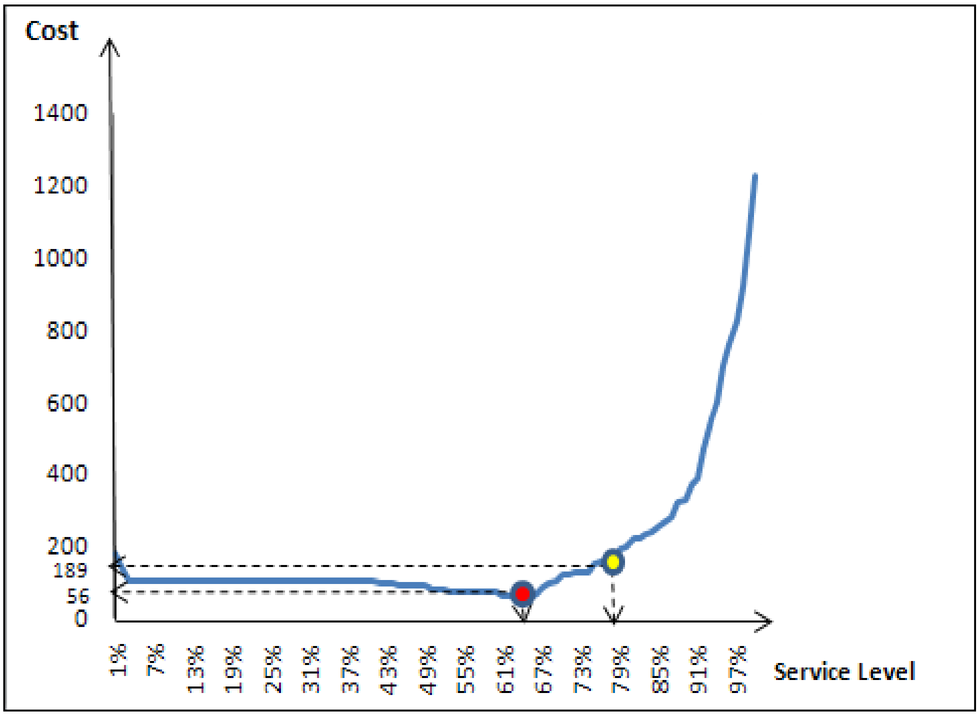

Figure 4.2 Cost vs service level results example

4.2 Markov Probabilities

The system is considered both a service and cost oriented system. In the service oriented system, the objective is to maximize the customer satisfaction or fill rate and in the cost oriented system, the objective is to minimize inventory costs. Fill rate can be defined that the service level as the fraction of demands that can be satisfied directly and completely from stock on hand. The cost savings approach in the inventory system by combining the improved forecasting technique and the assumed inventory policy is addressed.

The following are the notations and steps to compute the optimal inventory costs and the relative service level measures of the bootstrapping method:

X(t)=demand value at time t
X* =a randomly selected nonzero value of demand
T=number of historical demand values
L=Fixed lead time or forecast horizon
N=a nonzero demand
S=a jittered value of historical demand
P_{00}=Prob [next demand is zero, given last demand was zero]
P_{0n}=Prob [next demand is non-zero, given last demand was zero]
P_{no}=Prob [next demand is zero, give last demand was non-zero]
P_{nn}=Prob [next demand is non-zero, given last demand was non-zero]
U=random number uniformly distributed between 0 and 1.
Z=random number with a standard normal (i.e., Gaussian) distribution (mean=0, variance=1).

The initial phase is to determine if the next LTD value is zero or nonzero. The preferred methodology for performing this step is to employ a Markov model as explained below;

Depending on last value of demand, Markov model will determine the possibility of zero or nonzero for the next demand data. The Markov model has four transition probabilities, but two of them to be known is suffice.

$$P_{n0}+P_{nn}=1 \tag{4.1}$$

P_{00} and P_{nn} can be estimated from the history, and the other two values, P_{0n}, P_{no}, can be estimated using the relationships as given in 4.1.

After estimates of the Markov transition probabilities are made, they can be used to generate of zero and nonzero values over the lead time.

The jittering process employed to nonzero demand estimations to provide data variety. It gives a bias to forecasts to improve accuracy. It is applied as follows;

$$S = 1 + INT(X* + Z\sqrt{X*}) \tag{4.2}$$

$$IF\ S \leq 0, THEN\ S = X* \tag{4.3}$$

Above equation provides new S values in neighborhood of the X*. X* is referred to bootstrapped values.

This application provides systems and methods for forecasting intermittent demand over a lead time. First, a bootstrap methodology is provided that includes the steps of:

1) Providing a data set of intermittent data including a determined number of historical demand values;

2) Forecasting lead time demand values over the lead time by randomly sampling or selecting values from the historical demand values;

3) Jittering the nonzero demand estimations to provide more variety;

4) Summing the lead time values to provide a lead time demand value sum;

5) Repeating the calculating and summing steps as determined number of times to provide a distribution of lead time demand value sums;

6) Statistically analyzing the distribution and getting regarding parameters for the considered customer service level into an inventory control system.

After simulations and jittering processes application order up to values are estimated and employed to calculate inventory costs.

4.3 Data Set and Assumptions

Real data set (535 spare parts items) that is employed in Chapter 3 is used in non-parametric forecasting for inventory cost calculations of spare parts. Data set (each spare parts has 106 months demand data) is divided into three parts with overlapping as follows;

Initialization: The first 24 months of data are used to initialize the model.

Performance Measure: Last 36 month of data set is used to measure the performances of the method by applying base stock policy.

- Ordering costs and part prices are real market values.

- Lead time is given as 1 month.

- Stock out cost=5*Part Price

- Holding cost= Part Price*0.2.

4.4 Results

Holding, Stock out costs, Ordering costs of the bootstrapping method are given in Table 4.1 for the first 50 spare parts. Inventory cost results of the bootstrapping method with CSL=0.95 for 200 data series are given in Appendix B.1. Comparison results of parametric forecasting methods applied in Chapter 3 and bootstrapping method are given in Table 4.2.

Table 4.1 Bootstrapping forecasting inventory cost results

No	Nb orders	Part Price	Order Price	Holding Cost	Stockout Cost	Ordering Cost	Total Costs
1	13	1.39	5.36262	3.08	11.00	69.71	83.80
2	26	1.53	5.90274	5.56	3.19	153.47	162.22
3	28	0.51	1.96758	1.53	5.31	55.09	61.93
4	5	19.2	74.0736	48.96	64.00	370.37	483.33
5	23	1.29	94.09	1.35	11.83	2164.07	2177.25
6	6	0.11	0.42438	0.11	0.18	2.55	2.84
7	16	2.31	98.34	6.01	0.96	1573.44	1580.41
8	15	8.9	48.65	5.34	22.25	729.75	757.34
9	30	1.53	12.84	4.79	12.75	385.20	402.74
10	10	1.35	2.58	2.12	2.25	25.80	30.17
11	22	0.58	2.23764	0.71	6.28	49.23	56.22
12	10	4.9	4.92	10.62	30.63	49.20	90.44
13	21	265.7	32.47	146.14	221.42	681.87	1049.42
14	32	5.23	1.72	27.72	359.56	55.04	442.32
15	16	0.27	1.04166	2.18	0.68	16.67	19.52
16	31	1.01	95.99	1.21	35.77	2975.69	3012.67
17	24	5.69	5.39	5.97	52.16	129.36	187.49
18	11	0.5	1.929	6.70	53.33	21.22	81.25
19	7	3.05	302.97	29.28	34.31	2120.79	2184.38
20	22	2.4	98.23	17.16	139.00	2161.06	2317.22
21	10	6.69	93.7	31.67	2.79	937.00	971.45
22	9	8.95	94.84	17.45	22.38	853.56	893.39
23	21	66.43	22.35	117.36	415.19	469.35	1001.90
24	30	3.27	2.67	6.70	55.86	80.10	142.67
25	15	0.74	18.91	123.79	86.95	283.65	494.39
26	8	95.3	54.78	908.53	0.00	438.24	1346.77
27	5	9.5	36.651	74.42	47.50	183.26	305.17
28	15	3.59	17.91	3.77	55.35	268.65	327.77
29	18	0.58	4.25	6.80	11.84	76.50	95.14
30	13	284.03	109.579	449.71	591.73	1424.52	2465.97
31	7	0.1	0.3858	0.09	3.63	2.70	6.41
32	13	79.47	30.6595	425.16	0.00	398.57	823.74
33	8	0.41	1.58178	0.83	2.39	12.65	15.87
34	7	2.57	9.91506	6.04	0.00	69.41	75.44
35	18	1.98	46.88	0.73	22.28	843.84	866.84
36	8	4.35	32.6	4.86	7.25	260.80	272.91
37	15	30	8.89	44.50	12.50	133.35	190.35
38	11	4.88	4.78	7.65	18.30	52.58	78.53
39	12	68.6	4.36	116.62	142.92	52.32	311.86
40	10	1.97	25.29	2.46	0.00	252.90	255.36
41	15	64.94	2.58	349.59	378.82	38.70	767.11
42	19	14.64	15.51	24.89	79.30	294.69	398.88
43	5	67.89	19.92	70.15	0.00	99.60	169.75
44	16	2.86	16.06	5.10	30.98	256.96	293.04
45	12	11.81	11.33	14.96	19.68	135.96	170.60
46	5	155.84	11.93	210.38	259.73	59.65	529.77
47	5	1.68	63.05	1.57	1.40	315.25	318.22
48	20	676	18.61	1126.67	3098.33	372.20	4597.20
49	20	10.14	19.11	209.05	0.00	382.20	591.25
50	14	0.84	48.75	0.56	1.75	682.50	684.81

Table 4.2 Bootstrapping vs parametric forecasting methods inventory cost results

Data Type	No	Bootstrap ping	Naive	Exp. Smoothing	Croston	Syntetos
Lumpy	1	83.80	49.7	36.25	31.82	33.53
Erratic	2	162.22	94.84	118.54	114.87	159.44
Erratic	3	61.93	39.93	39.97	42.34	51.21
Lumpy	4	483.33	352.63	325.8	300.89	319.99
Lumpy	5	2177.25	1139.38	1140.02	1419.43	1330.07
Lumpy	6	2.84	2.75	3	3.29	3.44
Lumpy	7	1580.41	1189.78	997.72	1299.48	1328.01
Intermittent	8	757.34	555.18	458.62	801.99	663.3
Intermittent	9	402.74	251.93	200.74	167.56	218.74
Intermittent	10	30.17	14.85	21.68	11.85	23.06
Intermittent	11	56.22	31.82	31.4	32.4	43.78
Lumpy	12	90.44	77.21	69.42	79.34	70.23
Intermittent	13	1049.42	4193.58	1550.59	1465.35	966.8
Erratic	14	442.32	306.2	255.98	287.79	304.52
Lumpy	15	19.52	7.62	6.64	9.02	9.75
Lumpy	16	3012.67	1549.19	1454.58	1644.91	1649.72
Lumpy	17	187.49	138.7	140.53	144.21	154.08
Lumpy	18	81.25	54.9	56.59	53.01	60.55
Lumpy	19	2184.38	1897.68	1907.11	703.4	2217.32
Lumpy	20	2317.22	1074.26	965.65	899.39	1098.74
Lumpy	21	971.45	353.35	241.25	707.64	445.71
Intermittent	22	893.39	376.11	431.12	362.98	536.1
Lumpy	23	1001.90	849.46	817.24	818.51	903.64
Lumpy	24	142.67	100.38	84.41	88.55	95.97
Erratic	25	494.39	520.95	536.78	517.14	720.42
Lumpy	26	1346.77	1384.96	1100.15	1605.17	1542.17
Lumpy	27	305.17	326.08	354.66	371.36	388.94
Lumpy	28	327.77	158.34	159.53	159.24	193.38
Lumpy	29	95.14	44.98	42.35	57.14	65.41
Lumpy	30	2465.97	2182.47	2154.06	1975.58	2264.34
Lumpy	31	6.41	6.31	5.79	6.04	6.09
Lumpy	32	823.74	458.72	412.11	412.11	3352.95
Lumpy	33	15.87	5.73	12.68	12.68	8.74
Lumpy	34	75.44	59	62.53	77.04	118.11
Intermittent	35	866.84	539.97	486.55	536.68	579.23
Lumpy	36	272.91	12.04	138.38	92.29	136.35
Intermittent	37	190.35	3903.07	1711.96	2054.74	1974.46
Intermittent	38	78.53	50.03	54.24	60.8	64.29
Intermittent	39	311.86	268.76	189.82	269.07	206.38
Lumpy	40	255.36	155.38	130.39	56.53	131.05
Lumpy	41	767.11	1588.61	903.43	903.43	878.6
Lumpy	42	398.88	1059.36	516.33	477.61	585.73
Intermittent	43	169.75	140.33	134.68	198.73	172.02
Lumpy	44	293.04	176.38	217.79	191.73	215.41
Intermittent	45	170.60	113.95	112.84	133.64	130.88
Intermittent	46	529.77	445.11	351.61	427.41	427.41
Intermittent	47	318.22	130.52	254.55	257.63	193.71
Intermittent	48	4597.20	4591.87	3783.59	3156.74	4966.59
Erratic	49	591.25	6710.67	4097.99	4028.38	5821.99
Lumpy	50	684.81	490.13	392.65	733.38	489.84

Bootstrapping and four forecasting methods results comparisons are given in Table 4.3 for each data categories.

Table 4.3 Comparison results of forecasting methods vs data categories

Method	Erratic	Intermittent	Lumpy	Smooth	Grand Total
Bootstrapping	10	40	24	7	76
Croston	10	31	67	5	113
Exp. Smoothing	21	100	86	5	217
Naive	18	33	36	8	95
Syntetos		13	21		34
Grand Total	59	217	234	25	535

Since the complexity of the application of bootstrapping and getting advantage over the other forecasting methods is uncertain. Comparing to applicability for inventory planners, it is decided to not to include this method to other inventory policy and approach calculations. Bootstrapping give minimum inventory costs comparing to other methods for 76 data series out of 535 spare parts.

CHAPTER 5

INVENTORY COST COMPARISONS USING (Q,R) POLICY

In this Chapter the analytical and simulated performance of the forecasting methods are investigated. The continuous review (r, Q) inventory policy is implemented to inventory of the system. The order size Q is calculated according to the economic order quantity using the average annual demand. Using the calculated reorder points, the inventory costs for all demand forecasting methods are compared. Cost based inventory performance results are given with the application of (r, Q) policy based on forecasting methods such as Exponential Smoothing, Croston, Syntetos and Naive.

5.1 Application of (Q, R) Policy

When the level of on-hand inventory decreases to R point, an order as Q amount is supposed to be placed as represented in Figure 5.1. Q is the order quantity that is updated in every period and R is the reorder level in units of inventory.

Ordering policy in this inventory system is given as below;

Q: Order amount

R: Reorder point.

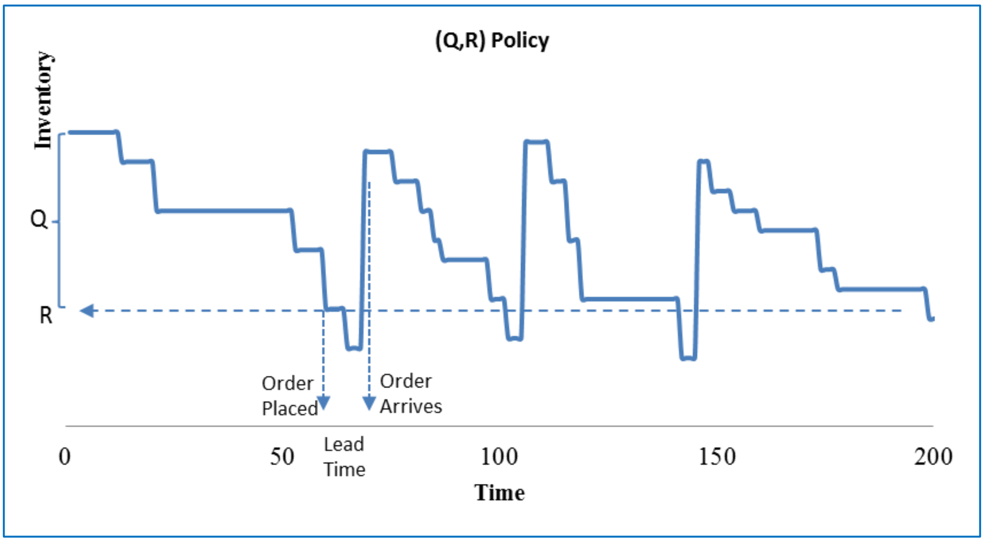

Figure 5.1 (Q,R) policy inventory system

K: Ordering cost per order

Holding cost (h): \$h per unit held per year

Penalty Cost (p): \$p per unit of unsatisfied demand

Λ: Mean demand unit per year

D: Demand over lead time

τ=1/12

The following assumptions are made;

1- Lead time is considered as 1 month and fixed.
2- Demand is random and the system is continuous review.
3- Penalty cost is taken as 5 times of the part price.
4- Holding cost is taken as 0.2*part price.
5- Ordering cost and part price are real market values.
6- Demand during lead time is continuous random variable D with probability density function. Demand during lead time μ=e(D) and $\sigma = \sqrt{var(D)}$ be the mean and standard deviation of demand during lead time.

Expected average annual inventory costs by employing optimal values of (Q,R) decision variables are minimized.

Inventory costs;

Holding cost=$h(\frac{Q}{2} + R - \Lambda\tau)$ (5.1)

Ordering cost= $K\Lambda/Q$ (5.2)

Expected number of shortages that occur in one cycle;

$$n(R) = E(max(D\text{-}R,0)) = \int_R^{\infty}(x-R)f(x)dx \quad (5.3)$$

Expected number of stock outs incurred per unit of time;

$$\frac{n(R)}{T} = \Lambda \mathrm{n(R)}/\mathrm{Q} \quad (5.4)$$

Stock out cost=$p\Lambda \mathrm{n(R)}/\mathrm{Q}$ (5.5)

5.1.1 Cost Functions

G(Q,R) is expected average cost of holding , ordering and stock-outs.

$$G(Q,R) = h\left(\frac{Q}{2} + R - \Lambda\tau\right) + \frac{K\Lambda}{\mathrm{Q}} + \mathrm{p}\Lambda\mathrm{n(R)}/\mathrm{Q} \quad (5.6)$$

In order to minimize *G (Q,R)* for each item in the stock, derivative of the cost function with respect to *Q* and *R* individually should be equalized to zero to satisfy necessary conditions for minimization.

$$\frac{\partial G(Q,R)}{\partial Q} = 0,\ \frac{\partial G(Q,R)}{\partial R} = 0 \quad (5.7)$$

$$Q = \sqrt{\frac{2\Lambda(\mathrm{K}+\mathrm{pn(R)})}{h}} \quad (5.8)$$

$$1 - F(R) = Qh/p\Lambda \quad (5.9)$$

To select initial Q_0 value, Economic order quantity (EOQ) which is best starting point is defined. Then R_0 value is found from the above equation (using Z table). After solving iteratively, Q and R values are found to optimize values.

$$\mathrm{Q0} = EOQ = \sqrt{\frac{2\Lambda\mathrm{K}}{\mathrm{h}}} \quad (5.10)$$

In here, n(R) is calculated by using standardized loss function. L(z) is given as follows;

$\emptyset(t)$ is the standard normal density, lead time demand is normal with mean μ and standard deviation σ.

$$n(R) = \sigma L(\frac{R-\mu}{\sigma}) = \sigma L(z) \tag{5.11}$$

$$L(z) = \int_z^\infty (t-z)\phi(t)\mathrm{dt} = \int_z^\infty t\Phi(t)\mathrm{dt} - \mathrm{z}\big(1-\Phi(\mathrm{z})\big) = \phi(z) - \mathrm{z}(1-\Phi(\mathrm{z})) \tag{5.12}$$

5.1.2 Iterative Methodology

1. Determine the use of the forecast
2. Select the item to be forecasted
3. Calculate the EOQ and Q_0
4. Calculate R_0 and F(R) values

   $$1 - F(R) = Qh/p\Lambda \tag{5.13}$$
5. Find n(R),

   $$n(R) = \sigma L(z) \tag{5.14}$$
6. Calculate $Q_{i,}$

   $$\mathrm{Qi} = \sqrt{\frac{2\Lambda\big(\mathrm{K}+\mathrm{pn(R)}\big)}{h}} \tag{5.15}$$
7. Repeat the steps of 4, 5 and 6 until reaching Q4, F(R)4 and n(R)4.
8. Last Q4 value is taken to define the order amount for the regarding month.
9. F(R)4 is employed to calculate Reorder point (R) value.

   $$R = \mu + Z * \sigma \tag{5.16}$$

5.1.3 Service Level Measures

Type 1 and Type 2 service level measures are computed based on last 36 months (it is considered as validation period).

β= Proportion of demand that is met from stock.

n(R)/Q= Average fraction of the number of stock out occasion to total demand occasion in each cycle.

Service Level: $\frac{\mathrm{n(R)}}{\mathrm{Q}} = 1 - \beta$ (5.17)

Type 2 service level which is defined as fill rate is the proportion of the satisfied demand to total number of demand.

5.1.4 Employed Forecasting Methods

Naïve method, Exponential Smoothing, Croston and Syntetos methods are used to update inventory parameters as applied in Chapter 3. Since the bootstrapping method in Chapter 4 does not yield the expected results, it was decided not to consider this method in the inventory comparisons of (Q, R).

The first 24 months of data are used to initialize the model. Last 36 month of data set is used to measure the performances of the forecasting methods by applying (Q, R) ordering policy. The inventory cost results of forecasting methods are given in Table 5.1 for the 50 data series. Results for the 200 data series under (Q,R) stock policy are given in Appendix C.1.

Table 5.1 Inventory cost comparisons of forecasting methods under (Q,R) policy

	Naive	Exp.Smoothing	Croston	Syntetos
1	83.17	26.46	36.65	40.38
2	62.56	62.60	58.95	44.89
3	24.39	18.36	20.76	23.22
4	397.76	282.56	224.96	294.08
5	234.08	217.79	217.55	217.14
6	1.19	1.52	1.55	1.55
7	166.05	166.05	166.05	166.05
8	202.32	192.98	174.29	172.65
9	90.58	73.43	94.61	88.23
10	34.41	18.39	19.72	17.09
11	22.61	20.81	17.85	15.05
12	152.43	109.52	69.13	74.48
13	1226.62	926.97	869.40	811.83
14	261.92	247.41	223.17	254.27
15	22.14	14.40	13.63	11.60
16	271.61	347.84	268.54	268.03
17	84.72	88.28	71.92	74.16
18	46.05	62.58	46.96	48.75
19	236.83	236.83	236.83	236.83
20	687.54	574.90	424.46	404.98
21	975.74	281.31	305.40	273.29
22	857.05	636.58	499.95	481.15
23	729.55	638.97	692.32	652.05
24	71.72	62.02	69.21	70.85
25	777.60	591.48	617.99	627.41
26	2063.25	1610.54	1535.88	1878.96
27	612.27	203.78	352.76	335.82
28	151.98	144.90	92.54	86.80
29	32.51	43.30	47.19	40.26
30	2099.89	2515.07	2118.83	1943.67
31	7.95	6.58	6.28	6.33
32	618.54	695.75	616.28	577.87
33	36.23	13.84	6.22	5.73
34	28.61	28.61	31.70	31.70
35	145.50	150.41	137.98	136.72
36	45.97	45.97	45.97	45.97
37	253.78	197.06	150.06	165.56
38	123.43	43.09	56.21	52.47
39	388.09	269.69	231.53	241.61
40	32.21	32.21	32.21	32.21
41	954.53	759.46	681.95	729.15
42	308.45	228.31	262.85	270.90
43	480.89	171.09	238.98	238.98
44	91.57	95.14	83.07	99.70
45	66.55	144.72	107.69	108.87
46	1043.56	640.97	563.53	410.29
47	43.06	43.06	43.06	43.06
48	3926.13	3602.82	3478.38	3478.38
49	463.11	461.93	417.29	448.75
50	33.87	33.87	33.87	33.87

5.2 Results

Considering the inventory costs as performance measure, four forecasting methods are applied and results are compared for the given demand data set under (Q, R) inventory policy. Each forecasting method that give the minimum cost results are counted for each demand series. Comparison results of forecasting methods are given for each data category in Table 5.2.

Table 5.2 Inventory cost comparison results vs demand category

	Erratic	Intermittent	Lumpy	Smooth	Grand Total
Croston	14	47	42	7	110
Exp.Smoothing	13	55	61	6	135
Naive Method	14	36	42	2	94
Syntetos	18	79	89	10	196
Grand Total	59	217	234	25	535

5.3 Statistical Testing of Comparisons

Chi-square statistics results are given in Table 5.3 and Table 5.4 to find out whether there is statistically significant difference between forecasting methods for non-smooth and smooth demand data respectively.

Table 5.3 Chi-Square statistics results for smooth demand data

	Smooth	**Expected**	**(Oi-Ei)^2/Ei**
Croston	4	6.25	0.81
Exp.Smoothing	8	6.25	0.49
Naive Method	4	6.25	0.81
Syntetos	9	6.25	1.21
Total	**25**		**3.32**

Chi-Square Statistics=3.32; Critical Value for 0.05 is 7.81;

There is statistically no evidence that forecasting methods for smooth data is different when inventory cost is considered.

Table 5.4 Chi-Square statistics results for non-smooth demand data

	Non-Smooth	**Expected**	**(Oi-Ei)^2/Ei**
Croston	103	127,5	4,7078
Exp.Smoothing	129	127,5	0,0176
Naive Method	92	127,5	9,8843
Syntetos	186	127,5	26,841
Total	**510**		**41,451**

Chi-Square Statistics=41.45; Critical Value for 0.05 is 7.8

There is statistically evidence that forecasting methods for non-smooth data is different when inventory cost is considered.

One tail statistical testing is applied to the forecasting methods inventory cost results to compare the differences significance.

H0: P1=P2=0.5

H1: P1>P2 or P1>0.5 the methods will be significantly different.

Significance level α= 0.05

$$Zstat = \frac{X-nPo}{\sqrt{nPo(1-Po)}} \tag{5.18}$$

N=25 X=14 and $Po = 0.5$

Exponential smoothing and Syntetos methods pairwise comparisons are given in Table 5.5. They are selected for statistical testing as they have close results comparing to other methods.

Table 5.5 Inventory cost comparison results of Exponential smoothing vs Syntetos

	Erratic	Intermittent	Lumpy	Smooth	Grand Total
Exp.Smoothing	22	85	96	14	217
Syntetos	37	132	138	11	318
Grand Total	59	217	234	25	535

Table 5.6 Exponential smoothing vs Syntetos in smooth series

	Smooth
Exp.Smoothing	14
Syntetos	11
	25

ZStat = 0.60; p-value=0.27>0.05

The proportion test indicates that there is not sufficient evidence that the Exponential Smoothing is better than the Syntetos method for the smooth data.

Table 5.7 Exponential smoothing vs Syntetos in non-smooth series

	Non_smooth
Exp.Smoothing	203
Syntetos	307
	510

ZStat = 4.61; p-value=0.0000021<0.05

The proportion test indicates that there is sufficient evidence that Syntetos is better than Exponential Smoothing for the non-smooth data.

Geometric mean of the inventory cost results of forecasting methods are given in Table 5.8. Croston and Syntetos give very close results when GMAMIC measure is used. Croston method gives the minimum GMAMIC value over other methods under (Q, R) stock policy.

Table 5.8 Geometric mean of inventory cost results of forecasting results

	Naive Method	**Exp.Smoothing**	**Croston**	**Syntetos**
GMAMIC	558.7795475	496.8064582	487.444195	488.06

CHAPTER 6

BASE STOCK POLICY WITH DIFFERENT ORDERING APPROACHES

There is a challenging forecasting area for spare parts because of the high variance and low occurrence of the data as it has been discussed in detail in previous chapters. In this chapter, the following research areas are investigated while establishing efficient spare parts management approach;

-Analyzing historical data set provided from aviation industry

-Categorization of the data to explore which method might perform well for each category of spare parts

-To investigate of the inventory implication of the forecasting methods

-Optimization of inventory costs for spare parts by keeping inventory at certain level

The main purpose of the research is to develop a better understanding of how forecasting methods perform in terms of the related error in predicting the operational performance measures. Historical data from industry (THY) analyzed and forecasting methods results feed the inventory parameters. Inventory costs are examined for different forecasting methods under different inventory policies. Throughout the experiments, it is expected that such inventory models preserving more general form will yield more quality of results in terms of approximating the desired inventory performance measures. The third and last research areas investigates and develops simulation optimization-based methods that exploit the structure of intermittent and highly variable demand.

6.1 Used Data Set

In this study, real spare parts demand data set in Turkish Airlines inventory and they are chosen among others for the diversity of their ADI is greater than 1.32 and CV^2 is lower than 0.49 and classified into intermittent demand category. The data covers 106 monthly periods from 2005 to 2013. Descriptive statistics of the demand data set was given in Table 3.1 in Chapter 3.

Examples from each data category is represented in Figure 6.1.

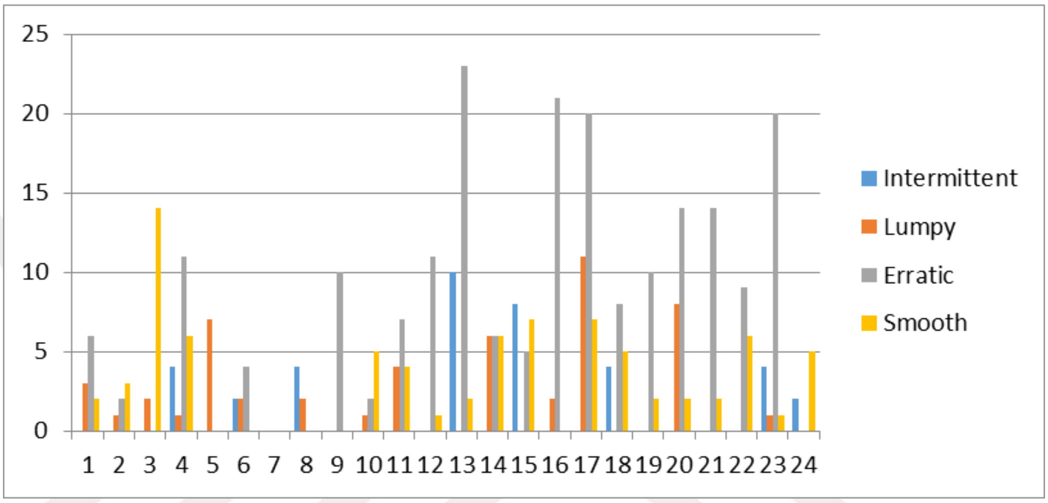

Figure 6.1 Different types of non-smooth demand data (monthly)

Two different inventory replenishment approaches are proposed considering different forecasting methods to update order up to levels. Based on forecasting results identifying and developing inventory control models that are well-suited for intermittent highly variable demand situations and investigating simulation based procedures for adjusting selected parameters (α, β, ϒ) to minimize inventory costs and maximize targeted service levels. The data set (each spare parts has 106 months demand data) is divided into three parts with overlapping as follows;

Initialization: The first 24 months of data are used to initialize the model. During that period of time smoothing parameter α is obtained as 0.2.

Optimization: Between 12th month and 96th month of the data is used for the minimization of total inventory costs. The parameters (α, β, ϒ) are searched between 0 and 1 (between 0 and ADI for β) using EXCEL VBA to give minimum total inventory costs. The parameters giving the minimum inventory cost are selected for use in validation.

Validation: Last 36 month of data set is used to measure the performances of the forecasting methods by applying proposed ordering approaches under base stock policy.

6.2 Modified Base Stock Policies Models

Model I: Modified Base Stock Policy with Inflated Coefficient

535 spare parts demand history data from THY inventory (as applied in previous chapters) is employed to make comparisons of proposed new approaches.

Assumptions

-Ordering cost and part prices are real market values that are provided by company for each item.

-Lead time is given as 1 month.

-Stock out cost=5*Part Price

-Instead of using order-up to level considering some distributions, forecasted values are used as base stock and ordering amounts when it is needed.

-For the following methods there is a inflation factor to update forecasted values. This factor is namely β. Optimum α and β values are calculated minimizing the cost of the inventory. β values are selected the range between from 0 to Average Demand Interval value of the regarding data.

-It is investigated direct relationship between inventory cost and those values.

Forecasting methods that employed:

1-Exp. Smoothing

2-Croston

3-Syntetos

Steps of inventory cost optimization applied in models;

- Apply intermittent demand forecasting methods (Exponential Smoothing, Croston and Syntetos) for the non-smooth data

- Apply proposed different models to these forecasts to calculate order up to levels and in ordering decisions.

- Optimize the inventory costs (holding, stock out and ordering costs) by setting α, β and ϒ parameters employed in forecasting methods. Optimum parameters that give minimum inventory costs are investigated in Microsoft Excel Visual Basic with written code. α is searched between 0 to 1 with increased range 0,01. β is increased from 0 to average demand interval value of the data increased range 0,01. ϒ is searched between 0 and 1 with increased range 0,01. For instance for one data (ADI value is 3) to apply Croston forecasting method with gradually ordering decision model. We have to search (for α 100, for β 300, for ϒ 100=100x300x100) 3.000.000 parameter to reach minimum costs provided by the best parameter set.

Model II- Gradually Ordering Decisions Inventory Model

-Demand interval estimates are used to allocate demand size estimation for the future periods in order to calculate order up to level in inventory model (if demand is nonzero).

-Backorder is allowed in the system. It will be fulfilled in next period if inventory is available.

-We expect that the estimated nonzero demand to be fulfilled during the demand interval estimate as gradually with the application of the following formula using ϒ parameter;

Period 1= $\gamma * D$

Period 2= $\gamma * (1 - \gamma)D$

Period 3= $\gamma * (1 - \gamma)2 * D$

Period 4= $\gamma * (1 - \gamma)3 * D$

-D indicates demand size estimate for the corresponding month,

- γ indicates a coefficient to allocate demand gradually in every month.

Estimated demand will be met during the estimated demand interval by the end of nth period (last period that is given in demand interval estimation).

n is assumed as maximum 12 months.

For n period;

n. period forecast: $\Upsilon*(1-\Upsilon)^{n-1}*D$

Forecast of last period is (it is as the forecasted demand interval);

Demand size estimation-all forecasts of the other periods allocated by ϒ parameter

6.3 Results

Modified base stock policy models (Gradually ordering decision and Inflated Coefficient model) are compared with simple approach. Simple approach means that values comes from the forecasting methods are directly used (not modified like in other models) in order to set the order up to levels. Comparisons of the simple approach versus proposed approaches after minimization of inventory costs are given in Figure 6.2.

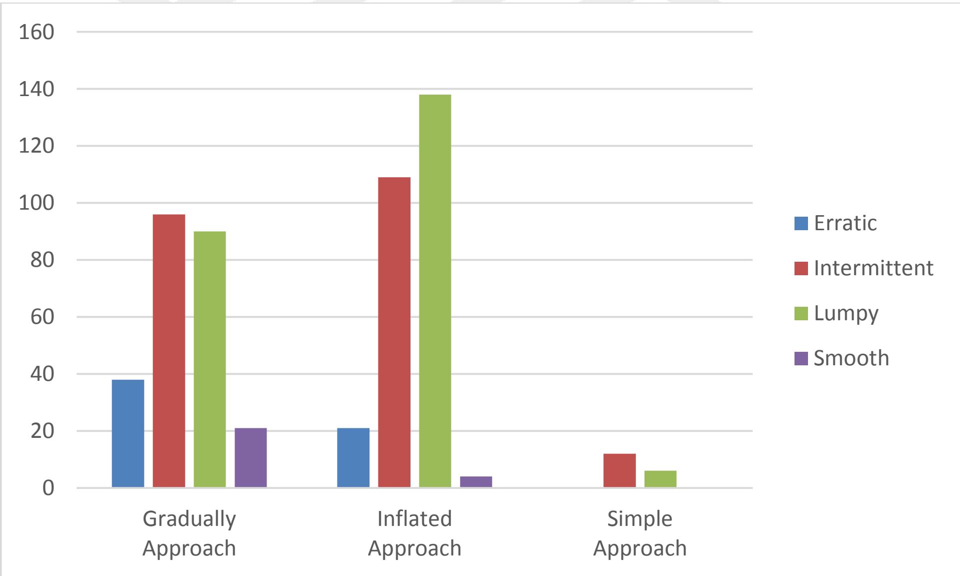

Figure 6.2 Comparison of modified base stock policy models that give the minimum cost results for selected data set

Total inventory costs of forecasting methods and proposed approaches are compared. Each forecasting method and ordering approaches that give the minimum cost results are counted for each case. Based on the comparisons the best forecasting method and ordering approaches for each data category is given in Figure 6.3.

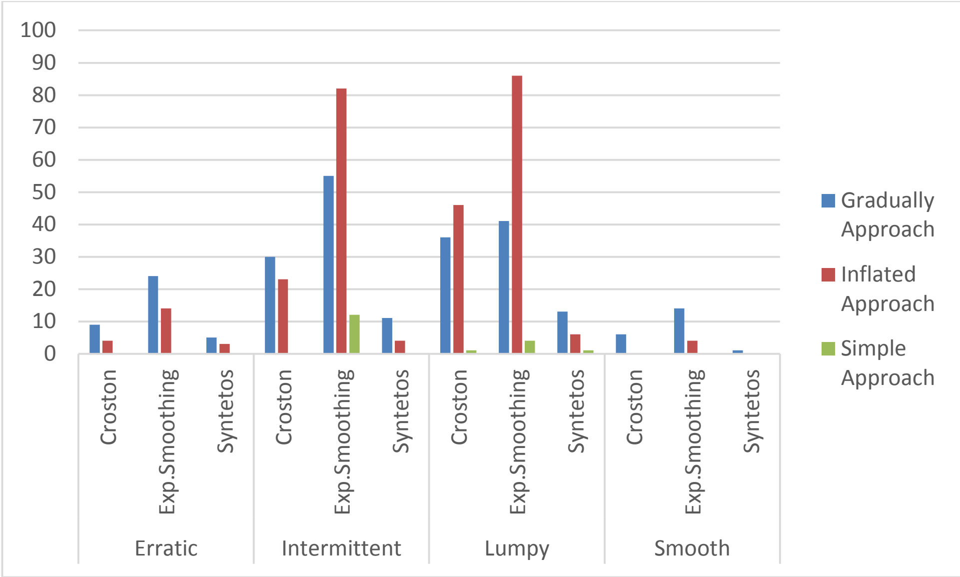

Figure 6.3 Comparison of modified base stock policy models based on proposed approaches and demand categories

Proposed approaches and simple approach are compared based on the number of minimum inventory cost results (data # 535) in Figure 6.4.

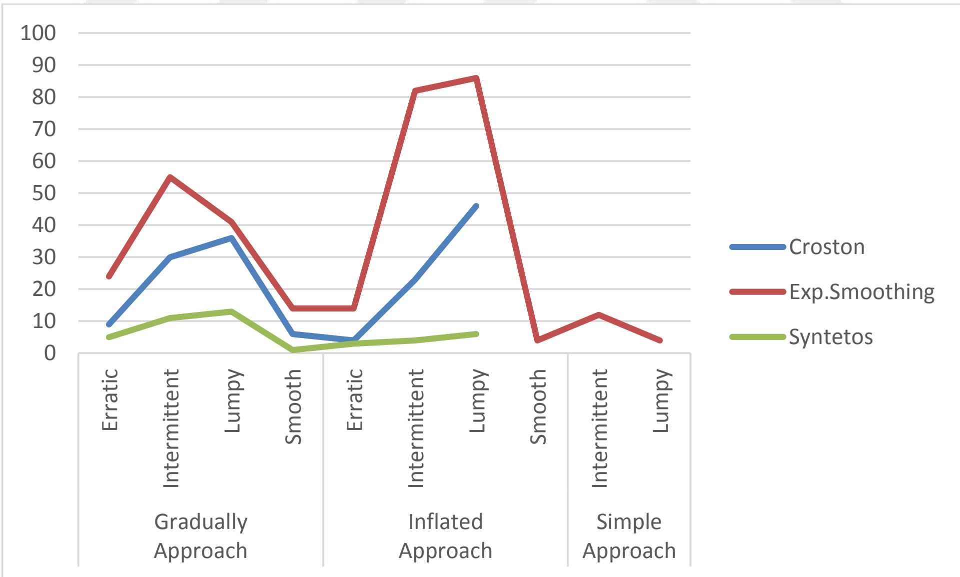

Figure 6.4 Comparison of modified base stock policy models

The best three models that give minimum inventory costs are as follows;

1-Exponential Smoothing with Inflated Decision Approach

2-Exponential Smoothing with Gradually Ordering Approach

3-Croston Method with Gradually Ordering Approach

Table 6.1 Best method and approach for each data types

Data Type	Forecasting Method	Best Inventory Approach
Intermittent	Exp.Smoothing	Inflated Approach
Erratic	Exp.Smoothing	Gradually Approach
Lumpy	Exp.Smoothing	Inflated Approach
Smooth	Exp.Smoothing	Gradually Approach

In this Chapter, gradually ordering decisions and inflated coefficient base stock policies are applied to find out the optimum inventory model with the choice of the parameters. Inventory cost results of the forecasting methods with the application of proposed ordering approaches for 200 data series are given in Appendix D.1.

Table 6.2 Best forecasting method and approach comparison results

Row Labels	Erratic	Intermittent	Lumpy	Smooth	Grand Total
Croston	**13**	**53**	**83**	**6**	**155**
Gradually Approach	9	30	36	6	81
Inflated Approach	4	23	46		73
Simple Approach			1		1
Exp.Smoothing	**38**	**149**	**131**	**18**	**336**
Gradually Approach	24	55	41	14	134
Inflated Approach	14	82	86	4	186
Simple Approach		12	4		16
Syntetos	**8**	**15**	**20**	**1**	**44**
Gradually Approach	5	11	13	1	30
Inflated Approach	3	4	6		13
Simple Approach			1		1
Grand Total	**59**	**217**	**234**	**25**	**535**

6.3.1 GMAMIC results of methods vs approaches

Geometric mean of inventory costs results are given in Table 6.3-6.5.

Table 6.3 GMAMIC results of Exponential smoothing vs proposed approaches

	Exp.Smoothing		
	Simple Approach	**Inflated Approach**	**Gradually Approach**
GMAIC	534.93	400.95	404.03

Table 6.4 GMAMIC results of Croston method vs proposed approaches

	Croston		
	Simple Approach	**Inflated Approach**	**Gradually Approach**
GMAIC	578.43	472.71	423.74

Table 6.5 GMAMIC results of Syntetos method vs proposed approaches

	Syntetos		
	Simple Approach	**Inflated Approach**	**Gradually Approach**
GMAIC	676.55	686.42	466.82

GMAMIC results of forecasting methods under different inventory policies and ordering approaches are given in Table 6.6. This measure which is proposed in this study validates directly comparison of inventory costs of forecasting methods which is given in Table 6.1. Base stock policy with the inflated approach using exponential smoothing is the best option while base stock policy with the gradually ordering approach is second alternative.

Table 6.6 Overall GMAMIC results of forecasting methods under different inventory policies and ordering approaches

	Naive Method	**Exp.Smoothing**	**Croston**	**Syntetos**
Base Stock (α=0.2)	624.55	678.62	723.68	752.66
Base Stock (αopt.)	624.55	534.93	578.43	676.55
(Q,R) Policy	**558.77**	496.80	487.44	488.06

Table 6.6 (cont'd)

Base Stock with Gradually	-	**404.03**	423.74	466.82
Base Stock with Inflated	**-**	**400.95**	472.71	686.42

6.3.2 Chi-square Testing of Comparisons

Chi-square statistics results are given in Table 6.7 and Table 6.8 to find out whether there is statistically significant difference between forecasting methods for non-smooth and smooth demand data respectively when proposed ordering approaches are employed.

Table 6.7 Chi-Square Statistics for non-smooth demand data

Methods	**Non-Smooth**	**Expected**	**(Oi-Ei)^2/Ei**
Croston	158	127,5	7,2961
Exp.Smoothing	290	127,5	207,11
Naive Method	0	127,5	127,5
Syntetos	62	127,5	33,649
Total	510		375,55

Chi-Square Statistics=375.55; Critical Value for 0.05 is 7.8.

There is statistically evidence that forecasting methods for non-smooth data is different when inventory cost is considered.

Table 6.8 Chi-Square Statistics for smooth demand data

	Smooth	**Expected**	**(Oi-Ei)^2/Ei**
Croston	15	127,5	99,265
Exp.Smoothing	9	127,5	110,14
Naive Method	0	127,5	127,5
Syntetos	1	127,5	125,51
Total	**25**		**462,41**

Chi-Square Statistics=462.41; Critical Value for 0.05 is 7.8.

There is statistically evidence that forecasting methods for non-smooth data is different when inventory cost is considered.

6.3.3 One-tail Testing of Comparisons

One tail statistical testing is applied to ordering approaches inventory cost results to compare whether the differences are statistically significant or not of those models.

H0: P1=P2=0.5

H1: P1>P2 or P1>0.5 the methods will be significantly different.

Significance level α= 0.05

If one tail testing is applied with below parameters;

$Po = 0.5$

Total inventory costs of forecasting methods and proposed approaches are compared. Each forecasting method and ordering approaches that give the minimum cost results are counted for each case. The comparison results of the ordering approaches for the data set is given in Figure 6.9.

Table 6.9 Ordering approaches comparison results vs applied forecasting methods

	Croston	**Exp.Smoothing**	**Syntetos**	Grand Total
Gradually Approach	78	111	36	225
Inflated Approach	84	167	23	274
Simple Approach	11	21	4	36
Grand Total	**173**	**299**	**63**	**535**

Gradually approach and inflated approach pairwise comparisons are given in Table 6.10. They are selected for statistical testing since they have close results.

Table 6.10 Gradually vs inflated approach in non-smooth series

	Non-Smooth
Gradually Approach	225
Inflated Approach	274
	510

ZStat = 1.68; p-value=0.046<0.05

The proportion test indicates that there is sufficient evidence that inflated approach is better than gradually approach for the non-smooth data.

In Table 6.11, all comparisons of inventory costs under different policies and developed different approaches are given with different demand data categories.

Table 6.11 All comparisons of forecasting methods under different policies and proposed approaches

		BS	BS	BS	BS	BS	(Q,R)	(Q,R)	(Q,R)	(Q,R)	Simple	Inflated	Gradually	Simple	Inflated	Gradually	Simple	Inflated	Gradually
Data Type	**No**	**Bootstrap ping**	**Naive**	**Exp. Smt.**	**Croston**	**Syntetos**	**Naive**	**Exp. Smt.**	**Croston**	**Syntetos**	**Exp. Smt.**	**Exp. Smt.**	**Exp. Smt.**	**Croston**	**Croston**	**Croston**	**Syntetos**	**Syntetos**	**Syntetos**
Lumpy	**1**	83.80	49.7	36.25	31.82	33.53	83	26	37	40	36.25	31.37	30.44	31.82	35.94	35.88	58.77	30.59	36.11
Erratic	**2**	162.22	94.84	118.54	114.87	159.44	63	63	59	45	107.69	63.98	62.14	104.36	65.18	58.91	107.46	103.25	75.67
Erratic	**3**	61.93	39.93	39.97	42.34	51.21	24	18	21	23	108.93	102.21	92.78	115.41	99.2	95.68	126.65	120.72	101.23
Lumpy	**4**	483.33	352.6	325.8	300.89	319.99	398	283	225	294	23.59	29.73	19.24	21.78	19.39	7.95	23.45	20.37	6.28
Lumpy	**5**	2177.25	1139	1140	1419.43	1330.07	234	218	218	217	76.14	45.2	45.96	89.15	49.54	48.7	105.21	74.73	67.84
Lumpy	**6**	2.84	2.75	3	3.29	3.44	1	2	2	2	37.92	24.13	23.24	41.52	24.82	25.55	51.51	33.44	22.35
Lumpy	**7**	1580.41	1190	997.72	1299.48	1328.01	166	166	166	166	62.24	32.96	33.32	82.39	52.18	43.84	83.52	82.39	44.95
Intermittent	**8**	757.34	555.2	458.62	801.99	663.3	202	193	174	173	51.51	40.86	32.1	89.49	70.27	73.46	85.23	65.7	67.15
Intermittent	**9**	402.74	251.9	200.74	167.56	218.74	91	73	95	88	94.14	67.42	69	82.9	73.28	75.4	106.44	73.33	70.28
Intermittent	**10**	30.17	14.85	21.68	11.85	23.06	34	18	20	17	41.27	17.65	16.79	32.33	9.48	11.98	32	16.68	17.69
Intermittent	**11**	56.22	31.82	31.4	32.4	43.78	23	21	18	15	75.24	35.72	49.33	77.66	36.94	37.68	106.05	41.49	41.74
Lumpy	**12**	90.44	77.21	69.42	79.34	70.23	152	110	69	74	35.56	30.23	38.13	30.44	30.65	30.46	36.72	35.96	30.46
Intermittent	**13**	1049.42	4194	1550.6	1465.35	966.8	1227	927	869	812	80.81	40.35	41.36	65.19	46.93	47.81	77.06	55.02	51.21
Erratic	**14**	442.32	306.2	255.98	287.79	304.52	262	247	223	254	196.12	153	158.58	198.13	153.46	161.84	217.62	185.74	176.42
Lumpy	**15**	19.52	7.62	6.64	9.02	9.75	22	14	14	12	34.19	42.08	36.75	46.41	46.41	41.79	49.01	48.45	38.04
Lumpy	**16**	3012.67	1549	1454.6	1644.91	1649.72	272	348	269	268	100.71	84.51	144.7	109.17	92.43	82.24	115.79	91.24	79.26
Lumpy	**17**	187.49	138.7	140.53	144.21	154.08	85	88	72	74	86.93	57.85	62.52	91.87	71.26	79.8	97.48	80.94	74.2
Lumpy	**18**	81.25	54.9	56.59	53.01	60.55	46	63	47	49	157.33	153.21	149.93	147.36	141.12	146.26	165.17	154.52	147.15
Lumpy	**19**	2184.38	1898	1907.1	703.4	2217.32	237	237	237	237	72.87	58.19	57.86	55.14	55.14	58.49	79.9	50.74	57.77
Lumpy	**20**	2317.22	1074	965.65	899.39	1098.74	688	575	424	405	95.51	83.53	84.06	108.66	93.29	93.98	116.98	96.87	91.46
Lumpy	**21**	971.45	353.4	241.25	707.64	445.71	976	281	305	273	21.91	25.16	26.21	48.29	37.6	38.03	34.24	33.66	43.6
Intermittent	**22**	893.39	376.1	431.12	362.98	536.1	857	637	500	481	29.49	27.58	19.95	28.27	29.18	30.08	36.43	20.29	30.24
Lumpy	**23**	1001.90	849.5	817.24	818.51	903.64	730	639	692	652	80.69	62.82	69.55	85.66	73.26	55.7	104.66	81.18	78.45
Lumpy	**24**	142.67	100.4	84.41	88.55	95.97	72	62	69	71	103.52	75.26	75.76	111.34	81.75	85.81	108.44	99.85	106.87
Erratic	**25**	494.39	521	536.78	517.14	720.42	778	591	618	627	687.32	674.65	543.83	689.57	689.57	551.03	693.46	693.46	548.72
Lumpy	**26**	1346.77	1385	1100.2	1605.17	1542.17	2063	1611	1536	1879	25.17	15.8	20.91	50.79	41.19	24.29	48.32	75.88	33.86
Lumpy	**27**	305.17	326.1	354.66	371.36	388.94	612	204	353	336	51.89	23.81	16.52	54.34	10.82	6.46	56.51	48.45	9.8
Lumpy	**28**	327.77	158.3	159.53	159.24	193.38	152	145	93	87	50.77	38.99	39.25	50.65	52.46	46.74	60.73	49.37	48.22
Lumpy	**29**	95.14	44.98	42.35	57.14	65.41	33	43	47	40	66.05	60.23	60.79	98.35	86.36	78.05	103.2	103.04	81.44
Lumpy	**30**	2465.97	2182	2154.1	1975.58	2264.34	2100	2515	2119	1944	44.33	25.05	25.34	34.25	20.58	21.57	41	29.35	42.26

CHAPTER 7

CONCLUSION

Building simple cost optimization procedure could help managers and planners to understand which costs are important and how critical the stock-outs can be. Traditional forecasting measures could not give practical or realistic results to compare the performances of the forecasting methods for items that have non-smooth pattern especially where the managers often focus on costs. The reduction of inventory levels is often an important goal of the planners of the inventory. The exact forecast can help to improve the satisfaction of the customer and can help to increase better control of the business. Therefore, companies need to have proper forecasting method and ordering methodology that consider the inventory cost performances. The inventory cost of a product might be decreased when improved forecast becomes the determinant of the amount of inventory.

In this study, the forecasting accuracy and inventory implications of forecasting methods for real data set from aviation industry are investigated. The best strategy is to consider the integrate inventory decision making and demand forecasting results for non-smooth demand. Uncertainty have high impact on the demand side and it leads to the choice of the forecasting method has an impact on the decisions of inventory items that need to be stocked, if one combines the forecasting results with the inventory ordering decisions, inventory costs might be decreased and thus performance of the system can increase.

This study will shed light on the comparing forecasting methods considering different forecasting methods with optimizing inventory costs. As a result, after the demand data categorization, companies may decide the most appropriate forecasting method that will provide minimum inventory costs. This information would help practitioners to give their ordering decisions with minimum inventory costs, suitable base stock policy and high service levels for each type of demand.

The motivation of this research was to determine the best forecasting technique and inventory replenishment methodology that provide minimum inventory cost to decrease spare parts demand problems. To do this, the data set (provided by THY) is employed to compare the parametric and non-parametric forecasting methods under different inventory policies and ordering approaches. Initially, historical demand data of spare parts is classified depending on its properties such as average inter-demand interval (ADI) and coefficient of variation based on Syntetos scheme. Four different groups of spare parts were determined based on that classification namely intermittent, lumpy, smooth, and erratic. Then, spare parts demand forecasting models are employed to evaluate inventory cost based performances considering the optimum alpha and constant alpha model has been presented in Chapter 3 with base stock policy. In chapter 4 nonparametric bootstrapping method is applied to determine order up to level and stock parameters for predetermined customer service level. In chapter 5, (Q, R) stochastic policy is applied to these forecasting methods and inventory cost based comparisons are made. In chapter 6, two new approaches are generated on base stock policy to investigate cost impact and minimize inventory holding and stock-out costs. Inventory cost based results are given in all chapters to make comparisons for each demand categories. The comparison is performed on 535 real non-smooth demand data series from the airline industry. The forecasting techniques are evaluated on the basis of holding, stock out and ordering costs. Proposed approaches give outstanding results when they are applied to traditional or non-traditional forecasting methods. They make even traditional forecasting methods outperforms to forecasting methods that are developed for non-smooth data.

There two objectives also are essential for inventory planners in addition to the aim of reducing inventory costs for spare parts: (a) demonstrating the decrease of inventory cost, the reason of which are the improved forecasts based on demand classes, and (b) determining the amount of procurement and the product order time with the aim of sustaining a satisfying customer service level. There are some methods which are essential for the forecast to be accurate. These methods are determined depending on the present conditions by demand data categorization. By the way, different demand categories could be the application area of different inventory control methods.

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APPENDIX-A

RMSE AND INVENTORY COST RESULTS

Table A.1 RMSE Results of forecasting methods (α=0.2)

No	Naive	ExpSmt	Croston	Syntetos	Best Method	Data Type
1	4.25	3.51	3.27	3.29	Croston	Lumpy
2	4.34	3.25	2.85	2.89	Croston	Erratic
3	7.41	5.19	4.31	4.42	Croston	Erratic
4	0.50	0.48	0.69	0.63	ExpSmt	Lumpy
5	3.94	2.82	2.66	2.66	Syntetos	Lumpy
6	1.08	0.95	0.89	0.90	Croston	Lumpy
7	2.13	1.72	1.60	1.62	Croston	Lumpy
8	1.19	0.89	0.86	0.88	Croston	Intermittent
9	6.03	4.00	3.63	3.63	Syntetos	Intermittent
10	1.08	1.03	1.01	1.00	Syntetos	Intermittent
11	3.66	2.63	2.40	2.42	Croston	Intermittent
12	4.01	3.09	2.81	2.83	Croston	Lumpy
13	1.02	0.65	0.61	0.62	Croston	Intermittent
14	16.47	12.40	9.97	10.39	Croston	Erratic
15	4.63	3.98	4.05	3.98	Syntetos	Lumpy
16	5.17	4.02	3.55	3.58	Croston	Lumpy
17	3.18	2.48	2.22	2.26	Croston	Lumpy
18	39.73	34.89	31.83	32.03	Croston	Lumpy
19	14.27	10.39	9.47	9.52	Croston	Lumpy
20	16.15	12.36	11.15	11.16	Croston	Lumpy
21	4.34	3.07	2.83	2.81	Syntetos	Lumpy
22	1.98	1.41	1.29	1.29	Syntetos	Intermittent
23	1.98	1.47	1.37	1.34	Syntetos	Lumpy
24	4.53	4.37	3.66	3.79	Croston	Lumpy
25	202.63	142.55	116.60	117.80	Croston	Erratic
26	1.41	1.22	1.30	1.26	ExpSmt	Lumpy
27	0.41	0.78	1.08	0.97	Naive	Lumpy
28	5.37	3.81	3.61	3.63	Croston	Lumpy
29	5.37	10.04	9.16	9.13	Naive	Lumpy
30	2.70	1.95	1.77	1.78	Croston	Lumpy
31	21.85	16.18	14.84	14.89	Croston	Lumpy
32	0.82	0.64	0.67	0.63	Syntetos	Lumpy
33	2.45	2.11	2.07	2.09	Croston	Lumpy
34	0.58	0.45	0.49	0.48	ExpSmt	Lumpy

35	0.58	1.89	1.73	1.76	Naive	Intermittent
36	0.58	0.42	0.41	0.39	Syntetos	Lumpy
37	1.50	1.10	1.05	1.04	Syntetos	Intermittent
38	2.31	1.68	1.61	1.60	Syntetos	Intermittent
39	1.78	1.37	1.29	1.30	Croston	Intermittent
40	1.12	0.76	0.70	0.70	Syntetos	Lumpy
41	0.96	0.85	1.17	1.08	ExpSmt	Lumpy
42	0.96	2.27	2.11	2.09	Naive	Lumpy
43	0.50	0.36	0.35	0.34	Syntetos	Intermittent
44	5.13	3.76	3.45	3.50	Croston	Lumpy
45	1.15	0.98	0.96	0.96	Croston	Intermittent
46	0.29	0.35	0.52	0.48	Naive	Intermittent
47	0.29	0.74	0.67	0.67	Naive	Intermittent
48	1.00	1.81	1.71	1.70	Naive	Intermittent
49	4.37	3.57	3.39	3.37	Syntetos	Erratic
50	1.67	1.16	1.07	1.07	Croston	Lumpy
51	1.67	0.80	0.74	0.74	Syntetos	Lumpy
52	3.97	3.64	3.78	3.68	ExpSmt	Erratic
53	1.62	1.19	1.09	1.09	Syntetos	Lumpy
54	2.73	2.11	1.89	1.90	Croston	Lumpy
55	0.41	0.42	0.58	0.53	Naive	Lumpy
56	0.41	1.18	1.12	1.11	Naive	Lumpy
57	2.14	1.83	1.83	1.77	Syntetos	Lumpy
58	87.09	62.81	52.53	53.18	Croston	Lumpy
59	20.91	15.96	12.77	13.83	Croston	Lumpy
60	1.41	1.03	0.99	0.97	Syntetos	Lumpy
61	1.41	9.74	8.31	8.27	Naive	Lumpy
62	0.71	0.55	8.31	0.50	Syntetos	Intermittent
63	0.50	0.36	0.50	0.34	Syntetos	Intermittent
64	0.41	0.31	0.29	0.29	Syntetos	Intermittent
65	0.41	2.00	1.83	1.81	Naive	Lumpy
66	1.32	1.06	1.02	1.02	Syntetos	Intermittent
67	0.50	0.44	0.45	0.43	Syntetos	Intermittent
68	2.61	2.01	0.45	2.08	Croston	Intermittent
69	3.46	2.50	2.15	2.31	Croston	Lumpy
70	3.46	2.96	2.78	2.78	Syntetos	Lumpy
71	3.32	3.11	3.37	3.23	ExpSmt	Lumpy
72	5.31	4.60	4.49	4.44	Syntetos	Intermittent
73	6.53	5.67	5.71	5.60	Syntetos	Intermittent
74	6.53	5.55	5.71	5.53	Syntetos	Intermittent
75	6.33	82.07	5.65	76.45	Syntetos	Lumpy
76	0.50	0.36	0.36	0.36	Syntetos	Intermittent
77	6.39	4.67	4.32	4.34	Croston	Lumpy
78	6.39	0.52	0.50	0.49	Syntetos	Intermittent
79	2.60	2.09	1.94	1.95	Croston	Lumpy
80	1.38	0.60	1.94	0.46	Syntetos	Intermittent
81	7.05	6.33	0.47	5.49	Croston	Lumpy
82	7.05	47.71	5.39	39.88	Croston	Lumpy
83	1.78	1.21	1.13	1.12	Syntetos	Intermittent
84	1.38	1.09	1.05	1.05	Croston	Lumpy
85	5.45	4.50	4.20	4.16	Syntetos	Lumpy
86	1.38	0.97	0.92	0.92	Croston	Intermittent

87	2.26	1.73	0.92	1.59	Croston	Lumpy
88	2.26	5.55	1.59	5.25	Croston	Lumpy
89	0.91	0.67	5.26	0.62	Syntetos	Intermittent
90	2.73	1.94	1.82	1.80	Syntetos	Lumpy
91	1.19	0.88	0.81	0.81	Croston	Intermittent
92	1.19	15.36	15.26	14.81	Naive	Lumpy
93	4.48	3.76	5.00	4.74	ExpSmt	Lumpy
94	1.76	1.27	5.00	1.18	Syntetos	Intermittent
95	2.25	1.58	1.19	1.49	Croston	Intermittent
96	8.04	5.69	1.49	4.97	Croston	Lumpy
97	8.04	2.37	4.91	2.21	Syntetos	Intermittent
98	2.53	1.84	1.65	1.66	Croston	Lumpy
99	1.04	0.74	0.69	0.68	Syntetos	Intermittent
100	1.29	0.99	1.07	1.03	ExpSmt	Intermittent
101	1.29	1.03	1.08	1.06	ExpSmt	Intermittent
102	1.46	1.35	1.28	1.30	Croston	Intermittent
103	5.30	3.95	3.65	3.65	Syntetos	Lumpy
104	1.58	1.45	1.48	1.47	ExpSmt	Intermittent
105	1.58	1.04	1.48	1.00	Syntetos	Intermittent
106	1.49	1.04	0.99	0.99	Syntetos	Intermittent
107	1.26	2.72	33.31	29.96	Naive	Lumpy
108	1.26	1.58	1.45	1.46	Naive	Intermittent
109	3.01	2.49	2.37	2.38	Croston	Lumpy
110	9.86	6.94	5.73	5.71	Syntetos	Smooth
111	9.86	2.20	5.73	2.01	Syntetos	Lumpy
112	0.71	0.51	2.00	0.48	Syntetos	Intermittent
113	2.44	1.63	0.49	1.52	Croston	Smooth
114	6.00	4.82	4.53	4.52	Syntetos	Intermittent
115	6.00	5.05	4.73	4.71	Syntetos	Lumpy
116	34.07	26.87	21.52	22.50	Croston	Smooth
117	5.00	4.35	3.74	3.73	Syntetos	Erratic
118	7.06	4.94	4.01	4.06	Croston	Erratic
119	7.06	7.80	4.01	7.13	Croston	Erratic
120	0.50	0.36	7.26	0.36	Syntetos	Lumpy
121	0.79	0.54	0.37	0.50	Croston	Intermittent
122	0.87	0.61	0.50	0.56	Croston	Intermittent
123	0.87	0.47	0.45	0.45	Syntetos	Intermittent
124	4.38	3.17	2.74	2.74	Syntetos	Lumpy
125	3.42	2.70	2.46	2.44	Syntetos	Smooth
126	4.77	3.93	3.99	3.87	Syntetos	Lumpy
127	0.68	0.64	0.76	0.72	ExpSmt	Lumpy
128	0.68	1.77	1.62	1.65	Naive	Intermittent
129	0.71	0.54	0.54	0.53	Syntetos	Intermittent
130	1.85	1.28	0.54	1.19	Croston	Intermittent
131	10.17	7.44	1.18	7.00	Croston	Lumpy
132	10.17	3.75	3.65	3.52	Syntetos	Intermittent
133	2.13	1.64	1.50	1.49	Syntetos	Lumpy
134	6.61	4.78	4.11	4.17	Croston	Lumpy
135	1.98	1.30	1.23	1.21	Syntetos	Intermittent
136	0.65	0.47	0.46	0.45	Syntetos	Lumpy
137	0.65	0.77	0.81	0.78	Naive	Intermittent
138	0.89	0.82	0.80	0.81	Croston	Intermittent

139	65.17	47.26	40.41	40.86	Croston	Lumpy
140	6.47	5.17	4.66	4.71	Croston	Lumpy
141	19.02	14.15	4.66	12.17	Croston	Erratic
142	19.02	1.41	1.35	1.35	Syntetos	Intermittent
143	10.86	9.94	7.94	8.23	Croston	Erratic
144	94.93	66.15	54.66	56.05	Croston	Lumpy
145	94.93	29.54	24.00	24.29	Croston	Erratic
146	1.24	0.98	1.05	1.00	ExpSmt	Lumpy
147	2.08	1.45	1.31	1.31	Croston	Intermittent
148	0.68	0.52	0.58	0.55	ExpSmt	Intermittent
149	8.93	7.10	5.81	6.02	Croston	Erratic
150	1.83	1.69	5.81	1.50	Syntetos	Intermittent
151	2.75	1.89	1.58	1.77	Croston	Lumpy
152	3.88	3.39	1.75	2.92	Croston	Intermittent
153	2.79	2.07	2.79	1.94	Syntetos	Smooth
154	4.39	2.16	1.91	1.86	Syntetos	Lumpy
155	1.43	1.31	1.27	1.32	Croston	Intermittent
156	2.77	2.17	1.94	1.98	Croston	Lumpy
157	2.18	1.58	1.43	1.45	Croston	Intermittent
158	1.40	0.98	0.91	0.92	Croston	Intermittent
159	8.76	6.66	0.91	5.85	Croston	Erratic
160	0.96	0.85	5.85	0.83	Syntetos	Lumpy
161	6.73	4.58	3.76	3.92	Croston	Lumpy
162	1.00	0.67	0.62	0.63	Croston	Intermittent
163	1.66	1.28	1.20	1.20	Croston	Lumpy
164	0.71	0.46	0.42	0.41	Syntetos	Intermittent
165	1.17	0.91	0.87	0.88	Croston	Intermittent
166	31.14	22.74	19.58	20.00	Croston	Lumpy
167	0.74	0.67	19.58	0.65	Syntetos	Intermittent
168	1.53	1.05	0.66	0.99	Croston	Lumpy
169	0.94	0.67	0.99	0.62	Syntetos	Intermittent
170	3.82	2.61	0.62	2.23	Croston	Intermittent
171	3.28	3.37	2.20	3.20	Croston	Lumpy
172	3.52	2.54	2.31	2.30	Syntetos	Lumpy
173	12.47	8.78	7.43	7.49	Croston	Erratic
174	1.71	1.35	1.26	1.23	Syntetos	Lumpy
175	0.71	0.52	0.49	0.50	Croston	Intermittent
176	2.25	2.08	2.01	2.03	Croston	Intermittent
177	9.98	6.73	2.01	6.15	Croston	Erratic
178	1.10	0.90	5.77	0.89	Syntetos	Intermittent
179	0.91	0.76	0.92	0.72	Syntetos	Intermittent
180	2.21	1.64	1.49	1.49	Syntetos	Lumpy
181	14.47	10.21	9.35	9.30	Syntetos	Lumpy
182	4.70	3.50	3.23	3.23	Croston	Erratic
183	70.38	54.46	48.86	48.52	Syntetos	Lumpy
184	1.86	1.40	3.36	3.05	ExpSmt	Lumpy
185	37.18	29.43	26.23	26.56	Croston	Lumpy
186	25.01	22.85	19.49	19.70	Croston	Erratic
187	1.84	1.16	19.49	1.04	Syntetos	Intermittent
188	2.65	1.94	1.04	1.85	Croston	Lumpy
189	0.41	0.33	0.35	0.34	ExpSmt	Intermittent
190	2.19	1.80	1.74	1.72	Syntetos	Intermittent

191	1.04	0.72	0.67	0.67	Croston	Intermittent
192	1.47	1.14	1.09	1.09	Syntetos	Lumpy
193	1.32	1.06	1.01	1.01	Syntetos	Lumpy
194	2.38	2.05	1.01	1.97	Croston	Lumpy
195	1.66	1.11	1.96	1.05	Syntetos	Intermittent
196	6.18	5.23	1.04	4.38	Croston	Lumpy
197	7.84	6.67	4.37	6.12	Croston	Lumpy
198	0.91	0.68	0.65	0.64	Syntetos	Lumpy
199	10.23	7.52	6.69	6.68	Syntetos	Lumpy
200	1.73	1.39	1.36	1.33	Syntetos	Intermittent

Table A.2 RMSE Results of forecasting methods ($\alpha_{optimum}$)

No	Naive	ExpSmt	Croston	Syntetos	Data Type	Best Method
1	4.25	3.30	3.23	3.25	Lumpy	Croston
2	4.34	3.07	2.50	2.58	Erratic	Croston
3	7.41	4.87	1.71	3.63	Erratic	Croston
4	0.50	0.63	0.68	0.50	Lumpy	Syntetos
5	3.94	2.73	2.87	2.72	Lumpy	Syntetos
6	1.08	0.91	1.10	1.04	Lumpy	ExpSmt
7	2.13	2.12	1.57	1.58	Lumpy	Croston
8	1.19	0.93	0.93	0.93	Intermittent	ExpSmt
9	6.03	3.90	3.78	3.60	Intermittent	Syntetos
10	1.08	1.00	1.01	0.98	Intermittent	Syntetos
11	3.66	2.58	2.28	2.33	Intermittent	Croston
12	4.01	2.86	4.88	2.98	Lumpy	ExpSmt
13	1.02	0.63	0.61	0.62	Intermittent	Croston
14	16.47	12.13	0.16	10.00	Erratic	Croston
15	4.63	4.19	3.11	3.03	Lumpy	Syntetos
16	5.17	3.92	3.05	3.27	Lumpy	Croston
17	3.18	3.17	2.10	1.88	Lumpy	Syntetos
18	39.73	33.90	31.76	31.68	Lumpy	Syntetos
19	14.27	9.75	9.38	9.42	Lumpy	Croston
20	16.15	12.04	10.74	9.55	Lumpy	Syntetos
21	4.34	2.98	2.89	2.88	Lumpy	Syntetos
22	1.98	1.30	1.29	1.29	Intermittent	Syntetos
23	1.98	1.38	1.14	1.24	Lumpy	Croston
24	4.53	4.37	1.81	3.04	Lumpy	Croston
25	202.63	131.75	56.56	85.66	Erratic	Croston
26	1.41	1.55	1.16	1.08	Lumpy	Syntetos
27	0.41	0.99	1.24	0.67	Lumpy	Naive
28	5.37	3.75	3.32	3.26	Lumpy	Syntetos
29	5.37	9.50	7.73	8.31	Lumpy	Naive
30	2.70	1.88	1.81	1.81	Lumpy	Croston
31	21.85	15.39	23.93	16.35	Lumpy	ExpSmt
32	0.82	0.64	0.62	0.56	Lumpy	Syntetos
33	2.45	2.08	1.97	1.86	Lumpy	Syntetos
34	0.58	0.45	0.66	0.66	Lumpy	ExpSmt
35	0.58	1.82	1.61	1.65	Intermittent	Naive
36	0.58	0.42	0.41	0.39	Lumpy	Syntetos
37	1.50	1.03	1.04	1.03	Intermittent	ExpSmt

38	2.31	1.60	1.64	1.63	Intermittent	ExpSmt
39	1.78	1.30	0.89	1.03	Intermittent	Croston
40	1.12	0.71	0.70	0.70	Lumpy	Croston
41	0.96	2.09	0.93	0.83	Lumpy	Syntetos
42	0.96	2.17	2.27	2.11	Lumpy	Naive
43	0.50	0.35	0.35	0.35	Intermittent	Syntetos
44	5.13	3.62	3.23	3.34	Lumpy	Croston
45	1.15	0.95	0.87	0.83	Intermittent	Syntetos
46	0.29	0.37	0.51	0.32	Intermittent	Naive
47	0.29	0.67	0.67	0.67	Intermittent	Naive
48	1.00	1.74	1.70	1.70	Intermittent	Naive
49	4.37	3.46	3.02	3.14	Erratic	Croston
50	1.67	1.09	1.07	1.07	Lumpy	Syntetos
51	1.67	0.76	0.72	0.73	Lumpy	Croston
52	3.97	3.64	4.51	3.72	Erratic	ExpSmt
53	1.62	1.14	1.07	1.04	Lumpy	Syntetos
54	2.73	2.06	1.89	1.87	Lumpy	Syntetos
55	0.41	0.50	0.60	0.52	Lumpy	Naive
56	0.41	1.11	1.17	1.06	Lumpy	Naive
57	2.14	1.77	1.83	1.72	Lumpy	Syntetos
58	87.09	59.83	13.80	36.41	Lumpy	Croston
59	20.91	15.94	0.82	12.96	Lumpy	Croston
60	1.41	0.99	1.07	0.96	Lumpy	Syntetos
61	1.41	8.85	7.34	7.22	Lumpy	Naive
62	0.71	0.50	0.50	0.50	Intermittent	Croston
63	0.50	0.34	0.34	0.34	Intermittent	Syntetos
64	0.41	0.28	0.29	0.29	Intermittent	ExpSmt
65	0.41	1.92	1.50	1.63	Lumpy	Naive
66	1.32	1.04	1.02	1.01	Intermittent	Syntetos
67	0.50	0.40	0.43	0.43	Intermittent	ExpSmt
68	2.61	1.99	2.06	2.27	Intermittent	ExpSmt
69	3.46	2.32	2.32	2.36	Lumpy	Croston
70	3.46	2.78	2.85	2.86	Lumpy	ExpSmt
71	3.32	4.77	1.80	1.79	Lumpy	Syntetos
72	5.31	4.49	4.41	5.07	Intermittent	Croston
73	6.53	5.58	5.53	6.24	Intermittent	Croston
74	6.53	5.49	7.63	6.15	Intermittent	ExpSmt
75	6.33	76.67	78.26	77.69	Lumpy	ExpSmt
76	0.50	0.34	0.35	0.36	Intermittent	ExpSmt
77	6.39	4.48	4.37	4.26	Lumpy	Syntetos
78	6.39	0.52	0.50	0.49	Intermittent	Syntetos
79	2.60	2.01	1.92	1.91	Lumpy	Syntetos
80	1.38	0.54	0.48	0.45	Intermittent	Syntetos
81	7.05	6.21	5.00	3.91	Lumpy	Syntetos
82	7.05	47.05	6.71	38.09	Lumpy	Croston
83	1.78	1.15	1.13	1.14	Intermittent	Croston
84	1.38	1.04	1.04	1.03	Lumpy	Syntetos
85	5.45	4.44	4.55	3.88	Lumpy	Syntetos
86	1.38	0.93	0.92	0.92	Intermittent	Syntetos
87	2.26	1.64	1.54	1.57	Lumpy	Croston
88	2.26	5.39	5.19	5.03	Lumpy	Syntetos
89	0.91	0.63	0.62	0.62	Intermittent	Syntetos

90	2.73	2.12	1.54	1.73	Lumpy	Croston
91	1.19	0.82	0.81	0.82	Intermittent	Croston
92	1.19	19.49	13.45	13.39	Lumpy	Naive
93	4.48	4.37	5.02	3.69	Lumpy	Syntetos
94	1.76	1.27	1.21	1.18	Intermittent	Syntetos
95	2.25	1.50	1.51	1.51	Intermittent	ExpSmt
96	8.04	5.42	4.62	4.67	Lumpy	Croston
97	8.04	2.42	1.10	1.74	Intermittent	Croston
98	2.53	1.68	1.66	1.67	Lumpy	Croston
99	1.04	0.72	0.68	0.68	Intermittent	Croston
100	1.29	0.98	1.37	1.07	Intermittent	ExpSmt
101	1.29	1.04	1.07	0.98	Intermittent	Syntetos
102	1.46	1.33	1.30	1.31	Intermittent	Croston
103	5.30	3.73	3.74	3.69	Lumpy	Syntetos
104	1.58	1.47	1.48	1.46	Intermittent	Syntetos
105	1.58	0.99	1.01	1.06	Intermittent	ExpSmt
106	1.49	1.04	1.00	0.99	Intermittent	Syntetos
107	1.26	1.51	3.96	3.27	Lumpy	Naive
108	1.26	1.57	1.38	1.44	Intermittent	Naive
109	3.01	2.45	2.01	2.07	Lumpy	Croston
110	9.86	6.85	2.97	5.41	Smooth	Croston
111	9.86	2.05	2.04	2.04	Lumpy	Croston
112	0.71	0.51	0.47	0.48	Intermittent	Croston
113	2.44	1.60	1.23	1.46	Smooth	Croston
114	6.00	4.74	5.74	5.10	Intermittent	ExpSmt
115	6.00	4.89	4.33	3.92	Lumpy	Syntetos
116	34.07	26.18	0.34	21.00	Smooth	Croston
117	5.00	4.65	1.25	3.15	Erratic	Croston
118	7.06	4.88	0.85	3.60	Erratic	Croston
119	7.06	7.86	4.42	5.87	Erratic	Croston
120	0.50	0.37	0.35	0.34	Lumpy	Syntetos
121	0.79	0.54	0.50	0.50	Intermittent	Croston
122	0.87	0.57	0.59	0.57	Intermittent	Syntetos
123	0.87	0.45	0.44	0.44	Intermittent	Syntetos
124	4.38	3.07	2.12	2.48	Lumpy	Croston
125	3.42	2.58	2.86	2.50	Smooth	Syntetos
126	4.77	3.92	4.13	4.15	Lumpy	ExpSmt
127	0.68	0.72	0.71	0.67	Lumpy	Syntetos
128	0.68	1.81	1.65	1.67	Intermittent	Naive
129	0.71	0.57	0.55	0.51	Intermittent	Syntetos
130	1.85	1.23	1.27	1.15	Intermittent	Syntetos
131	10.17	7.22	6.74	6.94	Lumpy	Croston
132	10.17	3.66	4.45	3.55	Intermittent	Syntetos
133	2.13	1.57	1.83	1.40	Lumpy	Syntetos
134	6.61	4.60	3.85	3.97	Lumpy	Croston
135	1.98	1.30	1.43	1.26	Intermittent	Syntetos
136	0.65	0.47	0.58	0.58	Lumpy	ExpSmt
137	0.65	0.77	0.78	0.74	Intermittent	Naive
138	0.89	0.81	0.80	0.81	Intermittent	Croston
139	65.17	45.68	22.29	30.31	Lumpy	Croston
140	6.47	5.04	4.78	4.74	Lumpy	Syntetos
141	19.02	14.23	7.27	10.33	Erratic	Croston

142	19.02	1.35	1.35	1.35	Intermittent	Syntetos
143	10.86	9.98	0.11	7.36	Erratic	Croston
144	94.93	66.42	31.79	45.20	Lumpy	Croston
145	94.93	28.38	16.54	19.51	Erratic	Croston
146	1.24	1.00	0.85	0.81	Lumpy	Syntetos
147	2.08	1.34	1.30	1.31	Intermittent	Croston
148	0.68	0.55	0.55	0.55	Intermittent	ExpSmt
149	8.93	7.07	1.76	5.09	Erratic	Croston
150	1.83	1.65	1.27	1.42	Intermittent	Croston
151	2.75	1.78	1.50	1.63	Lumpy	Croston
152	3.88	3.38	1.41	2.39	Intermittent	Croston
153	2.79	2.44	1.26	1.88	Smooth	Croston
154	4.39	1.89	2.31	2.11	Lumpy	ExpSmt
155	1.43	1.42	1.16	1.21	Intermittent	Croston
156	2.77	2.18	1.50	1.68	Lumpy	Croston
157	2.18	1.52	1.45	1.46	Intermittent	Croston
158	1.40	0.94	0.88	0.90	Intermittent	Croston
159	8.76	6.43	2.98	4.95	Erratic	Croston
160	0.96	0.90	1.39	0.98	Lumpy	ExpSmt
161	6.73	4.48	1.60	3.42	Lumpy	Croston
162	1.00	0.64	0.62	0.62	Intermittent	Croston
163	1.66	1.20	1.21	1.08	Lumpy	Syntetos
164	0.71	0.41	0.41	0.42	Intermittent	ExpSmt
165	1.17	0.89	0.79	0.85	Intermittent	Croston
166	31.14	23.83	16.93	18.23	Lumpy	Croston
167	0.74	0.67	0.63	0.62	Intermittent	Syntetos
168	1.53	1.01	0.96	0.95	Lumpy	Syntetos
169	0.94	0.63	0.62	0.62	Intermittent	Croston
170	3.82	2.53	1.17	2.05	Intermittent	Croston
171	3.28	3.21	2.55	2.67	Lumpy	Croston
172	3.52	2.31	2.34	2.34	Lumpy	ExpSmt
173	12.47	8.31	6.40	6.89	Erratic	Croston
174	1.71	1.21	1.31	1.28	Lumpy	ExpSmt
175	0.71	0.51	0.49	0.51	Intermittent	Croston
176	2.25	2.03	2.02	2.05	Intermittent	Croston
177	9.98	7.20	5.08	6.14	Erratic	Croston
178	1.10	0.87	0.94	0.89	Intermittent	ExpSmt
179	0.91	0.73	0.73	0.79	Intermittent	ExpSmt
180	2.21	1.66	1.51	1.51	Lumpy	Syntetos
181	14.47	9.57	9.69	9.70	Lumpy	ExpSmt
182	4.70	3.31	3.85	3.27	Erratic	Syntetos
183	70.38	57.41	36.47	43.09	Lumpy	Croston
184	1.86	1.85	1.43	1.31	Lumpy	Syntetos
185	37.18	37.00	10.44	20.28	Lumpy	Croston
186	25.01	21.81	6.43	15.63	Erratic	Croston
187	1.84	1.06	1.04	1.04	Intermittent	Syntetos
188	2.65	1.90	1.78	1.75	Lumpy	Syntetos
189	0.41	0.32	0.34	0.31	Intermittent	Syntetos
190	2.19	1.80	2.09	1.68	Intermittent	Syntetos
191	1.04	0.68	0.66	0.67	Intermittent	Croston
192	1.47	1.12	1.14	1.12	Lumpy	Syntetos
193	1.32	1.03	1.01	1.00	Lumpy	Syntetos

194	2.38	2.04	1.42	1.71	Lumpy	Croston
195	1.66	1.65	1.05	1.01	Intermittent	Syntetos
196	6.18	6.17	1.80	3.68	Lumpy	Croston
197	7.84	6.70	3.51	5.19	Lumpy	Croston
198	0.91	0.65	0.66	0.65	Lumpy	Syntetos
199	10.23	7.16	6.60	6.53	Lumpy	Syntetos
200	1.73	1.37	1.33	1.26	Intermittent	Syntetos

Table A.3 Inventory cost results of forecasting methods (α =0.2)

No	Naive	Exp.Smoothing	Croston	Syntetos	Best Method
1	49.70	33.15	58.77	43.86	Exp.Smoothing
2	94.84	140.20	141.73	149.29	Naive
3	39.93	46.86	47.47	47.90	Naive
4	352.63	301.53	306.01	305.59	Exp.Smoothing
5	1139.38	1609.16	1609.94	1797.17	Naive
6	2.75	3.24	4.05	4.11	Naive
7	1189.78	1299.75	1299.48	1299.48	Naive
8	555.18	795.85	861.88	811.03	Naive
9	251.93	278.08	277.57	292.72	Naive
10	14.85	23.10	24.62	24.62	Naive
11	31.82	43.10	46.33	46.33	Naive
12	77.21	85.81	81.54	80.81	Naive
13	4193.58	1570.52	1656.87	2652.51	Exp.Smoothing
14	306.20	285.07	292.81	314.11	Exp.Smoothing
15	7.62	7.53	9.69	9.24	Exp.Smoothing
16	1549.19	1839.90	1936.92	1842.38	Naive
17	138.70	171.70	174.75	187.74	Naive
18	54.90	64.84	67.48	68.49	Naive
19	1897.68	3121.62	2505.92	3110.63	Naive
20	1074.26	1175.21	1190.15	1192.21	Naive
21	353.35	705.63	527.15	527.15	Naive
22	376.11	534.46	541.47	541.47	Naive
23	849.46	1002.92	1075.83	913.40	Naive
24	100.38	108.01	106.32	107.74	Naive
25	520.95	654.14	634.04	639.97	Naive
26	1384.96	1820.94	2395.91	2548.39	Naive
27	326.08	368.83	356.48	356.48	Naive
28	158.34	197.51	199.60	202.59	Naive
29	44.98	60.18	57.91	57.48	Naive
30	2182.47	2210.87	2808.73	2808.73	Naive
31	6.31	5.82	6.88	6.06	Exp.Smoothing
32	458.72	1314.98	1108.80	1443.02	Naive
33	5.73	8.67	9.90	8.70	Naive
34	59.00	91.82	79.45	73.28	Naive
35	539.97	673.64	818.28	679.49	Naive
36	12.04	221.48	323.92	334.36	Naive
37	3903.07	1974.46	1974.46	1974.46	Exp.Smoothing
38	50.03	68.94	73.69	63.62	Naive
39	268.76	241.87	319.40	351.80	Exp.Smoothing
40	155.38	257.90	333.36	181.99	Naive

41	1588.61	771.63	861.47	787.69	Exp.Smoothing
42	1059.36	596.01	676.37	730.27	Exp.Smoothing
43	140.33	172.02	219.09	219.09	Naive
44	176.38	275.46	307.65	307.77	Naive
45	113.95	117.56	149.25	130.88	Naive
46	445.11	351.61	493.40	427.41	Exp.Smoothing
47	130.52	257.13	256.51	256.51	Naive
48	4591.87	3783.59	4722.64	4966.59	Exp.Smoothing
49	6710.67	5401.50	5348.40	5320.84	Syntetos
50	490.13	538.56	734.05	588.07	Naive
51	16082.89	10482.94	10735.19	10129.79	Syntetos
52	1844.35	2047.36	2101.04	2087.84	Naive
53	723.44	846.88	814.57	768.44	Naive
54	661.48	757.15	692.38	662.00	Naive
55	154.47	184.64	221.45	184.78	Naive
56	260.24	304.77	380.39	367.65	Naive
57	16.56	16.97	18.71	17.41	Naive
58	1038.74	1277.16	1278.41	1282.05	Naive
59	1040.32	869.28	880.02	946.20	Exp.Smoothing
60	296.70	152.36	139.64	104.25	Syntetos
61	474.73	498.91	506.57	521.91	Naive
62	584.72	999.01	999.01	720.35	Naive
63	1084.83	506.08	982.42	1241.67	Exp.Smoothing
64	985.73	1563.49	1269.79	1306.13	Naive
65	2217.54	2244.61	2277.83	2546.09	Naive
66	140.72	183.51	220.54	214.76	Naive
67	5974.28	6838.45	6408.05	6510.33	Naive
68	199.16	205.16	200.87	203.50	Naive
69	1157.53	1056.41	1070.20	1065.61	Exp.Smoothing
70	31556.08	13816.95	27933.64	21068.62	Exp.Smoothing
71	179.13	234.35	211.97	211.77	Naive
72	148.46	114.48	132.39	144.65	Exp.Smoothing
73	275.27	234.06	233.86	243.54	Croston
74	122.54	125.52	126.07	127.48	Naive
75	8354.63	9617.63	9505.70	9523.20	Naive
76	8327.31	6077.52	4587.64	6415.05	Croston
77	331.17	383.63	434.24	393.07	Naive
78	367.75	345.59	445.73	445.73	Exp.Smoothing
79	416.03	426.64	560.20	539.15	Naive
80	2.50	2.37	2.25	2.25	Croston
81	190.07	278.95	218.54	218.95	Naive
82	226.24	281.52	282.96	298.35	Naive
83	35.00	56.62	50.71	42.93	Naive
84	80.34	130.84	86.91	139.18	Naive
85	263.96	314.92	331.68	374.48	Naive
86	2.93	2.19	2.60	2.60	Exp.Smoothing
87	3962.96	4550.18	5138.22	5475.39	Naive
88	102.21	101.58	141.11	140.63	Exp.Smoothing
89	495.87	672.90	624.88	501.46	Naive
90	1407.13	1316.32	1594.33	1689.50	Exp.Smoothing
91	1048.96	697.85	666.29	679.87	Croston
92	980.12	130.32	118.24	118.95	Croston

93	49.01	51.78	65.55	61.44	Naive
94	139.50	140.71	140.71	138.54	Syntetos
95	5047.67	4178.88	4294.86	4683.59	Exp.Smoothing
96	867.56	939.40	977.27	1021.96	Naive
97	256.42	222.01	224.10	303.43	Exp.Smoothing
98	1243.92	1354.69	1139.96	826.25	Syntetos
99	209.69	339.38	276.97	328.51	Naive
100	14.74	10.47	14.52	14.52	Exp.Smoothing
101	71.72	94.13	104.37	103.21	Naive
102	124.73	148.54	124.89	128.73	Naive
103	49.06	47.02	47.47	47.47	Exp.Smoothing
104	87.46	82.81	83.30	87.76	Exp.Smoothing
105	231.01	303.38	281.37	281.37	Naive
106	122.58	134.81	116.07	125.44	Croston
107	43862.05	24809.63	24809.63	22807.67	Syntetos
108	1013.62	1547.30	1431.87	1362.99	Naive
109	1259.09	1648.90	1558.90	1567.45	Naive
110	268.39	220.84	219.02	236.61	Croston
111	169.23	154.52	171.50	156.30	Exp.Smoothing
112	53.92	144.02	156.54	176.73	Naive
113	422.29	483.56	487.15	519.44	Naive
114	363.58	637.41	903.27	901.07	Naive
115	1523.12	1486.75	1475.17	1568.29	Croston
116	80.79	93.39	94.96	98.66	Naive
117	1602.51	1718.25	1651.92	1753.02	Naive
118	2377.59	2786.81	2774.81	2856.19	Naive
119	58.87	66.16	66.16	67.74	Naive
120	4.88	10.75	20.46	20.46	Naive
121	22.52	27.49	44.80	36.41	Naive
122	12.57	18.97	18.65	18.65	Naive
123	413.20	425.67	473.28	473.28	Naive
124	75.57	75.38	81.04	78.94	Exp.Smoothing
125	2989.48	3513.51	3526.38	3351.80	Naive
126	70.45	86.72	86.75	98.65	Naive
127	7070.15	7748.08	7445.37	6945.60	Syntetos
128	908.01	1031.81	1113.41	1113.41	Naive
129	44.85	89.60	82.91	92.65	Naive
130	1321.25	1627.39	1706.87	2223.83	Naive
131	129.48	118.56	125.64	129.55	Exp.Smoothing
132	206.76	245.02	243.66	285.95	Naive
133	377.37	586.96	527.61	532.87	Naive
134	676.32	752.82	791.96	799.87	Naive
135	65.82	158.01	208.63	256.55	Naive
136	72.65	75.09	93.20	93.20	Naive
137	439.95	553.02	526.51	526.51	Naive
138	440.93	397.39	397.39	464.95	Exp.Smoothing
139	135.21	157.52	166.50	169.61	Naive
140	162.14	223.39	239.84	192.08	Naive
141	15470.95	11437.08	11155.21	12482.84	Croston
142	70.08	97.72	101.41	86.22	Naive
143	2574.29	2362.40	2389.07	2593.92	Exp.Smoothing
144	316.54	350.60	366.52	368.72	Naive

145	32867.04	28478.30	28565.30	30316.72	Exp.Smoothing
146	246.04	328.14	346.75	358.77	Naive
147	421.97	525.07	550.54	616.59	Naive
148	1678.29	1455.17	2258.09	2668.09	Exp.Smoothing
149	3567.50	2308.63	2383.39	2616.59	Exp.Smoothing
150	948.38	1188.68	1225.75	1310.60	Naive
151	192.50	251.06	267.32	255.28	Naive
152	407.44	473.47	532.20	503.03	Naive
153	176.49	227.46	226.30	227.07	Naive
154	810.16	590.38	564.48	504.11	Syntetos
155	2752.94	1706.59	2949.31	3184.44	Exp.Smoothing
156	5158.50	3814.88	4096.53	5012.43	Exp.Smoothing
157	855.27	595.05	646.70	642.22	Exp.Smoothing
158	221.57	240.38	291.95	279.69	Naive
159	3177.76	3039.17	2973.23	3058.35	Croston
160	1805.67	1309.15	1223.98	1189.06	Syntetos
161	615.11	783.78	798.89	788.51	Naive
162	338.77	559.12	546.90	546.90	Naive
163	1564.97	2004.31	2004.31	1861.46	Naive
164	1012.56	891.04	937.77	1066.26	Exp.Smoothing
165	5211.67	6524.89	8065.98	7380.25	Naive
166	241.42	293.49	306.35	310.54	Naive
167	957.49	1348.56	1221.57	1391.03	Naive
168	117.84	419.97	418.13	414.55	Naive
169	369.27	477.28	490.04	490.04	Naive
170	882.95	1037.78	1192.72	1245.16	Naive
171	694.85	808.66	931.49	938.11	Naive
172	1017.56	1126.09	1418.63	1608.18	Naive
173	1173.53	1379.88	1450.82	1498.66	Naive
174	363.83	665.17	1129.48	1129.48	Naive
175	1327.95	2218.53	2474.48	2474.48	Naive
176	6297.60	9240.68	8111.91	8878.99	Naive
177	1549.19	1890.18	1881.67	1926.23	Naive
178	537.98	631.09	665.00	662.00	Naive
179	616.95	1280.58	1107.40	1123.80	Naive
180	6665.60	10369.37	9472.30	10673.25	Naive
181	609.54	689.97	757.46	741.84	Naive
182	91.45	80.73	85.06	97.67	Exp.Smoothing
183	76.46	78.35	87.18	92.35	Naive
184	439.66	83.98	149.19	149.19	Exp.Smoothing
185	459.75	480.29	510.30	521.23	Naive
186	305.83	418.76	403.25	424.47	Naive
187	901.24	955.31	1156.11	1190.22	Naive
188	162.51	187.22	175.97	186.05	Naive
189	402.66	2414.68	2414.68	1692.83	Naive
190	114.66	176.19	155.51	162.46	Naive
191	573.02	564.00	623.77	623.77	Exp.Smoothing
192	397.39	302.86	320.95	308.11	Exp.Smoothing
193	394.97	399.28	391.87	445.10	Croston
194	20.39	17.59	18.90	18.90	Exp.Smoothing
195	270.83	405.27	590.99	589.04	Naive
196	181.11	200.68	200.68	203.84	Naive

197	60.78	58.90	62.03	65.52	Exp.Smoothing
198	770.84	835.83	908.87	744.59	Syntetos
199	192.24	319.22	270.52	270.76	Naive
200	1844.32	2718.43	2697.19	2272.64	Naive

Table A.4 Inventory cost results of forecasting methods ($\alpha_{optimum}$)

No	Naive	Exp.Smoothing	Croston	Syntetos	Best Method
1	49.70	36.25	31.82	33.53	Croston
2	94.84	118.54	114.87	159.44	Naive
3	39.93	39.97	42.34	51.21	Naive
4	352.63	325.80	300.89	319.99	Naive
5	1139.38	1140.02	1419.43	1330.07	Exp.Smoothing
6	2.75	3.00	3.29	3.44	Exp.Smoothing
7	1189.78	997.72	1299.48	1328.01	Naive
8	555.18	458.62	801.99	663.30	Exp.Smoothing
9	251.93	200.74	167.56	218.74	Croston
10	14.85	21.68	11.85	23.06	Naive
11	31.82	31.40	32.40	43.78	Exp.Smoothing
12	77.21	69.42	79.34	70.23	Exp.Smoothing
13	4193.58	1550.59	1465.35	966.80	Croston
14	306.20	255.98	287.79	304.52	Exp.Smoothing
15	7.62	6.64	9.02	9.75	Exp.Smoothing
16	1549.19	1454.58	1644.91	1649.72	Exp.Smoothing
17	138.70	140.53	144.21	154.08	Exp.Smoothing
18	54.90	56.59	53.01	60.55	Naive
19	1897.68	1907.11	703.40	2217.32	Naive
20	1074.26	965.65	899.39	1098.74	Naive
21	353.35	241.25	707.64	445.71	Exp.Smoothing
22	376.11	431.12	362.98	536.10	Naive
23	849.46	817.24	818.51	903.64	Naive
24	100.38	84.41	88.55	95.97	Exp.Smoothing
25	520.95	536.78	517.14	720.42	Naive
26	1384.96	1100.15	1605.17	1542.17	Exp.Smoothing
27	326.08	354.66	371.36	388.94	Exp.Smoothing
28	158.34	159.53	159.24	193.38	Naive
29	44.98	42.35	57.14	65.41	Exp.Smoothing
30	2182.47	2154.06	1975.58	2264.34	Croston
31	6.31	5.79	6.04	6.09	Exp.Smoothing
32	458.72	412.11	412.11	3352.95	Naive
33	5.73	12.68	12.68	8.74	Naive
34	59.00	62.53	77.04	118.11	Exp.Smoothing
35	539.97	486.55	536.68	579.23	Syntetos
36	12.04	138.38	92.29	136.35	Naive
37	3903.07	1711.96	2054.74	1974.46	Exp.Smoothing
38	50.03	54.24	60.80	64.29	Exp.Smoothing
39	268.76	189.82	269.07	206.38	Exp.Smoothing
40	155.38	130.39	56.53	131.05	Croston
41	1588.61	903.43	903.43	878.60	Exp.Smoothing
42	1059.36	516.33	477.61	585.73	Croston
43	140.33	134.68	198.73	172.02	Exp.Smoothing
44	176.38	217.79	191.73	215.41	Naive
45	113.95	112.84	133.64	130.88	Exp.Smoothing

46	445.11	351.61	427.41	427.41	Exp.Smoothing
47	130.52	254.55	257.63	193.71	Syntetos
48	4591.87	3783.59	3156.74	4966.59	Croston
49	6710.67	4097.99	4028.38	5821.99	Syntetos
50	490.13	392.65	733.38	489.84	Exp.Smoothing
51	16082.89	8803.05	9019.89	11360.96	Exp.Smoothing
52	1844.35	1958.86	1754.42	1827.11	Naive
53	723.44	563.87	513.52	734.49	Croston
54	661.48	478.75	474.86	566.77	Croston
55	154.47	176.74	203.13	188.48	Syntetos
56	260.24	306.41	311.34	367.65	Exp.Smoothing
57	16.56	13.63	14.47	15.81	Naive
58	1038.74	826.15	825.98	1191.05	Naive
59	1040.32	885.38	928.63	923.94	Exp.Smoothing
60	296.70	139.64	139.64	180.87	Exp.Smoothing
61	474.73	379.49	452.09	552.65	Exp.Smoothing
62	584.72	630.34	322.62	623.78	Croston
63	1084.83	181.02	669.02	204.67	Exp.Smoothing
64	985.73	909.32	710.57	870.03	Croston
65	2217.54	2147.47	2267.50	2312.73	Exp.Smoothing
66	140.72	189.70	165.14	179.78	Croston
67	5974.28	4224.66	6510.33	6222.05	Exp.Smoothing
68	199.16	228.43	164.47	175.37	Naive
69	1157.53	1088.59	1070.20	1065.61	Syntetos
70	31556.08	5063.38	12347.86	25992.04	Exp.Smoothing
71	179.13	57.40	73.22	154.68	Exp.Smoothing
72	148.46	103.61	159.63	144.65	Exp.Smoothing
73	275.27	162.46	258.50	252.89	Exp.Smoothing
74	122.54	66.72	143.95	136.75	Exp.Smoothing
75	8354.63	8081.58	7018.46	6670.05	Naive
76	8327.31	1961.35	2516.70	973.95	Exp.Smoothing
77	331.17	285.66	387.54	404.69	Exp.Smoothing
78	367.75	318.13	445.73	445.73	Exp.Smoothing
79	416.03	426.64	405.59	405.59	Croston
80	2.50	2.36	2.84	2.24	Syntetos
81	190.07	217.88	232.00	218.20	Exp.Smoothing
82	226.24	219.61	247.00	294.05	Exp.Smoothing
83	35.00	43.92	48.70	42.94	Syntetos
84	80.34	75.15	86.91	127.02	Exp.Smoothing
85	263.96	248.55	267.98	464.83	Naive
86	2.93	2.18	2.62	2.60	Exp.Smoothing
87	3962.96	3389.04	5097.22	5226.41	Exp.Smoothing
88	102.21	99.55	115.36	124.86	Exp.Smoothing
89	495.87	588.16	564.29	558.23	Syntetos
90	1407.13	1222.61	858.29	982.78	Naive
91	1048.96	540.07	664.30	516.90	Exp.Smoothing
92	980.12	113.04	120.56	117.74	Exp.Smoothing
93	49.01	40.76	50.02	59.33	Exp.Smoothing
94	139.50	139.26	96.25	94.81	Syntetos
95	5047.67	4906.86	4433.01	4578.11	Croston
96	867.56	896.66	985.55	928.97	Exp.Smoothing
97	256.42	213.30	178.68	361.80	Croston

98	1243.92	983.36	983.36	821.10	Syntetos
99	209.69	226.87	302.74	276.97	Exp.Smoothing
100	14.74	14.42	10.47	10.62	Croston
101	71.72	58.05	76.90	106.70	Naive
102	124.73	150.78	138.15	178.75	Naive
103	49.06	49.17	46.60	47.46	Croston
104	87.46	46.20	99.13	81.83	Exp.Smoothing
105	231.01	205.85	253.99	256.61	Exp.Smoothing
106	122.58	94.61	116.07	165.87	Exp.Smoothing
107	43862.05	31636.56	31636.56	7894.14	Syntetos
108	1013.62	1168.21	1214.28	1821.67	Exp.Smoothing
109	1259.09	1494.40	1663.30	2138.05	Exp.Smoothing
110	268.39	162.77	162.77	464.88	Syntetos
111	169.23	171.50	156.30	155.93	Naive
112	53.92	37.83	54.41	57.79	Exp.Smoothing
113	422.29	422.50	459.00	498.32	Exp.Smoothing
114	363.58	449.84	649.42	731.10	Exp.Smoothing
115	1523.12	1329.46	1380.20	1658.88	Exp.Smoothing
116	80.79	77.04	82.31	190.21	Exp.Smoothing
117	1602.51	1317.66	1378.30	1793.90	Exp.Smoothing
118	2377.59	2503.56	2690.30	3311.60	Exp.Smoothing
119	58.87	54.33	61.61	88.56	Exp.Smoothing
120	4.88	3.39	10.75	10.75	Exp.Smoothing
121	22.52	27.49	27.38	18.78	Syntetos
122	12.57	12.57	18.65	18.65	Naive
123	413.20	369.02	481.67	426.74	Naive
124	75.57	71.77	71.93	72.69	Syntetos
125	2989.48	2806.61	3010.72	3377.20	Exp.Smoothing
126	70.45	67.67	71.21	76.98	Naive
127	7070.15	5662.27	7640.87	8538.73	Exp.Smoothing
128	908.01	899.90	899.90	958.36	Naive
129	44.85	41.41	98.21	45.05	Exp.Smoothing
130	1321.25	1432.08	1457.90	1870.83	Exp.Smoothing
131	129.48	129.78	119.46	120.13	Croston
132	206.76	241.83	228.89	276.99	Naive
133	377.37	531.02	431.98	532.87	Croston
134	676.32	597.52	528.12	724.03	Croston
135	65.82	112.09	109.40	219.25	Naive
136	72.65	71.50	45.10	74.75	Croston
137	439.95	315.04	419.77	353.07	Exp.Smoothing
138	440.93	340.46	428.29	411.65	Exp.Smoothing
139	135.21	144.28	139.53	157.28	Naive
140	162.14	123.65	66.32	144.19	Croston
141	15470.95	13176.34	13433.47	19457.17	Syntetos
142	70.08	76.50	82.52	86.22	Exp.Smoothing
143	2574.29	2134.88	2282.88	3798.40	Exp.Smoothing
144	316.54	288.02	303.26	398.12	Naive
145	32867.04	27124.04	27013.04	34395.30	Croston
146	246.04	213.70	270.39	500.86	Exp.Smoothing
147	421.97	421.06	502.91	538.03	Exp.Smoothing
148	1678.29	1610.98	1440.15	2668.09	Naive
149	3567.50	2279.28	2623.59	3528.01	Exp.Smoothing

150	948.38	1030.38	1090.28	964.79	Exp.Smoothing
151	192.50	164.76	164.72	202.70	Naive
152	407.44	389.56	419.00	473.69	Exp.Smoothing
153	176.49	214.46	193.97	293.58	Naive
154	810.16	564.48	504.11	504.11	Croston
155	2752.94	1339.27	1640.62	1136.35	Exp.Smoothing
156	5158.50	2789.33	3250.82	2190.37	Exp.Smoothing
157	855.27	581.72	563.80	749.90	Naive
158	221.57	199.90	229.12	294.98	Exp.Smoothing
159	3177.76	2774.71	2744.09	4190.76	Croston
160	1805.67	1277.63	944.63	1049.39	Syntetos
161	615.11	580.68	619.68	718.57	Exp.Smoothing
162	338.77	335.58	546.90	546.90	Exp.Smoothing
163	1564.97	1343.89	1147.18	1010.69	Naive
164	1012.56	240.71	540.02	295.29	Exp.Smoothing
165	5211.67	4486.17	6880.93	5585.04	Exp.Smoothing
166	241.42	236.32	280.62	305.36	Exp.Smoothing
167	957.49	877.71	1103.79	1268.88	Naive
168	117.84	118.41	610.60	414.27	Exp.Smoothing
169	369.27	349.55	386.66	505.61	Exp.Smoothing
170	882.95	882.35	934.43	1089.45	Exp.Smoothing
171	694.85	738.10	676.58	837.33	Naive
172	1017.56	1122.05	1118.55	1149.03	Naive
173	1173.53	1230.81	1320.09	1826.01	Exp.Smoothing
174	363.83	382.15	562.80	852.61	Exp.Smoothing
175	1327.95	840.03	2474.48	2474.48	Exp.Smoothing
176	6297.60	5910.91	6494.80	7966.34	Exp.Smoothing
177	1549.19	1731.35	1871.41	2699.31	Exp.Smoothing
178	537.98	454.03	537.40	676.59	Exp.Smoothing
179	616.95	787.36	1025.54	921.75	Exp.Smoothing
180	6665.60	5824.27	5824.27	20151.07	Exp.Smoothing
181	609.54	614.40	501.99	714.54	Croston
182	91.45	78.34	70.99	133.99	Croston
183	76.46	62.64	72.91	107.28	Exp.Smoothing
184	439.66	64.54	75.73	82.31	Exp.Smoothing
185	459.75	394.30	388.60	482.75	Naive
186	305.83	317.67	322.02	675.97	Naive
187	901.24	752.78	678.65	753.06	Naive
188	162.51	209.48	207.26	1345.06	Naive
189	402.66	298.89	763.58	1489.81	Naive
190	114.66	126.81	122.07	131.37	Croston
191	573.02	321.53	623.77	575.47	Exp.Smoothing
192	397.39	309.30	345.19	393.69	Exp.Smoothing
193	394.97	358.18	428.05	421.20	Exp.Smoothing
194	20.39	14.36	14.42	17.17	Exp.Smoothing
195	270.83	267.76	342.69	293.29	Naive
196	181.11	171.59	172.91	193.38	Exp.Smoothing
197	60.78	45.32	48.93	69.98	Exp.Smoothing
198	770.84	757.96	400.89	716.74	Naive
199	192.24	166.90	141.92	220.44	Croston
200	1844.32	2248.38	1992.81	3647.26	Naive

APPENDIX-B

INVENTORY COST RESULTS OF BOOTSTRAPPING

Table B.1 Inventory costs of Bootstrapping method (CSL=%95)

No	Nb orders	Holding Cost	Stockout Cost	Ordering Cost	Total Cost
1	13	3.08	11.00	69.71	83.80
2	26	5.56	3.19	153.47	162.22
3	28	1.53	5.31	55.09	61.93
4	5	48.96	64.00	370.37	483.33
5	23	1.35	11.83	2164.07	2177.25
6	6	0.11	0.18	2.55	2.84
7	16	6.01	0.96	1573.44	1580.41
8	15	5.34	22.25	729.75	757.34
9	30	4.79	12.75	385.20	402.74
10	10	2.12	2.25	25.80	30.17
11	22	0.71	6.28	49.23	56.22
12	10	10.62	30.63	49.20	90.44
13	21	146.14	221.42	681.87	1049.42
14	32	27.72	359.56	55.04	442.32
15	16	2.18	0.68	16.67	19.52
16	31	1.21	35.77	2975.69	3012.67
17	24	5.97	52.16	129.36	187.49
18	11	6.70	53.33	21.22	81.25
19	7	29.28	34.31	2120.79	2184.38
20	22	17.16	139.00	2161.06	2317.22
21	10	31.67	2.79	937.00	971.45
22	9	17.45	22.38	853.56	893.39
23	21	117.36	415.19	469.35	1001.90
24	30	6.70	55.86	80.10	142.67
25	15	123.79	86.95	283.65	494.39
26	8	908.53	0.00	438.24	1346.77
27	5	74.42	47.50	183.26	305.17
28	15	3.77	55.35	268.65	327.77
29	18	6.80	11.84	76.50	95.14
30	13	449.71	591.73	1424.52	2465.97
31	7	0.09	3.63	2.70	6.41

32	13	425.16	0.00	398.57	823.74
33	8	0.83	2.39	12.65	15.87
34	7	6.04	0.00	69.41	75.44
35	18	0.73	22.28	843.84	866.84
36	8	4.86	7.25	260.80	272.91
37	15	44.50	12.50	133.35	190.35
38	11	7.65	18.30	52.58	78.53
39	12	116.62	142.92	52.32	311.86
40	10	2.46	0.00	252.90	255.36
41	15	349.59	378.82	38.70	767.11
42	19	24.89	79.30	294.69	398.88
43	5	70.15	0.00	99.60	169.75
44	16	5.10	30.98	256.96	293.04
45	12	14.96	19.68	135.96	170.60
46	5	210.38	259.73	59.65	529.77
47	5	1.57	1.40	315.25	318.22
48	20	1126.67	3098.33	372.20	4597.20
49	20	209.05	0.00	382.20	591.25
50	14	0.56	1.75	682.50	684.81
51	7	230.05	0.00	105.28	335.33
52	22	393.65	726.92	365.64	1486.21
53	20	27.35	208.08	322.20	557.62
54	21	10.56	152.81	728.70	892.07
55	7	8.20	12.06	260.61	280.87
56	11	24.65	133.52	256.19	414.36
57	13	0.70	5.07	19.06	24.82
58	22	10.74	156.75	2193.40	2360.89
59	36	24.40	2981.38	173.52	3179.30
60	10	37.42	11.14	148.00	196.56
61	30	39.00	487.50	184.20	710.70
62	6	6.79	212.27	559.02	778.08
63	4	58.97	50.83	9.20	119.00
64	4	106.80	667.50	20.84	795.14
65	25	53.60	153.54	3231.08	3438.22
66	12	11.61	25.46	228.24	265.31
67	7	1070.77	5147.92	581.28	6799.96
68	8	17.83	46.50	287.04	351.36
69	9	66.20	1241.18	120.06	1427.43
70	7	622.05	3308.75	4.48	3935.28
71	12	21.00	4.08	16.32	41.41
72	12	46.66	3.05	6.12	55.83
73	8	93.71	34.10	5.12	132.93
74	8	46.02	2.29	4.08	52.39
75	16	344.58	14208.33	216.80	14769.72
76	4	139.52	112.51	1.84	253.87
77	14	5.53	2.80	626.64	634.97
78	6	93.04	66.46	154.20	313.70
79	10	39.57	296.80	96.20	432.57
80	6	0.09	0.31	3.47	3.87
81	28	0.24	4.90	424.76	429.90
82	32	12.73	488.73	55.04	556.50
83	17	5.25	3.75	45.73	54.73

84	7	0.54	8.00	168.42	176.96
85	21	107.29	0.00	313.74	421.03
86	5	0.00	0.42	1.93	2.35
87	18	457.36	1814.92	3024.84	5297.12
88	12	4.82	67.73	139.35	211.89
89	*4*	*27.97*	*209.76*	*258.96*	*496.70*
90	22	6.50	0.00	2046.88	2053.38
91	4	52.73	299.58	128.64	480.95
92	7	52.31	51.28	24.71	128.30
93	16	5.70	3.56	68.80	78.06
94	7	14.66	0.00	194.71	209.37
95	10	730.63	3970.83	215.90	4917.37
96	26	47.27	475.15	731.12	1253.54
97	27	58.75	20.83	10.26	89.84
98	16	219.22	548.05	82.40	849.67
99	7	107.39	53.70	65.03	226.12
100	10	1.24	0.00	21.60	22.85
101	11	2.59	2.74	92.94	98.27
102	13	3.68	52.00	143.39	199.07
103	9	1.13	2.33	190.08	193.54
104	9	17.62	36.70	5.76	60.08
105	15	2.76	0.90	372.60	376.26
106	12	108.00	0.00	53.16	161.16
107	3	9121.32	0.00	56.37	9177.69
108	15	571.78	0.00	480.90	1052.68
109	10	98.55	33.75	2494.10	2626.40
110	5	10.00	45.00	6.10	61.10
111	9	19.88	112.50	73.44	205.82
112	5	30.30	0.00	36.15	66.45
113	24	19.67	11.71	523.92	555.30
114	13	22.09	68.75	1152.45	1243.29
115	24	124.64	127.42	2574.06	2826.11
116	35	4.36	42.47	66.16	112.99
117	31	49.72	335.50	2188.64	2573.86
118	34	114.25	247.79	4105.68	4467.72
119	32	5.33	6.91	97.53	109.78
120	7	0.52	0.00	33.49	34.00
121	7	0.33	1.39	29.98	31.70
122	9	0.20	0.43	17.71	18.34
123	12	4.30	0.00	597.22	601.52
124	27	1.75	4.82	92.71	99.28
125	29	57.24	135.00	3624.98	3817.22
126	17	2.97	39.01	99.03	141.01
127	10	1426.02	532.10	4926.78	6884.89
128	21	44.84	543.47	828.24	1416.54
129	6	10.62	0.00	36.60	47.22
130	16	119.62	1495.27	983.68	2598.57
131	19	5.70	81.62	115.90	203.22
132	26	4.70	7.20	366.34	378.24
133	20	3.40	3.30	987.40	994.10
134	26	4.13	17.33	963.04	984.51
135	14	5.27	0.00	664.44	669.71

136	8	6.98	0.00	131.52	138.50
137	14	155.26	316.87	58.38	530.51
138	16	35.78	365.96	136.16	537.91
139	26	5.28	192.75	30.16	228.19
140	17	0.85	16.87	265.71	283.43
141	23	1468.42	1163.28	357.19	2988.89
142	16	15.00	37.50	39.04	91.54
143	32	678.00	345.00	783.36	1806.36
144	18	29.38	334.00	82.44	445.82
145	33	2010.00	16350.00	3214.86	21574.86
146	10	105.03	12.87	190.40	308.30
147	19	23.87	13.26	471.39	508.51
148	9	956.67	0.00	470.52	1427.19
149	34	144.87	2699.17	63.58	2907.61
150	30	68.45	784.30	748.80	1601.55
151	10	11.48	42.50	153.40	207.38
152	30	3.48	187.88	469.50	660.86
153	28	14.62	63.80	138.60	217.02
154	17	63.99	606.83	14.28	685.11
155	18	56.75	2026.92	89.10	2172.77
156	25	122.55	4998.75	19.00	5140.30
157	22	112.03	392.12	47.96	552.11
158	8	38.81	147.02	69.84	255.67
159	30	687.66	1354.13	1635.41	3677.19
160	10	119.23	851.67	318.40	1289.30
161	29	10.13	198.69	709.34	918.16
162	8	52.03	464.58	34.00	550.62
163	9	107.73	168.33	1592.82	1868.89
164	8	40.40	168.33	45.52	254.25
165	10	191.45	2015.30	6655.80	8862.55
166	24	6.46	90.29	338.16	434.91
167	14	360.09	353.03	69.30	782.43
168	7	1.43	23.75	698.53	723.71
169	10	34.79	86.98	424.10	545.87
170	32	0.59	1.79	1654.72	1657.11
171	26	27.72	63.00	1263.88	1354.60
172	12	8.88	159.73	1143.84	1312.45
173	34	146.37	822.63	482.80	1451.81
174	10	7.17	70.13	970.70	1047.99
175	9	245.07	1531.67	255.78	2032.51
176	19	798.39	8218.70	1873.40	10890.49
177	34	69.12	2182.80	731.00	2982.92
178	17	48.11	43.48	559.98	651.57
179	12	2.70	125.40	1122.00	1250.10
180	24	1082.84	0.00	3305.35	4388.19
181	16	65.40	944.67	95.20	1105.27
182	22	9.16	0.65	133.26	143.07
183	21	34.37	19.00	38.08	91.45
184	8	68.67	0.00	49.36	118.03
185	26	36.66	230.91	324.22	591.79
186	29	13.90	50.05	460.81	524.76
187	9	114.35	351.08	253.62	719.05

188	6	76.86	0.00	325.46	402.32
189	3	345.13	0.00	234.98	580.11
190	23	1.84	26.83	162.61	191.28
191	9	2.68	737.92	15.39	755.99
192	8	89.61	115.88	44.56	250.05
193	9	69.87	68.50	285.41	423.78
194	13	0.75	11.93	5.85	18.53
195	10	22.10	97.50	196.80	316.40
196	28	4.90	37.10	329.84	371.84
197	28	4.99	33.00	28.56	66.55
198	10	51.24	111.40	841.80	1004.44
199	21	0.94	16.33	530.25	547.52
200	23	239.88	134.77	180.32	554.97

APPENDIX-C

INVENTORY COSTS OF METHODS UNDER (Q,R) POLICY

Table C.1 Inventory cost results of forecasting methods under (Q,R) stock policy

No	Naive	Exp.Smoothing	Croston	Syntetos	Data Type	Best Method
1	83	26	37	40	Lumpy	Exp.Smoothing
2	63	63	59	45	Erratic	Syntetos
3	24	18	21	23	Erratic	Exp.Smoothing
4	398	283	225	294	Lumpy	Croston
5	234	218	218	217	Lumpy	Syntetos
6	10	22	13	11	Lumpy	Naive Method
7	166	166	166	166	Lumpy	Naive Method
8	202	193	174	173	Intermittent	Syntetos
9	91	73	95	88	Intermittent	Exp.Smoothing
10	34	18	20	17	Intermittent	Syntetos
11	23	21	18	15	Intermittent	Syntetos
12	152	110	69	74	Lumpy	Croston
13	1227	927	869	812	Intermittent	Syntetos
14	262	247	223	254	Erratic	Croston
15	22	14	14	12	Lumpy	Syntetos
16	272	348	269	268	Lumpy	Syntetos
17	85	88	72	74	Lumpy	Croston
18	46	63	47	49	Lumpy	Naive Method
19	237	237	237	237	Lumpy	Naive Method
20	688	575	424	405	Lumpy	Syntetos
21	976	281	305	273	Lumpy	Syntetos
22	857	637	500	481	Intermittent	Syntetos
23	730	639	692	652	Lumpy	Exp.Smoothing
24	72	62	69	71	Lumpy	Exp.Smoothing
25	778	591	618	627	Erratic	Exp.Smoothing
26	2063	1611	1536	1879	Lumpy	Croston
27	612	204	353	336	Lumpy	Exp.Smoothing
28	152	145	93	87	Lumpy	Syntetos
29	33	43	47	40	Lumpy	Naive Method
30	2100	2515	2119	1944	Lumpy	Syntetos
31	8	7	6	6	Lumpy	Croston
32	619	696	616	578	Lumpy	Syntetos
33	36	14	6	6	Lumpy	Syntetos
34	29	29	32	32	Lumpy	Naive Method

35	146	150	138	137	Intermittent	Syntetos
36	46	46	46	46	Lumpy	Naive Method
37	254	197	150	166	Intermittent	Croston
38	123	43	56	52	Intermittent	Exp.Smoothing
39	388	270	232	242	Intermittent	Croston
40	32	32	32	32	Lumpy	Naive Method
41	955	759	682	729	Lumpy	Croston
42	308	228	263	271	Lumpy	Exp.Smoothing
43	481	171	239	239	Intermittent	Exp.Smoothing
44	92	95	83	100	Lumpy	Croston
45	67	145	108	109	Intermittent	Naive Method
46	1044	641	564	410	Intermittent	Syntetos
47	43	43	43	43	Intermittent	Naive Method
48	3926	3603	3478	3478	Intermittent	Croston
49	463	462	417	449	Erratic	Croston
50	34	34	34	34	Lumpy	Naive Method
51	668	813	799	726	Lumpy	Naive Method
52	2004	1564	1611	1684	Erratic	Exp.Smoothing
53	495	325	289	279	Lumpy	Syntetos
54	580	275	390	359	Lumpy	Exp.Smoothing
55	47	260	36	36	Lumpy	Croston
56	253	259	234	225	Lumpy	Syntetos
57	17	21	11	16	Lumpy	Croston
58	724	506	595	559	Lumpy	Exp.Smoothing
59	677	607	683	561	Lumpy	Syntetos
60	585	393	265	184	Lumpy	Syntetos
61	478	399	386	373	Lumpy	Syntetos
62	380	503	258	460	Intermittent	Croston
63	267	181	181	181	Intermittent	Exp.Smoothing
64	1057	806	806	715	Intermittent	Syntetos
65	1278	1030	922	1053	Lumpy	Croston
66	130	135	118	151	Intermittent	Croston
67	5976	6839	5357	5151	Intermittent	Syntetos
68	143	339	255	222	Intermittent	Naive Method
69	1204	1192	888	888	Lumpy	Croston
70	2360	2400	2346	2611	Lumpy	Croston
71	123	60	71	52	Lumpy	Syntetos
72	115	120	123	113	Intermittent	Syntetos
73	252	242	212	239	Intermittent	Croston
74	131	118	116	118	Intermittent	Croston
75	7846	5134	6190	6711	Lumpy	Exp.Smoothing
76	447	57044	85397	85397	Intermittent	Naive Method
77	46	46	46	46	Lumpy	Naive Method
78	636	389	541	541	Intermittent	Exp.Smoothing
79	424	400	358	360	Lumpy	Croston
80	3	4	3	3	Intermittent	Syntetos
81	32	55	45	44	Lumpy	Naive Method
82	216	183	189	212	Lumpy	Exp.Smoothing
83	49	40	39	32	Intermittent	Syntetos
84	19	19	19	19	Lumpy	Naive Method
85	455	593	362	530	Lumpy	Croston
86	2	1	1	1	Intermittent	Syntetos

87	5022	3968	3932	4776	Lumpy	Croston
88	168	111	142	128	Lumpy	Exp.Smoothing
89	815	818	515	313	Intermittent	Syntetos
90	712	222	479	463	Lumpy	Exp.Smoothing
91	590	618	505	505	Intermittent	Croston
92	1524	632	500	407	Lumpy	Syntetos
93	36	60	44	46	Lumpy	Naive Method
94	251	73	119	113	Intermittent	Exp.Smoothing
95	4626	3678	3706	3378	Intermittent	Syntetos
96	895	688	573	534	Lumpy	Syntetos
97	166	224	401	1935	Intermittent	Naive Method
98	1023	719	872	733	Lumpy	Exp.Smoothing
99	372	429	386	417	Intermittent	Naive Method
100	13	9	14	14	Intermittent	Exp.Smoothing
101	31	26	29	26	Intermittent	Exp.Smoothing
102	120	99	103	102	Intermittent	Exp.Smoothing
103	34	34	34	34	Lumpy	Naive Method
104	89	78	69	69	Intermittent	Croston
105	74	75	71	70	Intermittent	Syntetos
106	171	176	197	195	Intermittent	Naive Method
107	11509	27317	17699	33423	Lumpy	Naive Method
108	2141	1742	1912	1250	Intermittent	Syntetos
109	533	549	598	501	Lumpy	Syntetos
110	56	54	53	54	Smooth	Croston
111	282	217	145	144	Lumpy	Syntetos
112	60	89	181	170	Intermittent	Naive Method
113	243	236	231	243	Smooth	Croston
114	916	487	332	279	Intermittent	Syntetos
115	1717	1299	1357	1368	Lumpy	Exp.Smoothing
116	84	82	85	79	Smooth	Syntetos
117	988	805	814	831	Erratic	Exp.Smoothing
118	1902	1908	1810	1712	Erratic	Syntetos
119	55	49	55	52	Erratic	Exp.Smoothing
120	24	35	15	13	Lumpy	Syntetos
121	22	22	17	15	Intermittent	Syntetos
122	9	9	6	6	Intermittent	Croston
123	137	176	137	122	Intermittent	Syntetos
124	36	35	36	36	Lumpy	Exp.Smoothing
125	1473	1142	1098	1052	Smooth	Syntetos
126	127	64	65	67	Lumpy	Exp.Smoothing
127	10301	8860	6793	8629	Lumpy	Croston
128	1057	650	595	724	Intermittent	Croston
129	49	52	77	52	Intermittent	Naive Method
130	2013	1232	1386	1220	Intermittent	Syntetos
131	164	136	119	118	Lumpy	Syntetos
132	67	100	92	92	Intermittent	Naive Method
133	39	39	39	39	Lumpy	Naive Method
134	200	167	163	158	Lumpy	Syntetos
135	175	170	163	160	Intermittent	Syntetos
136	185	26	30	30	Lumpy	Exp.Smoothing
137	540	583	603	565	Intermittent	Naive Method
138	535	376	349	349	Intermittent	Croston

139	99	113	106	123	Lumpy	Naive Method
140	71	61	58	57	Lumpy	Syntetos
141	4622	3382	3577	9577	Erratic	Exp.Smoothing
142	105	88	96	76	Intermittent	Syntetos
143	2728	2659	4371	3080	Erratic	Exp.Smoothing
144	266	225	246	246	Lumpy	Exp.Smoothing
145	12308	12452	12512	12048	Erratic	Syntetos
146	358	588	442	409	Lumpy	Naive Method
147	244	211	208	205	Intermittent	Syntetos
148	2004	2106	3011	3011	Intermittent	Naive Method
149	45201	43835	41585	54836	Erratic	Croston
150	1070	950	992	1051	Intermittent	Exp.Smoothing
151	209	150	110	209	Lumpy	Croston
152	182	216	237	228	Intermittent	Naive Method
153	168	178	153	155	Smooth	Croston
154	537	587	771	1380	Lumpy	Naive Method
155	863	2115	2282	2944	Intermittent	Naive Method
156	30916	26930	31399	36366	Lumpy	Exp.Smoothing
157	395	391	422	389	Intermittent	Syntetos
158	242	235	225	212	Intermittent	Syntetos
159	3997	3952	3926	4254	Erratic	Croston
160	1940	1936	1228	1383	Lumpy	Croston
161	392	338	328	346	Lumpy	Croston
162	336	336	336	336	Intermittent	Naive Method
163	894	797	1439	1318	Lumpy	Exp.Smoothing
164	279	198	231	210	Intermittent	Exp.Smoothing
165	10731	4687	5533	4898	Intermittent	Exp.Smoothing
166	174	153	170	169	Lumpy	Exp.Smoothing
167	990	971	809	2752	Intermittent	Croston
168	77	73	39	32	Lumpy	Syntetos
169	458	375	331	331	Intermittent	Croston
170	82	143	143	141	Intermittent	Naive Method
171	558	543	510	567	Lumpy	Croston
172	417	363	363	358	Lumpy	Syntetos
173	1213	1167	1139	1051	Erratic	Syntetos
174	374	346	155	138	Lumpy	Syntetos
175	1827	1575	1544	1315	Intermittent	Syntetos
176	8777	7049	6360	5779	Intermittent	Syntetos
177	1447	1294	1244	1239	Erratic	Syntetos
178	384	318	410	424	Intermittent	Exp.Smoothing
179	523	416	318	307	Intermittent	Syntetos
180	4739	3984	4353	4650	Lumpy	Exp.Smoothing
181	645	508	500	506	Lumpy	Croston
182	67	77	61	67	Erratic	Croston
183	92	103	104	100	Lumpy	Naive Method
184	653	635	499	618	Lumpy	Croston
185	486	403	387	333	Lumpy	Syntetos
186	223	163	166	189	Erratic	Exp.Smoothing
187	783	674	594	498	Intermittent	Syntetos
188	365	466	863	728	Lumpy	Naive Method
189	768	1499	1621	1012	Intermittent	Naive Method
190	62	64	82	78	Intermittent	Naive Method

191	503	281	281	281	Intermittent	Exp.Smoothing
192	383	405	432	456	Lumpy	Naive Method
193	636	363	636	456	Lumpy	Exp.Smoothing
194	16	18	11	12	Lumpy	Croston
195	909	287	227	301	Intermittent	Croston
196	138	136	121	122	Lumpy	Croston
197	52	50	51	39	Lumpy	Syntetos
198	929	342	342	528	Lumpy	Exp.Smoothing
199	196	80	76	71	Lumpy	Syntetos
200	900	848	813	851	Intermittent	Croston

APPENDIX-D

INVENTORY COSTS OF METHODS WITH PROPOSED ORDERING APPROACHES

Table D.1 Inventory cost results of forecasting methods with proposed approaches under base-stock policy

Method	**Exp. Smoothing**		**Croston**		**Syntetos**				
No	**Inflated Approach**	**Gradually Approach**	**Inflated Approach**	**Gradually Approach**	**Inflated Approach**	**Gradually Approach**	**Best Ordering Approach**	**Best Forecasting Method**	**Data Type**
1	27.51	30.21	33.36	34.28	36.93	35.19	Inflated Approach	Exp.Smoothing	Lumpy
2	86.91	71.00	94.78	72.93	214.20	115.42	Gradually Approach	Exp.Smoothing	Erratic
3	29.35	35.54	31.42	36.31	54.08	41.15	Inflated Approach	Exp.Smoothing	Erratic
4	402.71	98.24	203.03	98.24	428.31	63.68	Gradually Approach	Syntetos	Lumpy
5	577.55	576.56	665.83	668.71	1236.84	854.94	Gradually Approach	Exp.Smoothing	Lumpy
6	1.37	1.97	2.85	2.83	3.04	1.92	Inflated Approach	Exp.Smoothing	Lumpy
7	405.49	412.49	764.07	662.46	931.10	847.59	Inflated Approach	Exp.Smoothing	Lumpy
8	406.70	277.07	615.84	626.82	688.67	666.72	Gradually Approach	Exp.Smoothing	Intermittent
9	144.41	136.55	173.69	138.71	248.37	150.87	Gradually Approach	Exp.Smoothing	Intermittent
10	13.16	14.05	12.85	9.61	14.91	11.51	Gradually Approach	Croston	Intermittent
11	19.68	20.24	18.86	14.30	31.43	16.09	Gradually Approach	Croston	Intermittent

12	69.89	70.48	68.33	79.91	132.19	83.34	Inflated Approach	Croston	Lumpy
13	771.95	777.88	1641.37	1408.16	3343.30	1290.06	Inflated Approach	Exp.Smoothing	Intermittent
14	203.00	189.24	197.88	206.10	291.18	199.07	Gradually Approach	Exp.Smoothing	Erratic
15	7.78	7.23	7.30	6.69	36.18	7.08	Gradually Approach	Croston	Lumpy
16	876.80	1166.32	973.11	980.52	1456.11	1071.33	Inflated Approach	Exp.Smoothing	Lumpy
17	82.93	92.96	91.56	107.28	151.15	112.95	Inflated Approach	Exp.Smoothing	Lumpy
18	46.03	53.92	41.13	52.61	50.23	52.93	Inflated Approach	Croston	Lumpy
19	456.44	426.34	123.37	374.08	703.39	693.22	Inflated Approach	Croston	Lumpy
20	753.17	609.79	672.70	699.90	796.37	702.02	Gradually Approach	Exp.Smoothing	Lumpy
21	247.50	120.75	476.93	390.15	890.27	442.59	Gradually Approach	Exp.Smoothing	Lumpy
22	379.99	182.25	251.29	249.65	455.44	260.68	Gradually Approach	Exp.Smoothing	Intermittent
23	576.07	620.97	810.71	588.66	1096.08	636.19	Inflated Approach	Exp.Smoothing	Lumpy
24	70.08	69.75	69.92	72.59	108.34	82.07	Gradually Approach	Exp.Smoothing	Lumpy
25	546.55	537.65	513.45	516.21	727.19	535.79	Inflated Approach	Croston	Erratic
26	1771.77	889.40	3180.62	1106.19	6379.42	724.99	Gradually Approach	Syntetos	Lumpy
27	86.53	112.89	73.94	73.94	238.68	66.98	Gradually Approach	Syntetos	Lumpy
28	87.54	154.59	133.49	135.38	150.48	138.47	Inflated Approach	Exp.Smoothing	Lumpy
29	29.84	29.90	24.46	43.51	70.71	48.39	Inflated Approach	Croston	Lumpy
30	2459.66	2277.14	2325.88	1842.33	2598.51	2099.36	Gradually Approach	Croston	Lumpy
31	5.59	12.30	7.57	6.47	6.41	6.50	Inflated Approach	Exp.Smoothing	Lumpy
32	577.77	423.15	568.50	420.70	567.18	423.15	Gradually Approach	Croston	Lumpy
33	6.98	8.80	5.77	8.80	7.53	8.75	Inflated Approach	Croston	Lumpy
34	11.05	26.51	132.82	41.20	106.09	88.83	Inflated Approach	Exp.Smoothing	Lumpy
35	304.68	346.01	213.59	406.03	444.59	396.56	Inflated Approach	Croston	Intermittent
36	52.32	74.55	59.57	18.13	59.57	18.13	Gradually Approach	Croston	Lumpy
37	592.34	264.45	2635.29	674.68	2745.85	952.46	Gradually Approach	Exp.Smoothing	Intermittent
38	30.53	43.70	45.80	44.33	48.48	45.80	Inflated Approach	Exp.Smoothing	Intermittent
39	221.88	244.32	346.72	259.83	676.79	265.41	Inflated Approach	Exp.Smoothing	Intermittent
40	31.69	56.36	59.02	56.10	142.40	59.87	Inflated Approach	Exp.Smoothing	Lumpy
41	657.38	806.25	658.46	861.45	681.61	798.51	Inflated Approach	Exp.Smoothing	Lumpy
42	160.51	170.38	210.53	210.74	708.60	283.27	Inflated Approach	Exp.Smoothing	Lumpy
43	161.60	137.39	144.62	128.78	160.46	142.60	Gradually Approach	Croston	Intermittent

44	110.09	144.60	122.53	155.41	179.38	155.65	Inflated Approach	Exp.Smoothing	Lumpy
45	94.75	144.18	83.31	142.83	139.85	92.19	Inflated Approach	Croston	Intermittent
46	329.77	260.13	581.23	273.12	468.49	273.12	Gradually Approach	Exp.Smoothing	Intermittent
47	256.23	74.45	69.38	193.27	266.76	131.70	Inflated Approach	Croston	Intermittent
48	3058.60	2371.33	3216.83	3108.09	3960.43	2837.69	Gradually Approach	Exp.Smoothing	Intermittent
49	8331.25	3071.51	8434.66	3071.51	5292.63	3071.51	Gradually Approach	Exp.Smoothing	Erratic
50	7.15	10.68	391.65	151.49	396.13	395.03	Inflated Approach	Exp.Smoothing	Lumpy
51	555.86	470.54	9559.80	364.88	9559.80	421.19	Gradually Approach	Croston	Lumpy
52	2585.31	1690.68	2585.31	1345.58	3835.33	1657.13	Gradually Approach	Croston	Erratic
53	367.27	361.98	376.67	375.54	728.31	456.68	Gradually Approach	Exp.Smoothing	Lumpy
54	307.69	369.87	340.76	462.36	670.95	515.12	Inflated Approach	Exp.Smoothing	Lumpy
55	125.60	83.55	78.40	128.34	119.01	130.59	Inflated Approach	Croston	Lumpy
56	221.47	261.60	208.32	210.25	320.92	287.51	Inflated Approach	Croston	Lumpy
57	8.46	10.82	13.38	16.75	11.86	19.58	Inflated Approach	Exp.Smoothing	Lumpy
58	405.61	540.20	411.79	542.02	594.03	715.72	Inflated Approach	Exp.Smoothing	Lumpy
59	481.32	709.52	485.89	819.20	505.48	738.31	Inflated Approach	Exp.Smoothing	Lumpy
60	190.77	145.43	257.50	180.87	206.96	136.52	Gradually Approach	Syntetos	Lumpy
61	324.73	338.37	377.43	424.18	614.18	472.01	Inflated Approach	Exp.Smoothing	Lumpy
62	340.87	439.37	320.50	403.71	266.38	386.72	Inflated Approach	Syntetos	Intermittent
63	74.80	116.97	120.50	202.63	1336.43	202.63	Inflated Approach	Exp.Smoothing	Intermittent
64	524.45	740.22	661.64	576.33	524.45	576.33	Inflated Approach	Exp.Smoothing	Intermittent
65	1607.89	1649.76	1546.76	1541.74	2863.83	2233.18	Gradually Approach	Croston	Lumpy
66	144.59	93.31	128.83	204.10	209.72	173.39	Gradually Approach	Exp.Smoothing	Intermittent
67	2679.61	4203.39	5274.16	5891.91	8199.52	5891.91	Inflated Approach	Exp.Smoothing	Intermittent
68	149.41	145.69	113.38	134.53	190.17	134.53	Inflated Approach	Croston	Intermittent
69	1055.03	1110.64	1316.60	818.33	1451.75	818.33	Gradually Approach	Croston	Lumpy
70	3033.38	3916.70	8299.63	5184.70	39377.33	3853.95	Inflated Approach	Exp.Smoothing	Lumpy
71	20.23	36.55	78.54	23.46	222.01	26.30	Inflated Approach	Exp.Smoothing	Lumpy
72	63.08	88.81	166.47	136.67	146.90	143.39	Inflated Approach	Exp.Smoothing	Intermittent
73	113.42	183.42	317.88	209.08	381.26	244.15	Inflated Approach	Exp.Smoothing	Intermittent
74	53.74	64.65	148.70	116.17	131.75	101.79	Inflated Approach	Exp.Smoothing	Intermittent
75	8029.20	8045.08	7210.67	5131.30	8245.03	5499.63	Gradually Approach	Croston	Lumpy

76	145.86	226.41	1418.12	528.40	3826.35	1396.54	Inflated Approach	Exp.Smoothing	Intermittent
77	203.22	198.91	438.66	125.23	595.42	306.12	Gradually Approach	Croston	Lumpy
78	319.01	268.50	625.61	276.48	685.87	354.47	Gradually Approach	Exp.Smoothing	Intermittent
79	363.70	374.48	475.66	411.52	511.55	428.89	Inflated Approach	Exp.Smoothing	Lumpy
80	2.12	1.50	2.22	0.81	2.30	0.81	Gradually Approach	Croston	Intermittent
81	169.52	155.06	139.79	185.02	188.08	185.95	Inflated Approach	Croston	Lumpy
82	208.10	191.52	202.25	197.48	263.36	199.58	Gradually Approach	Exp.Smoothing	Lumpy
83	36.44	35.76	38.90	34.12	47.65	34.88	Gradually Approach	Croston	Intermittent
84	10.14	61.40	7.84	7.84	99.51	14.69	Inflated Approach	Croston	Lumpy
85	365.24	239.70	352.95	308.07	518.41	318.73	Gradually Approach	Exp.Smoothing	Lumpy
86	1.46	1.91	1.54	1.96	1.97	2.99	Inflated Approach	Exp.Smoothing	Intermittent
87	3100.14	3529.53	3492.16	3691.40	6226.09	4039.86	Inflated Approach	Exp.Smoothing	Lumpy
88	73.92	78.01	82.70	93.93	86.66	76.53	Inflated Approach	Exp.Smoothing	Lumpy
89	473.08	212.56	327.64	501.46	1068.80	501.46	Gradually Approach	Exp.Smoothing	Intermittent
90	866.34	773.89	784.76	491.48	1118.92	678.73	Gradually Approach	Croston	Lumpy
91	627.54	454.59	2615.77	385.47	2672.90	385.47	Gradually Approach	Croston	Intermittent
92	116.75	80.91	267.70	86.94	185.16	80.88	Gradually Approach	Syntetos	Lumpy
93	35.72	41.75	35.39	36.53	63.15	52.74	Inflated Approach	Croston	Lumpy
94	78.65	128.15	71.44	73.18	179.58	198.14	Inflated Approach	Croston	Intermittent
95	4100.37	2234.32	4862.77	2525.93	5452.93	2525.93	Gradually Approach	Exp.Smoothing	Intermittent
96	686.46	794.22	820.73	833.55	1071.56	951.04	Inflated Approach	Exp.Smoothing	Lumpy
97	221.68	165.36	380.39	213.51	653.36	215.97	Gradually Approach	Exp.Smoothing	Intermittent
98	1150.42	604.04	1009.42	607.03	1238.28	607.03	Gradually Approach	Exp.Smoothing	Lumpy
99	228.32	233.96	389.40	256.94	439.50	256.94	Inflated Approach	Exp.Smoothing	Intermittent
100	13.66	13.66	13.14	7.33	18.86	12.63	Gradually Approach	Croston	Intermittent
101	42.58	39.71	69.64	38.45	90.53	73.64	Gradually Approach	Croston	Intermittent
102	74.85	95.65	97.70	97.86	98.34	119.12	Inflated Approach	Exp.Smoothing	Intermittent
103	26.40	3.96	8.12	6.66	112.95	6.66	Gradually Approach	Exp.Smoothing	Lumpy
104	42.05	53.54	70.18	56.63	73.36	56.63	Inflated Approach	Exp.Smoothing	Intermittent
105	107.49	157.86	241.41	160.40	281.94	210.19	Inflated Approach	Exp.Smoothing	Intermittent
106	149.21	112.98	177.41	118.84	390.41	103.47	Gradually Approach	Syntetos	Intermittent
107	15834.53	48698.26	15834.53	48698.26	137244.64	8793.90	Gradually Approach	Syntetos	Lumpy

108	2239.52	864.75	2582.03	866.61	2582.03	811.34	Gradually Approach	Syntetos	Intermittent
109	696.37	852.97	503.66	880.87	2572.64	1116.78	Inflated Approach	Croston	Lumpy
110	350.63	126.33	350.63	126.33	352.90	126.33	Gradually Approach	Exp.Smoothing	Smooth
111	164.18	156.21	165.95	159.59	227.09	159.59	Gradually Approach	Exp.Smoothing	Lumpy
112	44.11	39.60	118.39	57.79	118.39	57.79	Gradually Approach	Exp.Smoothing	Intermittent
113	439.98	379.85	491.21	410.35	718.77	467.53	Gradually Approach	Exp.Smoothing	Smooth
114	404.27	536.84	287.57	475.88	366.05	457.36	Inflated Approach	Croston	Intermittent
115	1382.96	1454.55	1348.91	1408.46	2129.15	1472.86	Inflated Approach	Croston	Lumpy
116	99.33	73.87	108.87	77.34	181.82	95.91	Gradually Approach	Exp.Smoothing	Smooth
117	954.89	1093.66	960.54	1030.07	1934.96	1486.62	Inflated Approach	Exp.Smoothing	Erratic
118	2189.81	2475.66	2067.49	2158.51	3691.61	2568.25	Inflated Approach	Croston	Erratic
119	55.77	47.04	70.95	54.46	133.56	69.59	Gradually Approach	Exp.Smoothing	Erratic
120	11.30	8.17	11.37	20.42	21.06	10.75	Gradually Approach	Exp.Smoothing	Lumpy
121	6.50	10.75	14.49	19.70	31.12	18.85	Inflated Approach	Exp.Smoothing	Intermittent
122	9.49	6.21	8.68	7.56	14.18	11.00	Gradually Approach	Exp.Smoothing	Intermittent
123	367.30	189.29	311.94	277.65	369.02	282.81	Gradually Approach	Exp.Smoothing	Intermittent
124	40.00	47.67	48.28	45.42	72.32	72.38	Inflated Approach	Exp.Smoothing	Lumpy
125	2419.03	2322.91	2579.13	2269.19	3827.02	2924.42	Gradually Approach	Croston	Smooth
126	55.19	51.30	51.61	62.71	62.56	66.12	Gradually Approach	Exp.Smoothing	Lumpy
127	5041.88	5567.68	4780.18	4822.75	5056.87	4822.75	Inflated Approach	Croston	Lumpy
128	589.85	1061.47	653.71	1207.00	932.35	708.25	Inflated Approach	Exp.Smoothing	Intermittent
129	31.28	69.04	66.87	46.03	88.32	51.74	Inflated Approach	Exp.Smoothing	Intermittent
130	916.38	1386.07	1662.12	1323.33	2234.29	1524.10	Inflated Approach	Exp.Smoothing	Intermittent
131	102.56	112.82	113.18	126.70	131.66	129.30	Inflated Approach	Exp.Smoothing	Lumpy
132	172.25	185.76	173.49	214.85	297.44	203.30	Inflated Approach	Exp.Smoothing	Intermittent
133	286.15	164.97	286.15	216.39	522.14	389.45	Gradually Approach	Exp.Smoothing	Lumpy
134	507.15	469.39	506.32	533.44	772.72	711.07	Gradually Approach	Exp.Smoothing	Lumpy
135	105.28	15.13	163.48	31.61	326.81	121.64	Gradually Approach	Exp.Smoothing	Intermittent
136	60.51	76.57	42.86	46.37	135.30	42.54	Gradually Approach	Syntetos	Lumpy
137	231.66	306.70	218.98	287.69	224.32	305.54	Inflated Approach	Croston	Intermittent
138	211.59	314.44	305.55	450.31	267.65	414.90	Inflated Approach	Exp.Smoothing	Intermittent
139	96.99	134.13	137.14	104.73	152.65	127.33	Inflated Approach	Exp.Smoothing	Lumpy

140	62.61	98.08	45.69	97.64	80.98	72.04	Inflated Approach	Croston	Lumpy
141	18014.64	16738.93	18037.01	16293.62	22134.89	9426.67	Gradually Approach	Syntetos	Erratic
142	69.10	69.82	61.60	73.24	78.22	70.20	Inflated Approach	Croston	Intermittent
143	1913.44	2177.44	1936.59	2189.92	5738.99	2466.77	Inflated Approach	Exp.Smoothing	Erratic
144	253.32	242.04	246.20	246.44	420.54	322.00	Gradually Approach	Exp.Smoothing	Lumpy
145	16910.36	17414.36	16910.36	18627.78	50186.04	25169.04	Inflated Approach	Exp.Smoothing	Erratic
146	215.17	238.32	520.47	223.39	387.08	246.04	Inflated Approach	Exp.Smoothing	Lumpy
147	259.32	234.92	463.56	428.45	839.61	379.28	Gradually Approach	Exp.Smoothing	Intermittent
148	1749.71	1220.13	1458.26	1647.21	1458.26	1647.21	Gradually Approach	Exp.Smoothing	Intermittent
149	1898.51	2055.82	2134.95	2043.52	3357.82	1635.82	Gradually Approach	Syntetos	Erratic
150	802.19	775.83	918.41	831.44	1090.28	777.26	Gradually Approach	Exp.Smoothing	Intermittent
151	115.90	131.20	106.84	142.23	133.93	146.48	Inflated Approach	Croston	Lumpy
152	357.31	326.73	345.47	320.95	410.59	312.20	Gradually Approach	Syntetos	Intermittent
153	188.39	180.35	208.81	191.25	335.26	202.86	Gradually Approach	Exp.Smoothing	Smooth
154	611.87	539.68	553.40	524.23	659.37	532.48	Gradually Approach	Croston	Lumpy
155	571.55	730.54	795.41	860.27	1693.99	1060.70	Inflated Approach	Exp.Smoothing	Intermittent
156	2081.85	1965.75	2638.44	2229.44	2839.54	6172.67	Gradually Approach	Exp.Smoothing	Lumpy
157	422.88	530.31	588.45	447.41	682.25	447.41	Inflated Approach	Exp.Smoothing	Intermittent
158	175.88	177.37	248.80	194.33	252.15	194.33	Inflated Approach	Exp.Smoothing	Intermittent
159	2833.85	2416.40	2961.71	2411.69	4111.47	2932.49	Gradually Approach	Croston	Erratic
160	653.03	587.26	700.73	720.12	831.49	720.12	Gradually Approach	Exp.Smoothing	Lumpy
161	427.68	466.63	432.04	461.34	653.47	613.56	Inflated Approach	Exp.Smoothing	Lumpy
162	323.90	209.75	275.05	528.85	353.10	358.95	Gradually Approach	Exp.Smoothing	Intermittent
163	653.36	786.58	865.46	1200.68	1722.74	1099.68	Inflated Approach	Exp.Smoothing	Lumpy
164	138.10	132.41	282.63	245.20	1136.08	211.13	Gradually Approach	Exp.Smoothing	Intermittent
165	3497.61	5091.29	4889.23	4485.64	8367.74	5312.97	Inflated Approach	Exp.Smoothing	Intermittent
166	193.71	187.74	170.47	234.23	307.31	252.94	Inflated Approach	Croston	Lumpy
167	593.17	738.61	945.48	970.23	791.60	970.23	Inflated Approach	Exp.Smoothing	Intermittent
168	66.69	87.21	214.40	219.34	414.17	209.56	Inflated Approach	Exp.Smoothing	Lumpy
169	298.36	358.67	280.31	464.52	353.37	464.52	Inflated Approach	Croston	Intermittent
170	674.92	520.43	727.04	571.38	1040.24	830.36	Gradually Approach	Exp.Smoothing	Intermittent
171	891.90	601.72	854.00	553.32	1163.64	742.83	Gradually Approach	Croston	Lumpy

172	500.18	497.69	485.84	452.39	544.70	737.68	Gradually Approach	Croston	Lumpy
173	1178.57	903.43	1191.62	1015.24	1616.27	1129.84	Gradually Approach	Exp.Smoothing	Erratic
174	204.75	320.99	352.45	474.30	348.09	262.08	Inflated Approach	Exp.Smoothing	Lumpy
175	682.43	975.66	2424.28	864.02	4113.37	864.02	Inflated Approach	Exp.Smoothing	Intermittent
176	4976.30	5389.63	5384.96	5649.45	5740.35	6516.77	Inflated Approach	Exp.Smoothing	Intermittent
177	1887.60	1154.47	1954.58	1276.42	3304.05	1507.86	Gradually Approach	Exp.Smoothing	Erratic
178	369.60	398.10	496.72	414.71	666.94	512.57	Inflated Approach	Exp.Smoothing	Intermittent
179	509.94	333.75	477.02	461.20	720.86	596.50	Gradually Approach	Exp.Smoothing	Intermittent
180	12103.15	4313.06	12103.15	3669.61	12103.15	4059.86	Gradually Approach	Croston	Lumpy
181	457.30	497.18	498.22	492.46	643.92	505.90	Inflated Approach	Exp.Smoothing	Lumpy
182	96.16	80.17	110.70	75.16	136.29	71.27	Gradually Approach	Syntetos	Erratic
183	101.44	80.46	92.08	68.07	343.82	102.29	Gradually Approach	Croston	Lumpy
184	362.60	63.22	72.12	74.41	66.20	64.87	Gradually Approach	Exp.Smoothing	Lumpy
185	296.86	368.84	301.32	378.32	409.91	356.05	Inflated Approach	Exp.Smoothing	Lumpy
186	478.31	284.45	478.63	284.45	744.92	358.70	Gradually Approach	Exp.Smoothing	Erratic
187	674.35	650.84	869.04	835.22	1049.88	636.80	Gradually Approach	Syntetos	Intermittent
188	144.35	73.58	144.35	73.58	395.41	195.42	Gradually Approach	Exp.Smoothing	Lumpy
189	402.66	334.98	477.60	334.98	742.53	407.04	Gradually Approach	Exp.Smoothing	Intermittent
190	65.02	82.99	59.75	72.03	95.29	93.60	Inflated Approach	Croston	Intermittent
191	301.77	324.21	451.30	283.72	636.45	283.72	Gradually Approach	Croston	Intermittent
192	255.58	212.64	398.94	241.39	388.45	311.52	Gradually Approach	Exp.Smoothing	Lumpy
193	311.60	302.21	373.05	379.34	394.97	412.62	Gradually Approach	Exp.Smoothing	Lumpy
194	10.36	9.87	12.48	11.36	12.45	13.15	Gradually Approach	Exp.Smoothing	Lumpy
195	204.82	235.44	391.19	416.43	452.29	418.38	Inflated Approach	Exp.Smoothing	Intermittent
196	156.82	169.67	157.55	169.81	238.04	171.43	Inflated Approach	Exp.Smoothing	Lumpy
197	33.74	34.40	39.79	39.88	68.90	53.80	Inflated Approach	Exp.Smoothing	Lumpy
198	382.25	417.41	301.89	392.27	399.59	392.27	Inflated Approach	Croston	Lumpy
199	119.86	115.01	113.10	144.52	264.54	115.61	Inflated Approach	Croston	Lumpy
200	1248.17	863.47	1444.69	863.47	3751.64	927.67	Gradually Approach	Exp.Smoothing	Intermittent

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Undergraduate	Industrial Engineering	Uludağ University	2008
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WORK EXPERIENCE

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2014	Turkish Technic	2012

PUBLISHMENTS

Papers

1. Sahin M, Eldemir F., “Inventory Cost Minimization of Spare Parts in Aviation Industry: Turkish Airlines Technic Case”, An International Journal of Optimization and Control: Theories & Applications (IJOCTA), submitted (in review).

Conference Papers

1. Sahin M, Eldemir F., “Q-R Policy Application for Non-Smooth Demand Of Aviation Industry”, Global Joint Conference on Industrial Engineering and Its Application Areas, Vienna, Austria, 2017.
2. Şahin M., Eldemir F., “Kesikli Talebi Parametrik Olmayan Yaklaşımlar ile Tahmin Ederek Envanter Maliyetlerini Karşılaştırma”, 37. Yöneylem Araştırması ve Endüstri Mühendisliği Ulusal Kongresi, İstanbul, 2017.
3. Sahin M., Demirel OF, Kızılaslan R., “Forecasting intermittent demand with neural networks” ISCSE 2011, İzmir, Turkey
4. Eldemir F., Sahin M., "Decision Making Techniques in Disaster Management", Chemical, Biologic, Radiologic and Nuclear Congress, Istanbul, Dec. 2008, CBRN08, 109-121 pp.

Projects

1. Cargo Material Handling Systems Project, Turkish Airlines.
2. Türk hava yolları teknik satın alma birimi sık kullanılan malzemelerin otomatik Purchase Order sistemi ile temini
3. Modelling of Evacuation of Istanbul against to possible chemical, biological, radioactive and nuclear threats, University Research Project.