ABSTRACT

SHAFIK, ENGY OSAMA ABDELKADER. Forecasting and Inventory Management of Service Parts: Implications for Electronic Textiles (E-Textiles) Serviceable Components. (Under the direction of Dr. Jeffrey Joines and Dr. Kristin Thoney-Barletta).

Over the past decade, industrial and academic interest in e-textiles has increased dramatically. However, few researchers have considered the future of e-textiles' mass production. Upon reviewing e-textiles' literature, it can be concluded that most current products and prototypes are composed of fabric (usually embedded with sensors) and a removable electronic component. However, no research has been conducted to address the serviceability of the electronic components of e-textiles from a forecasting/inventory standpoint. As soon as the market for e-textiles matures, managing the flow of products and components required for maintenance is going to be quite complex. Furthermore, in-depth research and cost analyses need to be conducted to develop models and strategies that minimize costs. Subsequently, this highlights the need for new forecasting techniques and inventory models to service the reverse flow of e-textiles products under warranty.

To contribute to both the fields of e-textiles and service parts management, the existing knowledge and research needs of service parts management were integrated to propose new forecasting techniques. The newly proposed forecasting techniques demonstrated superior levels of accuracy compared to the benchmarked forecasting techniques in the field of spare parts management. Each of the new forecasting techniques incorporated different levels of information including demand, probability of demand occurrence, installed base and life cycle phase. The methods were designed with the goal of better handling the complexity of spare parts management, which exists due to the interplay between multiple factors affecting the decision making process (e.g., life cycle stage, product failure rates, installed base information, warranty period, technology

and innovation, and component demand patterns). Furthermore, the forecasting approaches were analyzed with respect to their inventory management performance within this study. The forecasting-inventory models were tested on both generated data sets and industrial data sets. The data sets represented different levels of demand intermittency and included parts in different life cycle phases. The results showed that the newly proposed methods achieved higher levels of accuracy compared to the benchmarked forecasting techniques and managed to carry lower levels of on-hand inventory for most of the considered scenarios.

Forecasting and Inventory Management of Service Parts: Implications for Electronic Textiles (E-Textiles) Serviceable Components

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DEDICATION

To my parents for their unconditional love, continuous support and for being my all-time role models. And to the love of my life and my partner Omar who has always believed in me and for being my support system for years. Lastly, I would like to dedicate my hard work as an inspiration and motivation to my daughter Noureen, wishing her success and happiness in her future.

BIOGRAPHY

Engy Shafik earned her bachelor's degree in logistics and international transport from AASTMT University in 2011. As the highest ranked graduate of class 2011, she was offered a scholarship to pursue her graduate studies and a full-time teaching associate position. She earned her master's degree in supply chain management from AASTMT University in 2013. Her research interests are in the area of supply chain analytics and optimization. She became a PhD candidate at NC State University in 2018. Engy presented her PhD research work through two campus-wide academic competitions where she won second-place in the three minute thesis (3MT) competition in 2018 and first-place in the poster presentations at the graduate student research symposium for the category of management and social sciences in 2019.

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Chapter 1

Introduction

Over the past few years, academic and industrial interest in electronic textiles (e-textiles) has grown drastically, motivating few researchers to consider the impact of e-textiles' mass production on sustainability. However, all of the studies addressing the issue mainly discussed the topic from a product reliability and materials selection point of view. The main industries adopting the innovation of e-textile products are the health/medical, fitness/athletic, and entertainment sectors. Upon reviewing the literature on e-textiles, it can be concluded that most current products and prototypes are composed of a textile apparel (usually embedded with sensors) and a removable electronic component.

Research studies have advocated for the ease of disassembly of the components of e-textile products to enable their serviceability (i.e., providing maintenance for the electronic component during the in-warranty period) (Köhler, 2008; Köhler et al., 2011; Arnette et al., 2011). However, no research has been conducted to address the serviceability of the electronic components of e-textiles from a forecasting/inventory standpoint.

This research aims to contribute to the fields of e-textiles and service parts management, by integrating existing knowledge of service parts management to propose forecasting-inventory models that could benefit the e-textiles industry. The majority of the recent studies have addressed the following industries; automotive, aviation, and computer/electronics when dealing with spare parts management. All these industries pose different challenges when dealing with service parts management (e.g., the product life time, the warranty period, the product's reliability and criticality, the part's price). The computer/electronics industry possesses the most similar characteristics to the electronic components of e-textiles. Given that the e-textiles sector is still in its infancy, it is challenging to acquire any real data regarding the failures of the electronic components of e-textile products. Hence, for the purposes of this study it was decided to use data from a multi-national electronics company.

This research aims to investigate and assess potential forecasting-inventory models for e-textiles serviceability. To achieve this, several forecasting techniques and safety stock calculations will be considered and analyzed under different assumptions. All of the forecasting-inventory models are practical and could be applied by companies in the field of e-textiles. Moreover, this study will attempt to address some of the main research needs in the area of service parts forecasting and inventory management identified in Chapter 2.

This document is structured as follows. Chapter 2 is the literature review, which includes an overview of e-textiles, service parts forecasting, and service parts inventory management. The initial analyses and results of the forecasting-inventory models are presented in Chapter 3. New forecasting techniques are proposed and analyzed in Chapter 4. The performance of all the forecasting techniques are assessed in terms of inventory management, the analyses are considered for different life cycle phases in Chapter 5

Chapter 2

Literature Review

This chapter will provide an overview of the literature related to the proposed research topic. Section 1 will overview the related literature on smart textiles and wearable electronics, Sections 2 and 3 will overview the related literature on service parts management from a forecasting and an inventory standpoint. The last section will discuss the synthesized research needs based on the reviewed literature across the different research avenues to highlight the main contributions of our research.

2.1. Introduction

Smart textiles and wearable electronics are still in their infancy, nevertheless, the future holds great potential for this industrial sector. Over the past decade industrial and academic interest in the introduction of smart textiles has increased dramatically. The Electronic textiles (E-textiles) area has expanded into a vast array of applications in various industries including healthcare, sportswear, and apparel and entertainment (Schwarz et al., 2010).

Each application represents a system that encompasses several technological elements. The technology behind each system differs according to the functions and usability of the smart textile product. The spectrum of smart wearable textile products introduced to the market is quite diverse. For instance in biometric monitoring apparel such as vests, t-shirts, sports bra, undergarments, and socks introduced to the market by "*Hexoskin*", "*Sensoria*" and "*SKIIN",* the main function of the products is to monitor and record bio-signals for fitness and health purposes. Another example of commercialized products is a functional jacket that connects to a cell-phone device, this jacket is commercially referred to as "Levi's commuter trucker jacket with jacquard by Google". However, the usage of the products is currently limited to niche-customer segments. The majority of the previously mentioned products are in the introduction phase and are often pre-ordered upon demand with very little competition.

Some of the products introduced to the market featured a heat method that provides the wearer with the necessary warmth through a heatable garment (Schwarz et al., 2010). Another stream of products involves technology that operates MP3 players utilizing an electro-conductive material embedded in apparel to remotely control music functions (Schwarz et al., 2010). Smart wearable textiles have had the most success in the field of sportswear and athletic apparel. For example, sports shoes with an embedded electronic unit measure the athletes' speed, weight as well as determine the type of terrain under the athletes' foot. Another example is a sports bra with integrated textile sensors with the ability to measure the heart rate during a work-out (Schwarz et al., 2010). Another area that is extensively being researched in e-textiles is the healthcare industry. Foreseeing the large future potentials of e-textiles, many entities and organizations are funding projects that will aid in commercializing smart e-textiles products (Stoppa and Chiolerio, 2014).

Many of the funded research projects have been geared towards deploying state of the art technology to design smart textile clothing that could be used in the healthcare sector as well as in athletic apparel (Trindade et al., 2014; Liang and Yuan, 2016). In many cases, the research seeks to monitor and measure vital biosignals like the heart rate and ElectroCardioGram (ECG).

In a broad sense, the smart-apparel designed to collect key health signals is composed of a system that incorporates an interface between hardware and software platforms. The hardware platform is depicted by a textile-electronic body which generally consists of sensors, connectors, and a power supply. The software platform handles the transmission, processing, visualization, and storage of the collected data. The following section will cover the technological advances and development in each platform, along with their implications primarily for smart vests.

2.2. Electronic Textiles (E-textiles)

E-textiles or smart textiles refers to the utilization of technology in textiles as well as electronics to expand the features of garments and/or apparel to provide a more interactive, smart platform for the wearer. The level of integration between textiles and the electronic component ranges from very basic to highly integrated products, and impacts multiple aspects including the functionality, durability, and sustainability of the end-product as well as the manufacturability.

2.3. Conductive Textiles in Smart-Apparel

There are a number of elements that are key to the introduction and development of smart-clothing. One of the main elements that is crucial to the interface between textiles and electronics is material conductivity. Advances in material conductivity will assist in developing smart-clothing products that possess the technological aspect as well as the desired features of apparel like comfort, washability, and durability. The need for designing smart textiles that possess both the technological advances as well as the desired features of apparel, has driven researchers to explore the possibilities of realizing an outcome that would satisfy both ends to ultimately gain customer's acceptance.

Fabrication of a conductive garment or apparel rely on a range of materials and manufacturing techniques (Kohler, 2008). Electro-textiles like metal monofilament fibers are either directly used in weaving and knitting or they are blended with other fibers. Each material possess specific electrical characteristics, thus the selection of the approach and the material relies on the end-product (Kohler, 2008; Kohler et al., 2011; Stoppa and Chioleri, 2014). For instance, optical fibers are used for signal transmission and light dispersion purposes, thus if these properties are required in the end-product optical fibers are utilized (Kohler et al., 2011). Another method used to create electrically conductive fibers is by utilizing a textile coating process. That entails coating fibers, yarns or fabrics with metals, galvanic substances, or metallic salts (Stoppa and Chiolerio, 2014).

Recent research has proposed of using conductive inks that combine highly conductive metals with a base element which is mostly pure water (Stoppa and Chiolerio, 2014). The method of sheet-based inkjets and screen printing are widely used to print the conductive ink and create e-textiles products (Stoppa and Chiolerio, 2014). The technology has been used by researchers to create electronically conductive patterns embedded within textile bodies to perform an array of functions. Some practical applications of the technology yielded a design of wearable e-textiles that monitor and record bio-signals, where inkjets, screen printing and conductive fibers/yarns were used in developing electronic circuits, sensors, electrodes and super capacitors (Gordon et al., 2006; Tada et al., 2015; Guzik et al., 2016; Weng et al., 2016).

2.4. Textile-Based Sensors and Electrodes for Bio-Signals Monitoring

Extensive research efforts are investigating extending the use of conductive fibers and yarns to develop a highly integrated e-textile product. The ultimate goal is for textile-based solutions to replace the functions of all the electronic hardware component. The development of textile sensors and electrodes helps in realizing both the functionality and the comfort fit of the smart-clothing which is a prime concern for end-users. Some researchers managed to develop textile sensors and electrodes using stainless steel fibers and yarns, in some cases blended with other yarns like cotton, spandex or Lycra to promote flexibility and the wearer's comfort (Cho et al., 2009; Anne et al., 2010). The textile-based sensors were further knitted or embroidered into garments or apparel where research results have shown that the sensors and electrodes provide accurate bio-signals (Cho et al., 2009).

Brady et al. (2005) presented a foam-based pressure sensor that measures the respiration rate where the functionality of the sensor was realized by applying conductive polymer, polypyrrole (PPy) on polyurethane foam. Trindade et al. (2014) proposed an embroidery technique that could be used in the mass production of textile sensors and electrodes for bio-monitoring. Results showed that this method could be further used in the production of other electro-textile components like batteries and antennas. A prototype that presented a single flexible printed circuit managed to integrate textile based sensors and electrodes with power and data transmission system to measure ECG signals (Coosemans et al., 2005). To develop a smart sensing garment for bio-potential sensing, Cheng et al. (2017) deployed a single measurement lead using textile electrodes to record ECG.

2.5. Wearable Technology Applications for Monitoring Bio-Signals: Smart Vests

Advanced research in the field of e-textiles has enabled the introduction of diverse applications and prototypes that have made real-time monitoring of key bio-signals feasible. Park and Jayaraman (2001) developed a smart wearable shirt for monitoring health vitals using a flexible conductive garment, and detachable sensors that plugged into T-connectors. The connectors were then used to transmit signals from the sensors to an external unit where the information is monitored and stored.

Ottenbacher et al. (2004) developed a smart T-shirt that integrated textile electrodes and cables in order to measure ECG signals which were transmitted using Bluetooth. The electronic hardware was designed to be removable in order to permit the washability of the smart t-shirt, two push buttons were used to attach and detach the electronic component. In another smart vest prototype developed by Pandian et al. (2008) sensors and wires were integrated into the fabric and a wearable data acquisition hardware was included to house the complete electronics needed to process and transmit the ECG signals along with a rechargeable battery for power-supply.

A jogging wear prototype was developed, comprising textile-based ECG sensors, textile based transmission lines, ECG electrode module and the main sensor module to monitor heart rates while jogging (Cho et al., 2009). A smart shirt that measures and transmits 12-Lead ECG signals using dry electrodes was developed, with the entire electronic package contained in a small pouch powered by a small coin cell battery (Morrison et al., 2014). A FitnessSHIRT prototype was developed and tested, integrating two textile electrodes with the electronic unit stored in a separate plastic box. Similar to the prototype introduced by Ottenbacher et al. (2004), push buttons were used for the interconnection between the sensors and the electronic unit, permitting the removal and attachment of the electronic unit (Leutheuser et al., 2017). The electronic unit managed to detect, process, filter and transmit ECG signals via Bluetooth (Leutheuser et al., 2017)

2.6. Smart Clothing from a Niche-Market to Mass Production

As discussed in earlier sections, the market of e-textiles is still limited to serving niche-market customers. Nevertheless, the market is expected is grow drastically over the coming years. In order to achieve this growth a number of challenges need to be addressed, some of which will be tackled in this section.

2.6.1. The Future of Smart Clothing - Current Market Situation and Challenges

As previously elaborated, recent studies predict that the future of e-textiles is quite promising and that the market will continue to grow over the years. However, studies also emphasized that there are some key elements that require deeper understanding.

2.6.1.1. Customers' Need and Buying Intentions

For the e-textiles market to reach maturity, products must fulfill customers' needs and expectations. The sustainability of smart textiles is also of prime importance as it could promote customers' willingness to purchase these innovative products (Cho, 2010; Hwang et al., 2016; Perry et al., 2016). However, a great emphasis needs to be given to the comfort of the wearable e-textile. Even though there have been many technological advances the fit comfort of the end-product will continue to be the prime determinant of consumer's acceptance (Stoppa and Chiolerio, 2014 and Hwang et al., 2016). Acutis and Rossi (2017) highlighted that some of the main drivers of customers' buying intention are the value they perceive, the tradeoff between cost and benefit, ease of use and reliability of the e-textiles.

2.6.1.2. Technological and Manufacturing Barriers

As the market for smart textiles transitions from the infancy to the maturity stage, there are several technological and manufacturing challenges that need to be addressed beforehand. One of these is the standardization of production processes. Acutis and Rossi (2017) argued that the lack of standardized laws and processes governing this new sector of the industry is one of the prime reasons delaying the widespread commercialization of smart textiles.

The fact that e-textiles products require collaboration between two distinct paradigms (i.e., electronics and textiles) makes it a highly complex industrial field. It was documented in the literature that despite the major technological advancements there are still just a few manufacturers who are experienced in both fields (Stoppa and Chiolerio, 2014). The hurdles that manufacturers face in an attempt to revamp their current businesses and processes to embrace both domains are quite significant (Acutis and Rossi, 2017). Materials selection and the choice of technology to deploy are additional concerns for manufacturers as there is a wide spectrum of alternatives and the pace of the technological change is tremendous (Acutis and Rossi, 2017). To address this concern manufacturers' ought to adopt robust systems that enable them to cope with rapid changes otherwise they will expose their systems to the risk of obsolescence.

The notion of transitioning smart textiles from niche markets to mainstream was investigated by Cheng et al. (2013) who advocated the separation of the electronic controller device from the garment. Designing e-textiles using separation will provide manufacturers with a system that is robust while minimizing both cost and complexity. Additionally, the authors argued that the software platform and applications ought to be initially developed to cover a wide spectrum of complex wearable sensing functions and to apply late customization to the features based on the customers' needs and budget through appropriate abstraction layers (Cheng et al., 2013). Thus, to realize the success and widespread use of electronic textiles, a deep understanding and synchronization of the cross-functional domains is needed.

2.6.1.3. E-Textiles Mass Production And Environmental Concerns

Another concern is associated with the possible repercussions of mass produced smart textiles from an environmental standpoint. The urge to address this concern promptly is driven by the fact that the market of e-textiles is still in its infancy and design phase, providing a golden opportunity to be proactive and avoid reactive measures and costs in the near future. Moreover, the realization that both business sectors have a history of short life cycle products and high risk of obsolescence is yet another driver to address this concern.

Despite the significant academic studies and projects addressing the future of smart wearables and e-textiles, however, the documented studies covering the environmental concerns for this new industrial paradigm are quite limited and needs further attention.

Kohler (2008) anticipated that the projected consumption levels of e-textiles will add significantly to the e-waste stream and will trigger new sets of challenges to arise. The study investigated the relevance of e-waste and future e-textiles' waste based on current materials and technology used in e-textiles prototypes and products, noting that currently there is no governing policy incorporated to handle waste and innovation of e-textiles (Kohler, 2008). A wide range of recommendations were proposed to aid in bridging the gap between innovations of e-textiles and potential e-waste streams. The study tackled the notion to create and adopt eco-designs for e-textiles and to consider their applicability and use in relevance to the current upcoming e-textiles innovation (Kohler, 2008). The fusion of components in e-textiles' products will be a chief impediment to implement eco-designs for products (Kohler, 2008 and Ossevoort, 2010).

2.6.2. Eco-Designs of E-Textiles Products

The notion of eco-designs for e-textile products has been discussed in a few studies focusing on materials' selection with respect to its impact on the product life cycle (Kohler, 2008; Kohler, 2013; Van der Velden et al., 2015). A literature review study addressed the concept of designing for sustainability, where an in-depth discussion of the intersection of various eco-designs and supply chain was presented (Arnette et al., 2014).

The following section will focus on some of the eco-design concepts, primarily those associated with the reverse flow of products during the post-sale phase. Design for disassembly mainly addresses the need for considering the operation of products' disassembly during the design phase with the goal of minimizing the cost and time of disassembly. Design for disassembly is one aspect of eco-design that realizes environmental rewards in addition to generating revenues for businesses (Arnette et al., 2014). The greatest advantage of designing for disassembly lies in the opportunities it grants for repair, re-use/re-manufacture and/or recycle of products. Design for serviceability is another relevant design concept which is strongly linked to the ease of maintenance and repair (Arnette et al., 2014).

2.6.3. The Need for Designing E-Textiles for Serviceability

Embracing eco-design concepts within the supply chain will promote a more sustainable future and may generate additional revenues for businesses. The e-textiles industry could drastically benefit from these concepts especially if they are realized prior to the mass production phase. In this study, the focal aspect will be from an inventory management standpoint which will be elaborated in the next section.

Since e-textiles' products contain electronics, they can be considered as serviceable products owing to the technological/electronical element similar to other types of electronics, which would necessitate providing consumers with warranties. As the market for e-textiles matures, managing the flow of products and components required for maintenance is going to be quite complex. Furthermore, in order to ensure financial benefits for businesses, in-depth research and cost analyses need to be conducted to develop models and strategies that would attain the desired environmental and financial advantages. Subsequently, this study will investigate the forecasting techniques and inventory models required to manage the reverse flow of products under warranty. The following section will review the literature on managing service parts from an inventory/forecasting standpoint. Additionally, it will highlight the needs and gaps in the academic research streams.

2.7. Service Parts Management

Spare parts management has always been an interesting yet challenging topic. Given the importance and the savings potential, the topic has captured the interest of many researchers. Nevertheless, due to the complex nature of the topic further investigations and contributions are still required. Spare parts management refers to the management of parts or components needed for the functionality of the produced or sold products upon their failure. The field of spare parts management is strongly tied with the service or maintenance required by sold products upon the failure of one or more component(s) as opposed to finished goods' management which entails servicing the customers only once.

Two general approaches to spare parts management have been discussed in the literature; preventive and corrective maintenance. The first approach refers to the scheduled maintenance of sold products based on the expected life of one or more of the critical components in an attempt to avoid failure. The latter, in contrast, takes place only when a part or component actually fails (Kennedy et al., 2002).

The management approach for each is quite different and necessitates consideration of slightly different variables. This research will consider the corrective maintenance that is triggered by the failure of component(s) during the warranty period. The reasoning is that e-textiles are likely to follow the serviceability pattern of computer/IT based products rather than an automotive or aircraft maintenance patterns. Computer/electronics based products generally don't require preventive maintenance due to their short life and the highly innovative products that are being constantly introduced to the market.

Within this study, failures per components will be referred to as demand and a forecasting/inventory management standpoint will be addressed.

The complexity of service parts management is due to the interplay between multiple factors affecting the decision model (e.g., life cycle stage, product failure rates, installed base information, warranty period, technology and innovation, and component demand patterns). As a general insight, proper service parts management breaks down to service parts forecasting and service parts inventory management. The ultimate goal is to determine the optimum stock quantity that meets the demand for products in warranty period while the overall stock level is minimized in order to avoid the costs associated with obsolescence. To achieve this goal an accurate demand forecasting technique is required in addition to a proper stock control approach.

2.7.1. Service Parts Demand Forecasting

Demand forecasting constitutes a significant challenge when dealing with service parts management. There are a lot of factors that impact service parts demand (e.g., random parts' failures, life cycle phase, warranty period). Moreover, the demand for service parts may have several periods with zero demand in addition to high variability. Therefore, some traditional forecasting methods fail to provide accurate demand estimates.

2.7.1.1. Time-Series Based Forecasting (TS)

Time series forecasting is one of the most widely used forecasting techniques in the literature as well as in practice. The basic idea is that the past information can be used to represent the future. Given that the latter assumption holds and sufficient historical data is available, time series forecasting has been proven to be an effective approach.

Some of the basic time series forecasting approaches such as simple moving averages (SMA) and single exponential smoothing (SES) have been applied to forecast the demand for components. However, the performance and accuracy of the models seemed less effective when dealing with service demand forecasting versus standard demand forecasting.

In 1972, Croston argued that the demand characteristics when dealing with service management are quite different, particularly the inherent intermittency nature of demand. The demand is regarded as intermittent when it exhibits random zero-demand periods. Croston proposed an approach that was tailored to overcome the inaccuracy of traditional techniques used for forecasting intermittent demand (Croston, 1972).

To address the nature of intermittent demand with zero-demand periods, Croston's method separately forecasts the demand size and the intervals of non-zero demand periods using single exponential smoothing. The forecasting method only updates when actual demand occurs. The demand estimate per period is generated by dividing the demand size forecast estimate over the demand interval forecast estimate.

$$\hat{z}_t = \alpha z_t + (1-\alpha)\ \hat{z}_{t-1}$$

$$\hat{p}_t = \alpha p_t + (1-\alpha)\ \hat{p}_{t-1}$$

$$\hat{d}_t = \frac{\hat{z}_t}{\hat{p}_t}$$

The estimated demand size at the end of period *t* is denoted by $\hat{z}_t$ while α is the smoothing constant, $\hat{p}_t$ is the estimated demand interval at the end of period *t*, and $\hat{d}_t$ is the estimated demand forecast at the end of period *t*.

The method assumed demand sizes and demand intervals to be independent and identically distributed. The same assumption was made by the subsequent forecasting techniques discussed below. Croston's approach prompted researchers to further investigate and modify the approach. An initial modification was to consider two distinct smoothing parameter (α and β) when forecasting the demand size and interval size, unlike what was proposed in the original method (Schultz, 1987).

Syntetos and Boylan (2001) claimed that Croston's estimate of demand was biased and proposed an approximation of the bias which is commonly referred to as the SBA approach. The

SBA approach adjusts the demand estimate by a factor of $(1-\frac{\alpha}{2})$ where α is the smoothing parameter used for updating the demand interval estimates.

The estimated demand forecast at the end of period *t* using the SBA modification is as follows.

$$\hat{d}_t = (1-\frac{\alpha}{2})\ \frac{\hat{z}_t}{\hat{p}_t}$$

Syntetos (2001) further argued that the SBA modification provides unbiased estimates when demand is intermittent, but is biased for non-intermittent demand. To overcome this issue he proposed another modification to adjust the demand estimate, referred to as SY. Nevertheless, it was argued that the proposed modification of SY never outperformed SBA or Croston when both bias and forecast variance are considered in the analytical study (Syntetos, 2001; Teunter and Sani, 2009; Prestwich et al., 2014).

The estimated demand forecast at the end of period *t* using the SY modification is as follows.

$$\hat{d}_t = (1-\frac{\alpha}{2})\ \frac{\hat{z}_t}{\hat{p}_{t-\frac{\alpha}{2}}}$$

Syntetos and Boylan (2005) conducted empirical research to compare the accuracy of SMA with 13-periods, SES, Croston’s, and their proposed method SBA. A real data set from the automotive industry consisting of 3000 SKUs with intermittent demand data was used to perform this analysis. The article assessed the accuracy of the different techniques based on a selection of error measures. The results showed that SBA had the most accurate demand estimate. In terms of the reorder level interval SES seemed to perform slightly better than Croston’s.

A new modified forecasting technique that aims to overcome the shortcomings and bias of both Croston's and SBA was proposed by Teunter et al. (2011), referred to as the TSB approach. The TSB approach was proposed mainly to address the high risk of obsolescence that is inherent in the nature of service parts management. TSB addresses the latter concern by calculating and updating the demand probability after each period and uses separate smoothing constants for demand probability and demand size.

If demand occurs the TSB updates the demand size and demand probability and computes the forecasted demand estimate as follows.

$$\hat{z}_t = \hat{z}_{t-1} + \alpha\,(z_t - \hat{z}_{t-1})$$

$$\hat{y}_t = \hat{y}_{t-1} + \beta\,(1 - \hat{y}_{t-1})$$

$$\hat{d}_t = \hat{y}_t \hat{z}_t$$

If zero demand is observed at period *t* then only the demand probability is updated as follows.

$$\hat{z}_t = \hat{z}_{t-1}$$

$$\hat{y}_t = \hat{y}_{t-1} + \beta\,(0 - \hat{y}_{t-1})$$

$$\hat{d}_t = \hat{y}_t \hat{z}_t$$

The estimated demand size at the end of period *t* is denoted by $\hat{z}_t$ while β is a smoothing constant used to update the probability of demand occurrence, $\hat{y}_t$ is the estimate of the probability of a demand occurrence at the end of period and $\hat{d}_t$ is the estimated mean demand at the end of period *t* for the period of *t+1*.

The study compared SES, Croston's, SBA and TSB in terms of bias and variance by comparing forecast errors. The authors simulated data sets that conform to the proposed objective of the TSB method. Three different data sets were simulated to depict different situations; the first replicated stationary demand patterns, the second exhibited linearly decreasing demand while the last showed a sudden obsolescence situation where demand remains stationary for a long period of time and then suddenly drops to zero demand.

Results showed that TSB outperforms Croston's and SBA approaches with respect to bias. Under stationary demand TSB provided accurate estimates conditioned that β value was sufficiently small. Results didn't show an advantage of using TSB over Croston's and SBA in the second case. In the case exhibiting sudden obsolescence, TSB clearly outperformed Croston's and SBA once the obsolescence is realized.

TSB provided a fast adaptation to changes in demand yielding a better approach to dealing with high risk of obsolescence. However, the results also showed the sensitivity of TSB performance to the choice of β values. This study indicated that further research is required to determine the proper values and the circumstances under which TSB would be optimum. No conclusive studies have been done with that objective. Moreover, TSB wasn't tested on real data sets and the above mentioned results were only in terms of its accuracy based on forecast errors, however it was not extended to include an inventory control model.

The TSB method was one of the early time-series based forecasting approach of intermittent demand that accounted for handling the risk of obsolescence. When managing service parts the notion of incorporating the risk of obsolescence is quite plausible, due to the fact that some of the parts feature high-technology and are highly expensive in some industries.

For instance in the computer and software industry new generations of products are regularly introduced to the market within a short span of time. The new generation of products might render some of the components in a slightly older generation completely obsolete. The impact of operating within such a high-tech business environment is that some components might experience different types of obsolescence risk. The obsolescence phase of components might occur gradually featuring a symmetric declining pattern of the ramp phase, or feature an exponential/linear decay or experience a sudden obsolescence.

Given such reasoning, Prestwich et al. (2014) proposed a forecasting method that deals with intermittency and obsolescence referred to as the hyperbolic-exponential smoothing (HES) technique. The forecasting method decomposes the demand into demand size and interval and forecasts them separately similar to Croston's approach. The main difference is how the HES updates the forecast when zero demand occurs. During periods of no demand HES forecasts decay hyperbolically, an assumption derived from Bayesian inference. During periods of demand the forecast is identical to Croston's approach. During zero demand periods the forecast is as follows.

$$\hat{d}_t = \frac{\hat{z}_t}{\hat{p}_t + \frac{\beta p_t}{2}}$$

The estimated demand size at the end of period t is denoted $\hat{z}_t$ while β is a smoothing constant used to update the inter-demand intervals, $\hat{p}_t$ is the estimated demand interval at the end of period t, and $\hat{d}_t$ is the estimated demand forecast at the end of period t.

The study compared the accuracy of the HES, TSB and SY approaches based on a selection of forecast error measures using simulated demand data. The results differed with the demand pattern generated, in other words no single approach outperformed others across all forecast error measures. HES was second best to TSB approach in the instances where obsolescence took place compared to other Croston's variants.

The overall results of the study weren't conclusive in terms of which method is superior when dealing with intermittent demand. Moreover, the results didn't show that the HES modification provided better performance compared to the TSB approach under the conditions tested. It was noted that the selection of different forecast error measures could sometimes lead to different conclusion. In addition, the study only relied on error measures to compare and the work has not been extended to investigate the effect on stock control policies or service performance measures.

Prestwich et al. (2014) proposed a new forecasting technique referred to as linear-exponential smoothing (LES) which was developed to deal with stochastic intermittent demand with possible demand obsolescence similar to TSB and HES. The main difference amongst the techniques is how they address the risk of obsolescence. Each approach tends to update estimates in the case of zero demand differently. TSB forecasts decay exponentially and HES hyperbolically. The new approach LES forecasts decay linearly to zero in a finite time. It was argued that neither TSB nor HES forecasts reach zero, while LES linearly reaches zero and remains at zero until a non-zero demand is observed (if any).

Similar to HES, the LES approach is identical to Croston's when observed demand is non-zero. However, when observed demand is zero the forecast is as follows, where the decay rate is controlled by the β parameter and x+ denotes the maximum between zero and x.

$$\hat{d}_t = \left(\frac{\hat{z}_t}{\hat{p}_t}\right)\left(1 - \frac{\beta p_t}{2\hat{p}_t}\right)^{+}$$

The model was tested and compared to TSB and HES using simulated demand data based on multiple forecast error measures. The simulated demand data depicted three situations similar to the study conducted by Teunter et al. (2011). The results showed that TSB performed better than HES and LES when dealing with decreasing demand. LES yielded favorable results in the case of sudden obsolescence. However, the results didn't show that one approach conclusively outperformed the rest under all the assumed scenarios.

Pennings et al. (2017) proposed a forecasting technique for intermittent demand investigating the aspect of cross-correlations between inter-arrival time and demand size. The study conducted a comparative analysis including SES, Croston, SBA, TSB as well as bootstrapping techniques. The performance of the different approaches were assessed according to forecast errors and inventory parameters. Results showed that their method worked well when positive cross correlation existed between inter-arrival time and demand size.

Owing to their simplicity, single exponential smoothing and simple weighted moving average are considered as the main competing forecasting techniques to Croston's in practice. This motivated some researchers to conduct comparative studies to assess the performance of these different approaches. Single exponential smoothing and Croston's approach are widely adopted by businesses and software for dealing with service parts forecasting. Ghobbar and Friend (2003) compared 13 different forecasting techniques using real data from airlines service parts with the performance of the techniques assessed based on different forecast errors. They concluded that weighted moving averages, Holt's and Croston methods were superior. In another empirical study using industrial data, Willemain (1994) showed the superiority of Croston's performance to its commonly used alternative single exponential smoothing since Croston's consistently provided lower forecast errors.

Snyder (2002) proposed a parametric bootstrap approach for forecasting slow and fast moving parts which the author integrated with the (R,S) inventory model. They mentioned that the new approach tends to underestimate the variability of lead-time demand, which could potentially affect the performance of the inventory model.

A comparative analysis was conducted to measure the accuracy of a modified bootstrapping approach, single exponential smoothing, and Croston's approach in terms of forecasting the distribution of lead time demand (Willemain et al., 2004). The proposed approach assumed autocorrelation of demand and used a two-state Markov model to generate a sequence of zero and non-zero values, after estimating the transition probabilities between the states. Every non-zero estimate was replaced by a value randomly sampled from observed demand in the data sets, followed by a jittering process for non-zero demand values. Lastly, the generated values were summed. The process was repeated to forecast the distribution of lead time demand.

The results showed the superiority of the modified bootstrapping approach, but the accuracy of the approach tended to decline as the lead time increased. The approach used for comparing the results relied on the forecasting techniques' performance with respect to the lead time demand distribution without considering inventory performance measures.

2.7.1.2. Life-Cycle Based Forecasting

Life cycle has always been an important aspect of a products' demand. Moreover, electronics and high-tech products tend to feature shorter life cycles compared to other products. Due to rapid innovations, and the level of technology which might render a product as obsolete in a short span of time. Owing to all of these issues the associated spares parts management tends to be extremely complex.

The shorter life cycle has always imposed several challenges when dealing with electronic parts and their components mainly because of the associated high risk of obsolescence. A related challenge arises when the original equipment manufacturer (OEM) realizes it is not profitable to produce a component anymore, which usually happens at the end of life (EOL) phase of products, and as a result the OEM decides to issue a last time buy (LTB). The last time buy is a decision made by the OEM to cease the production of a certain component and they ask the company to specify a LTB quantity at which they can have the product at the contracted price and benefit from economies of scale for the last time. This requires the company to predict the quantity needed to service the products that are still in warranty.

Another challenge associated with the life cycle of the product is the early life cycle phase of a newly introduced product (NPI) where the company needs to predict the estimated number of failures based on predicted or early sales. In a general sense, most of the research contributions gear their attention towards the challenges of the EOL and NPI life cycle product phases.

Minner (2011) proposed a dynamic forecasting approach that captured the evolution of product life cycle depicted by the installed base evolution. The approach forecasted the distribution of the future installed base by combining the estimated future product sales and product discards. Each component has a failure probability depending on its age. By summing the failures, they obtain an estimate for the total number of components that needs to be replaced by time *t*. The approach was tested and compared with SES and a naïve forecasting technique and the comparative analysis was extended to assess the forecasting techniques within the context of stock control. The new approach outperformed the result by substantially lowering the inventory stock level to achieve a targeted fill rate of 90%. However, the new approach was only compared to SES and naïve forecasting and none of the most commonly used time series based forecast methods for spare parts such as Croston's or its variants.

Kim et al. (2017) proposed forecasting the demand of spares during their EOL phase using installed base (IB) information. Installed base refers to the quantity of sold products that are still in use in the market (Kim et al., 2017). The study presented four types of installed base: life-time IB, warranty IB, economic IB and mixed IB. It was argued that warranty IB is best suited for products with a relatively short life cycle. The approach relied on the historic time series data of products' sales and spare parts' demand up until the start of the EOL phase, in addition to the warranty period when using warranty IB for forecasting. Even though the results showed the approach was viable, the challenge of automating the method across all products and spare parts is a limiting factor in terms of applicability.

Some other research studies were solely concerned with estimating the optimal quantity of last time buy considering the implications it has on inventory costs. The LTB quantity is optimized such that one doesn't overestimate the future demand leading to overstocking and obsolescence nor underestimate the required quantity needed to satisfy the demand by a targeted service level (Hong et al., 2008; Chou et al., 2016).

The calculation of how much to stock during the early life cycle of newly introduced products (NPI) has only been addressed in the literature a limited number of times (Hu et al., 2018). The difficulty of demand forecasting at this stage arises due to the limited historical data (if any) and the fact that spare parts demand is characterized by intermittency. Overall there is a lack of research studies covering this aspect compared to the LTB life cycle phase (Hu et al., 2018).

Bergman et al. (2017) proposed the integrated use of Bayes theorem and engineering estimates for forecasting the demand of service parts of newly introduced equipment. They argued that the Bayesian approach offers a lot of potential in this case as the method doesn't require historical demand data compared to traditional TS methods and just updates at each period as actual demand is observed. The study compared between the new Bayesian based approach, an engineering estimate approach, and a combined approach of engineering estimates and TS method referred to as baseline.

The comparative analysis assessed the three approaches based on their performance on inventory management metrics in terms of inventory costs and achieved fill rates. The study used 3.25 years of data for a new equipment program, where the equipment is at the early stages of its life cycle with low demand volumes. The results showed that the new approach and the baseline approach both provided similar performance, however, the new approach yielded more rewarding results during the first initial points of demand. This study discussed challenges pertaining to handling demand for newly introduced products, however the paper provided limited information regarding the data used for its case study.

Even though a number of studies have been conducted to compare different forecasting techniques of intermittent demand, the majority of the papers only assess the techniques based on measures of forecast errors. The importance of assessing the various forecasting approaches based on their impact on inventory performance parameters is crucial. The need for further research to address the latter concern has been discussed in a number of studies (Syntetos et al., 2005; Teunter and Duncan, 2008; Walstrom and Segerstedt, 2010; Teunter et al., 2011; Xu et al., 2012; Bacchetti and Saccani, 2012; Bergman et al., 2017; Hu et al., 2018). Only a limited number of studies have extended their analysis and assessment to include inventory management aspects. Some of these are discussed in the following section.

2.7.2. **Service Parts Inventory Management**

The vast majority of research studies conducted tend to assume a demand distribution and rely on standard stocking policies. Some studies opted for using the negative binomial distribution (NBD) to depict the demand of service parts (Kwan, 1991, Syntetos and Boylan 2006 and Hahn and Leucht 2015). Others use non-compound demand distributions such as gamma, poisson, lognormal, normal and Erlang (Leven and Segerstedt, 2004; Altay et al., 2008; Teunter et al., 2010). Nevertheless no consensus has been reached regards to which distribution would provide the best fit and resemblance of service parts demand.

Standard inventory models are usually categorized into continuous or periodic review systems. For the continuous review inventory systems, the most commonly considered models are (s,Q) and (s,S) policies where the inventory is monitored continuously. An (s,Q) policy refers to one where an order of quantity Q will be placed when the inventory level reaches a re-order point s while the (s,S) refers to a policy where an order will be placed when the inventory level is equal to or less than s to increase the inventory to an order up to level S.

As for the periodic review inventory systems, the most commonly considered models are (nQ, s,R), (S,R) and (s,S,R) policies, all of which are governed by a review period R. When using the (nQ, s, R) policy, if at the review period R the inventory level has dropped s or below then an order quantity of nQ is placed (n = 1,2,3,..), n is used such that after the order is placed the available inventory level is between (s, s+Q) (Hax and Candea, 1984).

The (S, R) inventory model refers to the policy where at each review period R, an order is placed to raise the inventory to an order up level of S sometimes referred to as (T, R). Finally, (s,S,R) method refers to a policy where if at the review period R the inventory level has dropped to s or below then an order is placed to raise the inventory to the level of S (Hax and Candea, 1984).

Most of the studies conducted for service parts inventory management have considered one of the previously mentioned stocking policies. A limited number of papers have linked inventory replenishment with forecasting (Hu et al., 2018). Syntetos and Boylan (2006) considered a (T, R) policy for their comparative study between different time series forecasting models and they have assessed their performance in terms of stock control where results showed that SBA method achieved superior performance.

A modified Croston approach was proposed to forecast slow and fast moving demand of parts, the study used an Erlang distribution to fit the data and determine the probability of stock out (Leven and Segerstedt, 2004). The results showed that an inventory control system for intermittent demand deploying the Croston approach and Erlang distribution outperformed the commonly used systems relying on single exponential smoothing and normal distribution. However, it was further argued that the enhanced performance was primarily due to the use of the modified Croston's method and not the assumption of the Erlang distribution.

Porras and Dekker (2008) proposed a new model for empirically estimating lead time demand (LTD) distribution from real data. The proposed approach estimated the LTD distribution by constructing a histogram of demands over the lead time from the real data set without sampling. Furthermore, they applied the modified bootstrap approach discussed by Willemain et al. (2004) to estimate lead time demand distribution and a comparative analysis of different distributions were conducted.

The study assessed the performance of the different approaches based on cycle service level and fill rate, where an (s, nQ) inventory control system was considered. The main interest of the study was to compare the performance of theoretical (e.g., normal or Poisson distribution) and empirically estimated lead time demand distributions (e.g., bootstrap approach and the empirical model proposed). For each lead time demand distribution, the reorder point s that achieves a satisfactory fill rate was specified and the models were compared. The results showed that normal distribution and the novel approach proposed outperformed the others while the poisson distribution yielded very poor results when dealing with intermittent demand.

A comparative study was conducted to assess the accuracy and performance of the modified Croston's method (SBA) and Wright's modification to Holt's exponential smoothing approach (Altay et al., 2008). Wright (1986) proposed a modification to Holt's approach to deal with the irregular time intervals of demand. Even though Wright's modification was originally tested for irregularity of demand data in time spacing with non-zero inputs, the results showed that the method outperformed the SBA approach with respect to service level and fill rate performance. The study used data from aircraft service parts and extended the assessment of the two forecasting models beyond error forecasts measures. Four distributions were considered for estimating demand for an (s,S) inventory model with one lead time period where the inventory parameters included average inventory levels, fill rates, and average service levels. In spite of Wright's superiority in achieving high service levels, the approach tended to carry higher inventory levels but at no significant cost.

Zhu et al. (2017) proposed a new approach that integrates extreme value theory (EVT) with empirical lead time demand forecasting, the approach was referred to empirical-EVT. EVT is a theory that models the tail (extreme) behavior of a distribution, moreover, EVT could be applied to forecast the possibility of exceeding a previously observed upper quartile value.The approach was tested and compared with SBA, Croston's and the bootstrap approach proposed by Willemain et al. (2004) using data sets from automotive and aircraft companies.. A base stock policy with periodic review and a constant lead time was applied to assess the performance of each approach relative to achieving a targeted service level. The results and data sets revealed interesting findings regarding the performance of each approach (Zhu et al., 2017). The empirical-EVT performed well when having a large set of historical data, however, the method was outperformed by the other approaches when demand history was limited. Furthermore, the accuracy of the bootstrapping approach varied according to the data set used and the high service levels obtained by this approach resulted in increasing the base-stock levels significantly compared to the other approaches.

This literature review mainly mentioned the research studies that dealt with approaches with corrective maintenance and didn't address approaches for preventive maintenance owing to the nature of e-textiles. Another stream of research studies were conducted to address the problem of determining the optimum last time buy (LTB) quantity. The interested reader could refer to (Bacchetti and Saccani, 2012; Altay and Litteral, 2011; Van der Auweraer et al., 2019; Hu et al., 2018) for a detailed discussion of the above research topics.

2.8. Research Gap

The future of E-textiles and smart wearable products hold great potential and might become one of the most promising business sectors in the near future as discussed in Section 1. Although the market of e-textiles is still in its infancy, research studies ought to investigate the challenges accompanied with managing the operations of this new field. There seems to be a clear lack of academic studies conducted to discuss the management and integration of operations of the e-textiles market as the industry shifts from a niche stage to mass production. To the best of our knowledge, no study has been conducted tackling the aspects of e-textiles supply chain management.

Given that e-textiles products are serviceable products by nature, exploring the well-documented field of service parts management was deemed relevant. In this literature review, the field of service parts management was explored from a demand forecasting/inventory management standpoint. Recent literature review studies have elaborated that there is a need for studies that integrate inventory control policies to demand forecasting of spare parts. Only a limited number of studies extended their analysis to investigate the impact of each demand forecasting technique on inventory parameters since the majority of the papers only assess the techniques based on measures of errors. The importance of assessing the various forecasting approaches based on their impact on inventory performance parameters is crucial. The need for further research to address the latter concern has been discussed in a number of studies (Syntetos et al., 2005; Teunter and Duncan 2008; Walstrom and Segerstedt, 2010; Teunter et al., 2011; Xu et al., 2012; Bacchetti and Saccani, 2012; Bergman et al., 2017; Hu et al., 2018).

Moreover, there is a clear gap between the research streams and practitioners, where the proposed models are either too complex to apply or too rigid with fixed assumptions. The latter need has been emphasized in the comprehensive academic reviews presented by Van der Auweraer et al., (2019) and Hu et al., (2018) where the necessity of testing the proposed models using real data rather than simulation was also highlighted.

Additionally, there is an evident need of a comprehensive integrated view when dealing with spare parts management. For instance, the incorporation of the life cycle process to the demand forecasting and inventory planning decision making (Hu et al., 2018). On a similar note, Van der Auweraer et al. (2019) emphasized the need for studies that integrate the installed base information with commonly used forecasting techniques. They also suggested exploring regions of superior performance to identify at which point in the life cycle phase where the installed base information could enhance the performance of forecasting techniques and inventory models. After reviewing the literature it could be concluded that in spite of all the rigorous contributions that have been to date, there is still a need for further studies to address some of the mentioned research gaps and needs.

Chapter 3

Initial Analysis

3.1. Introduction

This chapter will provide an in-depth comparative analysis of different forecasting techniques of service parts. The purpose of this chapter is to address some of the research gaps and provide some insight using real-data.

The lack of studies analyzing the performance of different forecasting techniques using real data rather than simulated data with theoretical assumptions was addressed by a number of recent literature review studies (Van der Auweraer et al., 2017 and Hu et al., 2018). Moreover, there is a lack of studies that assess the performance of forecasting techniques based on their effects on inventory measures such as costs, risks, and service performance. The majority of the studies conducted rely on forecast error metrics to assess the performance of techniques without extending the analysis to include the inventory control aspect (Bacchetti and Saccani, 2012; Bergman et al. 2017; Hu et al. 2018).

Thus to address this research need, this chapter will analyze and interpret the implications that each forecasting technique has on inventory and how this corresponds to forecast error metrics. Moreover, to bridge the gap between research and practitioners, a case study based analysis is included in order to provide recommendations to enhance business profitability and customer satisfaction.

Furthermore, to advocate a more sustainable future of e-textiles, designing e-textiles products for serviceability is highly recommended (Arnette et al., 2014). Designing e-textiles for serviceability and sustainability dictate that the products ought to be disassembled in a fashion where the electronic components could be either repaired/replaced and/or recycled. The virtues of proactively considering the future aspects of the e-textiles industry in terms of business profitability and environmental concerns are tremendous. This chapter will focus on the serviceability of components in terms of corrective maintenance during the In-Warranty (IW) phase of products.

3.2. The Data Sets and Demand Classification

To align with this pursuit, the real data set used in this chapter has characteristics that closely resemble the status of the electronic components currently used in e-textiles products. A detailed description of the data set, the company and the industry, as well as the similarities with e-textiles will be discussed in the following section. Additionally, another empirical data set from the automotive industry which was previously used in other academic papers was also considered in this chapter (Syntetos and Boylan, 2005; Syntetos and Boylan, 2006). The purpose of using the automotive data set is to further assess the forecasting techniques and inventory models on a previously studied data set.

3.2.1. The Electronics' Data Set

The industrial data set incorporated in this research belongs to one of the most prominent and fast growing global computer companies in the world. For confidentiality aspects the company will be referred to as Company A. Company A is a global Fortune 500 Company offering a range of high-tech products including PCs, laptops, tablets and a family of mobile products. Products sold are usually accompanied by a warranty period covering 12-18 months which indicates that Company A is committed to replacing defective components with new ones for at least a year after product sales. The business model challenges faced by the company are similar to other companies commercializing high-tech products. High-tech products are governed by the fast paced innovation of IT and software. This contributes to the short life of high-tech products and the associated high risk of obsolescence as new products are introduced frequently to the market. These two factors elevate the level of complexity when managing spare parts. The after-sale service represented by the maintenance of products' components is integral to the success and competitiveness of Company A.

3.2.1.1. Relevancy of E-Textiles and the Electronic Components

The limited number of research studies that utilized real data to test their forecasting techniques most commonly used data from the automotive and aircraft manufacturing industries. However, in this research the decision was made to use data from the electronics industry for many reasons. First and foremost, the similarity of the electronic component characteristics, used in both the e-textile and computer/IT products, was the main leading criteria for the data selection. The electronics components used in e-textile products are highly innovative with a relatively short life similar to the ones used in laptops and tablets for instance. Moreover, the in-warranty period of e-textile products and the computer industry is almost the same, ranging from 12-18 months. Lastly, the prices and values of the components are relatively similar in both industries.

Given that the e-textile market is still in its infancy and is highly competitive, it was challenging to acquire actual data of e-textile components' failures and other relevant data of service part management. Thus, the most relevant industrial data set to utilize is from the computer and IT industry sector.

3.2.1.2. Description of Company A's Data Set

The data set of Company A used in this chapter is composed of weekly historical demand data of components. The historical data set has 112 weekly demand observations of 523 different Stock-Keeping Units (SKUs) of the same component category which will be referred to as component type A. The different component SKUs are used to repair three different types of finished products desktops, laptops and monitors. Descriptive statistics of the average inter-demand interval (ADI), which refers to the average interval between the occurrence of two demand, and coefficient of variation squared (CV^2) for this data set are shown in Table 3.1.

Table 3.1: ADI and CV^2 of Demand Size for 532 SKUs-Company A

	ADI	CV^2
Min	1.00	0.00
Max	67.00	6.21
Average	4.75	0.36
Median	2.15	0.31
25%ile	1.39	0.14
75%ile	4.98	0.48

3.2.2. The Automotive Data Set

An additional data set of service parts demand data from the automotive industry was analyzed as well. This data set was considered in addition to the electronics data set for a number of reasons. Firstly, the prime reason is that this data set was used before by a number of research studies to verify their proposed models' performance for service parts forecasting and inventory management (Syntetos and Boylan, 2006; Pennings et al., 2017; Zhu et al., 2017). However, none of the previous studies considered Holt-DES as a forecasting technique for service parts demand. They have mainly considered SES, SMA (13), SBA and Croston and compared the traditional forecasting techniques with the performance of their proposed models. Secondly, this data set is composed of monthly historic demand data. Only 24 demand observations are available for each of the 3000 different SKUs. Thus, the challenges that this data set will impose on the different forecasting techniques are quite different and are worth investigating.

A number of features distinguish this data set from the electronics data set. First and foremost, the data is in monthly time buckets with much fewer data points for forecasting. Secondly, the demand characteristics of the automotive set are different than those of the electronics' data set. A detailed and in-depth description of the automotive data set is given by Syntetos and Boylan (2005).

Table 3.2: ADI and CV^2 of Demand Size for 3000 SKUs- Automotive Data Set

	ADI	CV^2
Min	1.04	0.00
Max	2.00	14.07
Average	1.29	0.44
Median	1.26	0.35
25%ile	1.10	0.26
75%ile	1.41	0.49

3.2.3. Classification of Demand Patterns for Forecasting

Syntetos et al. (2005) conducted a comparative theoretical analysis of Mean Squared Error (MSE) for EWMA, Croston and SBA forecasting techniques. Based on the analysis conducted, the study proposed cut-off values of 0.49 and 1.32 for the squared coefficient of variation (CV^2) of demand sizes and the average inter-demand interval (ADI), respectively. Defined by the cut-off values, the categorization scheme, referred to as SBC (Syntetos, Boylan and Croston), exhibited four demand patterns: erratic, lumpy, smooth and intermittent. The proposed classification scheme was also validated using the automotive data set (Syntetos et al., 2005). Results showed that SBA was the most suitable forecasting technique for erratic, lumpy and intermittent demand patterns. Croston was assumed to be the most suitable forecasting technique when demand is smooth.

In this chapter, the SBC classification approach will be applied to gain more insights about the different demand patterns of each data set. The percentage of SKUs falling under each classification scheme for both empirical data sets are summarized in Table 3.3. Examples of SKUs having different demand patterns from the electronics data set are shown in Figure 3-1 through Figure 3-4.

Table 3.3: Percentage of SKUs of Each Demand Pattern According to SBC Scheme

Industry	Erratic	Lumpy	Smooth	Intermittent
Electronics	8%	15%	15%	62%
Automotive	16%	10%	44%	31%

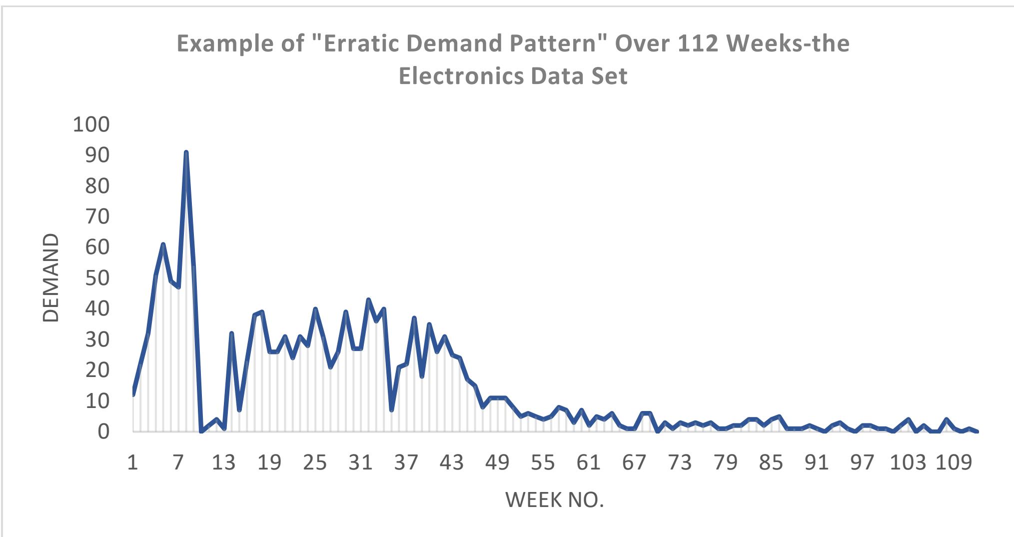

Figure 3-1: Example of Erratic Demand Pattern- Electronics Data Set

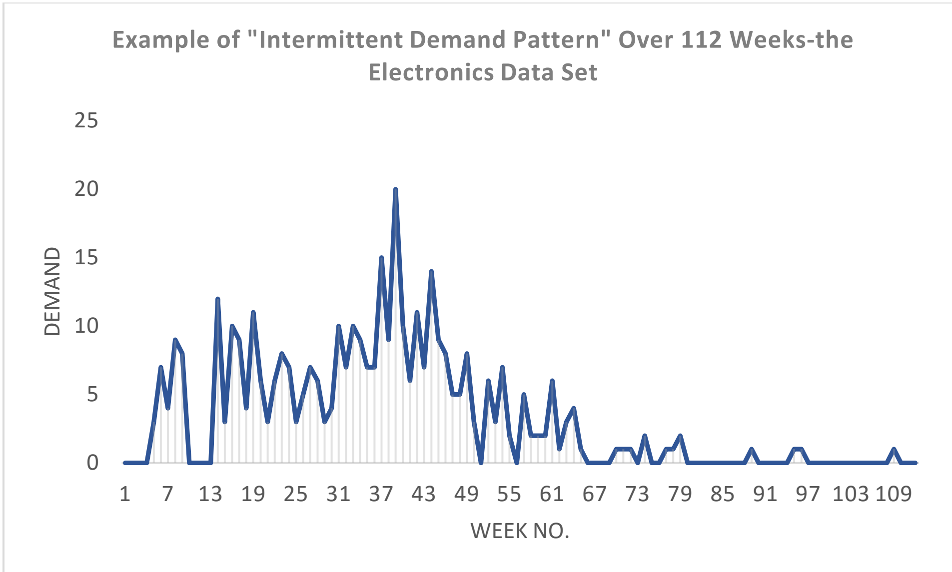

Figure 3-2: Example of Intermittent Demand Pattern- Electronics Data Set

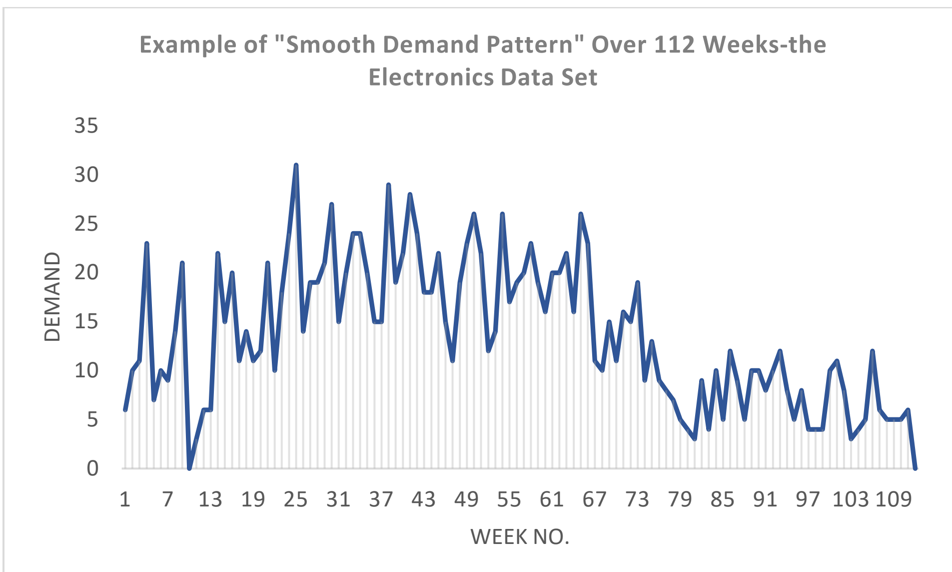

Figure 3-3: Example of Smooth Demand Pattern- Electronics Data Set

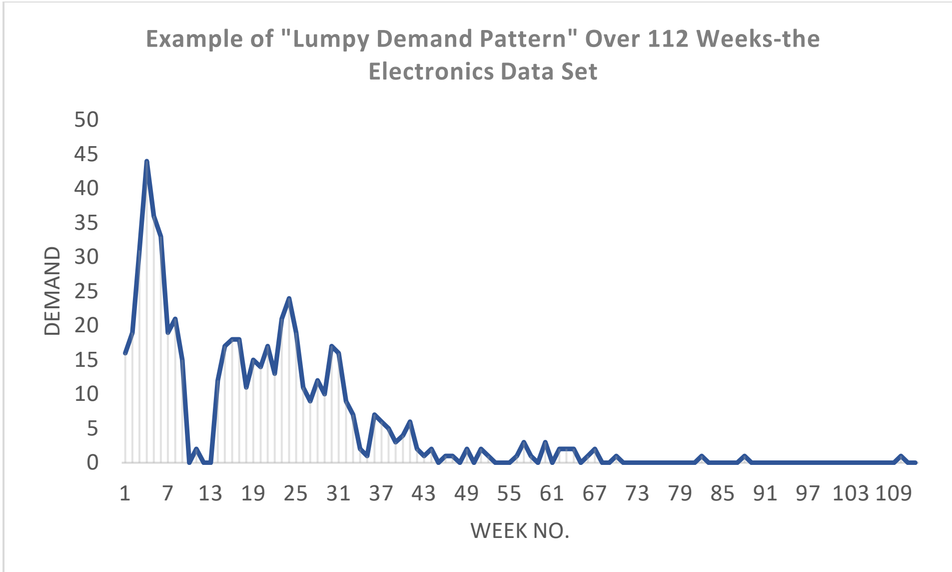

Figure 3-4: Example of Lumpy Demand Pattern- Electronics Data Set

3.3. Forecasting

3.3.1. Forecasting Techniques

Four different forecasting algorithms were used in this study, Holt's double exponential smoothing (DES), Croston, SBA and simple moving average (SMA). Croston and SBA are commonly used to forecast intermittent demand of service parts, and their efficiency has been proven empirically in a number of studies (Altay et al. 2008; Teunter and Duncan 2009; Hu et al. 2017). The simple moving average (SMA) approach was selected for its wide application in practice due to its simplicity and relatively good performance under some conditions. Moreover, SMA using a 13-period window is the current method applied by Company A.

Holt's double exponential smoothing (DES) was mainly selected to address the fact that the demand of service parts exhibits a trend element that needs to be factored in when forecasting. Despite the numerous studies that have been conducted for forecasting intermittent demand, only a limited number of studies have addressed the trend element in demand (Altay et al. 2008; Lindsey and Pavur 2005; Ghobbar and Friend 2003;Snyder 2002), some of which attributed the trend to the different life cycle (LC) stages of products. By studying the electronics data set it was found that the latter is quite evident. For instance, many SKUs exhibit a clear increasing trend during their early LC which later shifts to a more constant and then a decreasing trend, as the LC phase transitions from growth to maturity then decline. This observation will be further discussed and analyzed in the following chapter. Examples of the trend element of some selected SKUs of component type A from the Company A data set can be seen in Figure 3-5 through Figure 3-8. Similarly, examples of some SKUs with a trend element were selected from the automotive data set and are displayed in Figure 3-9 through Figure 3-12.

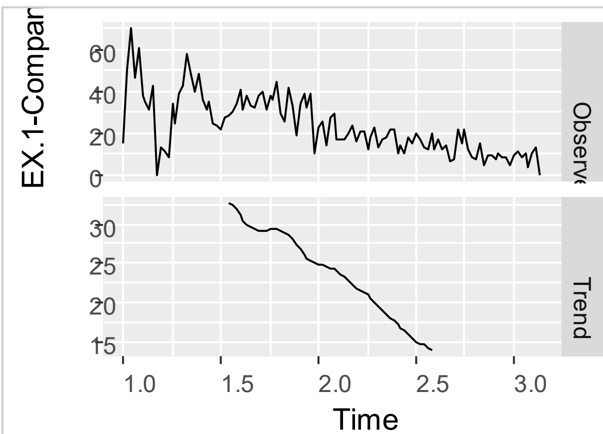

Figure 3-5: Example SKU Featuring a Decreasing Trend Element from the Electronics Data Set

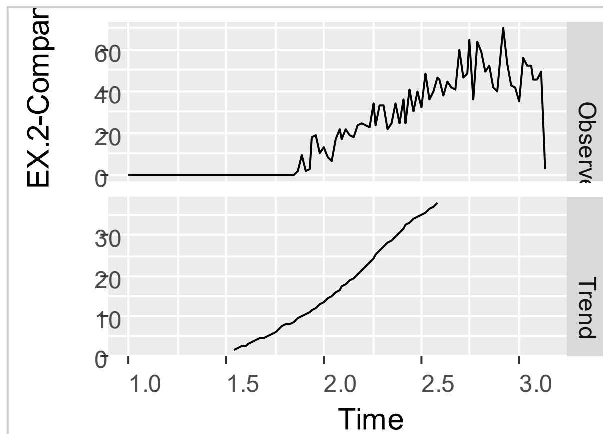

Figure 3-6: Example SKU Featuring an Increasing Trend Element from the Electronics Data Set

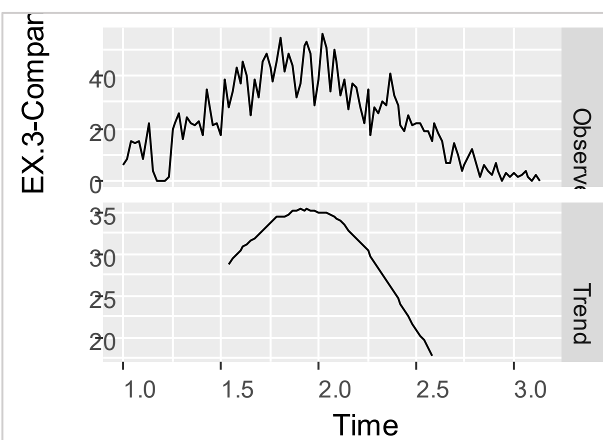

Figure 3-7: Example SKU Featuring a Full Life Cyle Trend Element from the Electronics Data Set

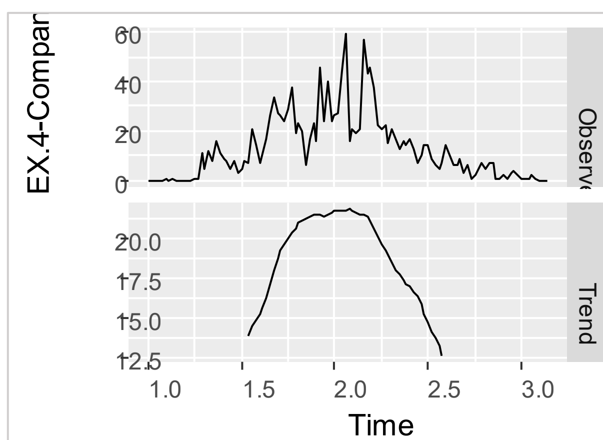

Figure 3-8: Example SKU Featuring a Trend Element from the Electronics Data Set

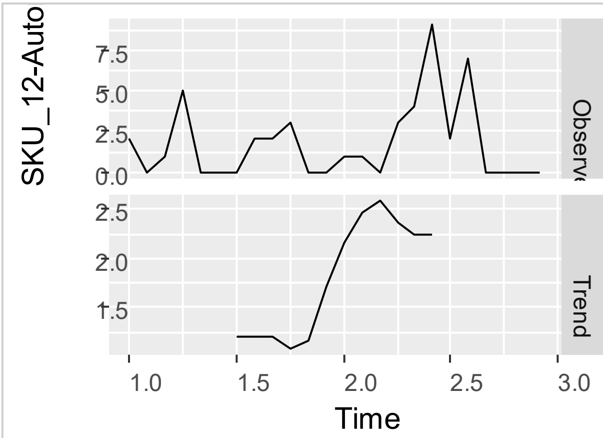

Figure 3-9: SKU_12 Featuring a Trend Element from the Automotive Data Set

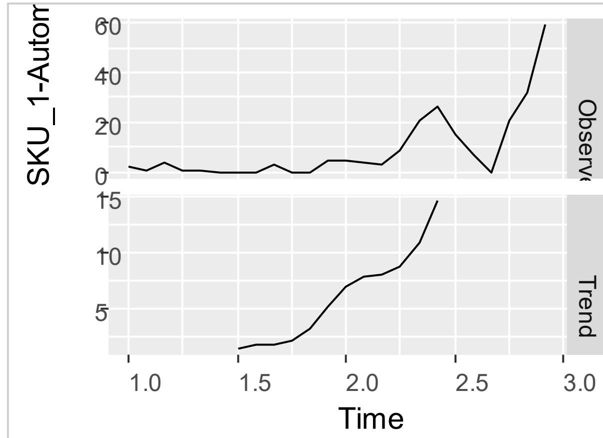

Figure 3-10: SKU_1 Featuring a Trend Element from the Automotive Data Set

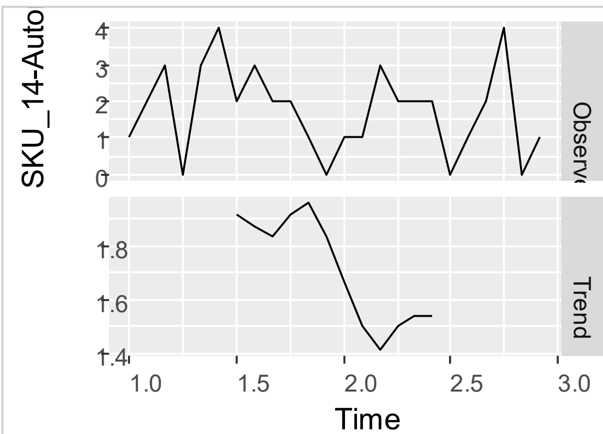

Figure 3-11: SKU_14 Featuring a Trend Element from the Automotive Data Set

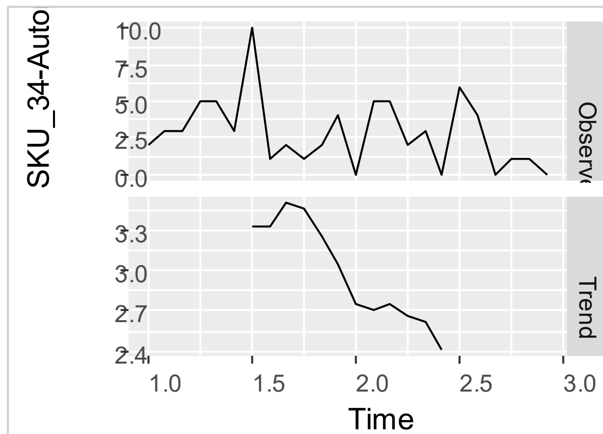

Figure 3-12: SKU_34 Featuring a Trend Element from the Automotive Data Set

3.3.2. Forecasting Accuracy and Error Metrics

In this chapter, two main error measures were considered mean error (ME) and the mean square error (MSE). ME was selected for its capability of capturing the sign of the estimates whether the sign is negative or positive and most importantly for its use in relevant research studies (Syntetos and Boylan, 2005; Teunter et al., 2011; Hu et al., 2018).

MSE is the most widely used measure for optimization and assessing forecast accuracy across different forecasting techniques (Gardner 2006; Teunter and Duncan 2009; Hu et al. 2017). Moreover, given that in this study, our prime concern is to extend the assessment of the techniques to include inventory parameters as well, MSE is believed to be a suitable choice and will be used to define the amount of safety stock needed. In a recent literature review study of spare parts management, research studies are recommended to consider measures of both bias and accuracy such as ME and MSE, particularly when inventory management is considered in the study (Hu et al., 2018).

3.3.3. Forecasting Procedure

Each set of demand data was divided into a training set and a test set. For double exponential smoothing (DES), the initialization set was used for initializing the forecasting model and optimizing the forecasting parameters α and β. The parameters that minimize the mean squared error (MSE) of each SKU were chosen using the Excel Solver. The range of values for the optimal smoothing parameters were set between 0.05 and 0.2, which is the recommended range in the literature when forecasting intermittent demand (Croston, 1972; Willemain et al., 1994; Johnston and Boylan, 1996; Syntetos and Boylan, 2005).

For the double exponential smoothing (DES) method, the initial value used for the level was computed using the average of the first 13 data points in the initialization set and the trend was set as zero.

Table 3.4: Summary of Characteristics of the Data Sets

Industry	No. of SKUs	Time Bucket	Total Data Points	Data Points in Training Set
Electronics	532	Weekly	112	86
Automotive	3000	Monthly	24	13

For Croston and SBA, the initial value used for the demand size was computed using the average of the first 13 data points in the initialization set and the demand interval was set as one. Additionally, we followed the alteration of Schultz (1987) to Croston’s approach and applied it to

SBA as well. Therefore, two smoothing parameters (α_1 α_2) were used for the demand size and interval size, respectively. The smoothing parameters that minimize the mean squared error (MSE) of each SKU were determined by using the Excel Solver. All the statistical results reported in this chapter reflect the values computed on the test set of the data solely.

3.3.3.1. The Electronics Data Set Forecasting

As can be seen from Table 3.5, the highest ME was achieved by SBA followed by Croston, SMA (13), and Holt-DES. The sign of the ME metric indicates that on average SBA tends to under forecast the per period demand estimate while Croston, SMA (13), and Holt-DES tend to over forecast the per period demand estimate. Box Plots of the ME metric across the four forecasting approaches can be seen in Figure 3-13.

Table 3.5: Averages and STDs of ME and MSE - The Electronics Data Set

Forecasting Technique	ME Means (STD)	MSE Means (STD)
SBA	0.16 (0.66)	7.21 (4.37)
Croston	-0.00 (0.42)	7.17 (3.75)
SMA(13)	-0.06 (0.37)	7.00 (4.51)
Holt-DES	-0.08 (0.89)	6.19 (5.03)

To further assess the accuracy of the different forecasting techniques and to evaluate the statistical significance of the forecast error metrics, the hypothesis that there is no statistical difference between the forecasting approaches with respect to the mean of the ME was tested. Since the sample size is large ($n = 523$), the Central Limit Theorem will be invoked to assume the normality of the data. Based on Levene's statistics, the null hypothesis that the variances are equal was rejected at a p-value of < 0.0001. Therefore, Welch's test was conducted, and the null hypothesis was again rejected at a p-value of <0.0001, which implies that at least one of the means of the forecasting methods is different

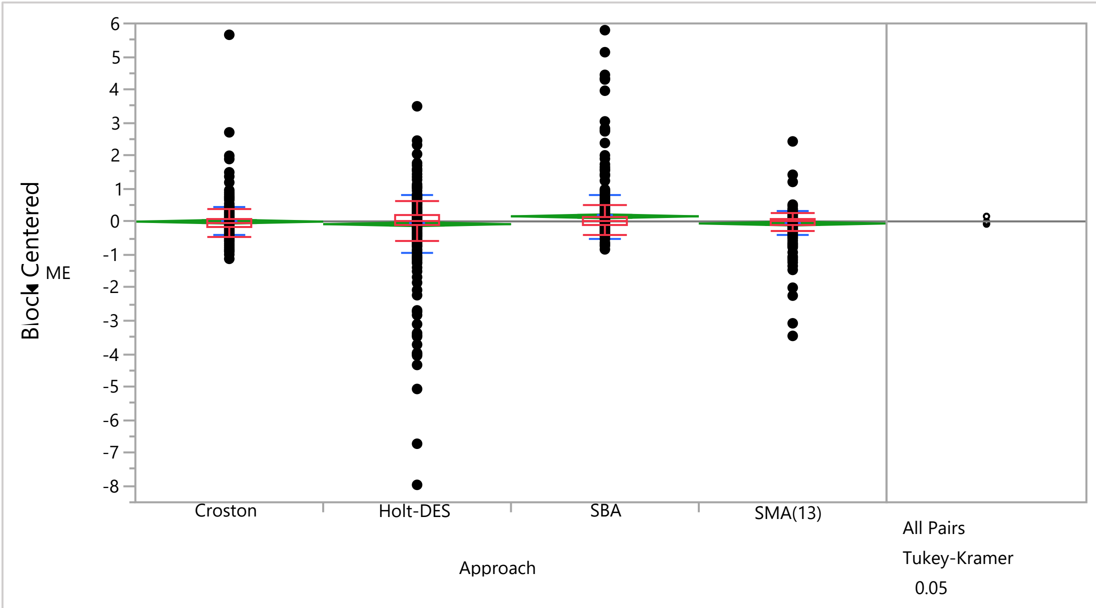

Figure 3-13: Box Plots of the "Mean Error (ME)" Metric –Electronics Data Set

In order to determine which methods are different, a Tukey-Kramer multi-comparison test was applied. Results showed that Croston, SMA (13), and Holt-DES are significantly different than SBA at an α level of 0.05. From Table 3.5, the highest MSE was achieved by SBA followed by Croston, SMA (13) and Holt-DES. The same statistical analysis was conducted for the MSE metric. Box plots and statistical analysis can be found in the Appendix. A summary of the results is shown in Table 3.6: Summary of Statistical Results of ME and MSE – Electronics Data Set

Table 3.6: Summary of Statistical Results of ME and MSE – Electronics Data Set

Forecasting Error Measure	Statistical Difference?	Statistical Comparison
ME	YES	Croston, SMA, Holt-DES < SBA
MSE	YES	SBA, Croston < Holt-DES

3.3.3.2. The Automotive Data Set Forecasting

Similarly both measures were also assessed for the automotive data set. Table 3.7 shows that the highest ME was achieved by SBA followed by Holt-DES, Croston, and SMA (13). The sign of the

ME metric indicates that SBA tends to over forecast the per period demand estimate, while the rest of the approaches tend to under forecast the per period demand estimate.

Table 3.7: Averages and STDs of ME and MSE - The Automotive Data Set

Forecasting Technique	ME Means (STD)	MSE Means (STD)
SBA	0.06 (0.60)	75.45 (16.12)
Holt-DES	-0.08 (0.54)	75.46 (17.09)
Croston	-0.09 (0.59)	75.58 (18.61)
SMA (13)	-0.11 (0.41)	76.01 (28.95)

A statistical comparison of means was conducted for both ME and MSE. The box plots and statistical analysis for each can be found in Appendix. An overall summary of the results is shown in Table 3.8.

Table 3.8: Summary of Statistical Results of ME and MSE –The Automotive Data Set

Forecasting Error Measure	Statistical Difference?	Statistical Comparison
ME	YES	Croston, SMA, Holt-DES < SBA
MSE	NO	NONE

3.4. Inventory Analysis

In this study, four different forecasting techniques were modelled and paired with inventory control approaches for proper safety stock calculation.

3.4.1. Inventory Model and Approach

A base stock policy was implemented and assessed for a periodic inventory model (L+1) with a review period of one week and a constant lead time of two weeks for each forecasting model with differing safety stock calculations. The inventory model permitted backorders. The following notation will be used to describe the inventory procedure applied:

I_t = amount of spare parts inventory on hand at period t

Q_t= number of units of spare parts ordered from the supplier at the end of period *t*
L = order lead time
B_t= number of units of spare parts backordered during period *t*
G_t= number of units of spare part demand during period *t*
M_t= max inventory level, base stock level.

The sequence of events is as follows.

1- At the beginning of period *t*, receive the order for spare parts $Q_{t-(L+1)}$, that was placed *(L+1)* periods ago with the spare parts supplier and update the on hand inventory $I_t = I_{t-1} + Q_{t-(L+1)}$.

2- Next fulfill as many backorders from the last period B_{t-1} as possible. Then fulfill as much demand in period t, G_t, from the remaining on hand inventory as possible. Any unfulfilled demand is counted towards the amount of B_t. Update on hand inventory and backorders as follows:

$$I_t = \max \{I_t - B_{t-1} - G_t, 0\}$$

$$B_t = \max \{B_{t-1} + G_t - I_t, 0\}$$

3- At the end of period *t*, compute the order up to level M_t and place an order, Q_t ,such that $Q_t = M_t - I_t - \sum_{t-1}^{k=t-L} Q_t + B_t$

The base stock level (M_t) was computed using eq. (1) or (2)

$$M_{t_{\text{MSE}}} = (L+1)\widehat{D} + K\sqrt{(L+1)MSE} \quad (1)$$

$$M_{t\ \text{Correction}} = (L+1)\widehat{D} + K\sqrt{(L+1)Var_d + (L+1)^2 Var_f} \quad (2)$$

Where

$\widehat{D}$ = Mean Demand Estimate
Var_f = Estimated Variance of the Forecast
Var_d = Estimated Variance of Demand Sample

K = Safety factor (z value corresponding to service level for normally distributed dem*and)*

Two different computations of Var_f were considered in this study. These are shown in Equations 3 and 4, where $\mathrm{Var}(\varepsilon_t)$ is the variance of the forecast error.

In Equation 3, the estimated variance of the forecast was calculated by taking into consideration only one smoothing factor "α". This computation was discussed in Prak et al., (2017) for simple exponential smoothing and will be referred to in this study as "Correction1" or "Corr1".

$$\mathrm{Var_f} = \mathrm{Var}(\varepsilon_t) * \alpha / (2 - \alpha) \qquad \textbf{3}$$

Boylan and Syntetos (2008) mentioned that a possible estimation of the standard deviation of the forecast error ($\mathrm{Var}(\varepsilon_t)$) is either the root of the mean squared error (RMSE) or the mean absolute deviation (MAD). Thus, in our study the variance of the error ($\mathrm{Var}(\varepsilon_t)$) is estimated using the squared mean absolute deviation.

The second calculation was computed using two smoothing factors for Holt's double exponential smoothing (α, β) according to Equation 4. This calculation will be referred to as "Correction2" or "Corr2". According to Hyndman et al. (2005), Equation 4 computes the variance of the steps ahead of the forecast.

$$\mathrm{Var_f} = \mathrm{Var}(\varepsilon_t) \left[1 + \sum_{j=1}^{L} \sum (\alpha + j\alpha\beta)^2\right] \qquad \textbf{4}$$

The decision of using different calculations for the safety stock (SS) computation was intended to explore the influence of considering one or more elements of the forecasting parameters and whether or not that significantly impacts the performance of the forecasting-inventory models. For all models, k= 1 was used, which would imply a service level of 84.13% if demand was normally distributed, which the data is not.

SBA, Croston, and Holt-DES will be paired with the base stock level calculation of Equation 1 and will be referred to as SBA-MSE, Croston-MSE, and Holt-MSE, respectively. Holt-

DES will also be paired with the base stock level calculation in Equation 2 and will have two different calculations of safety stock based on the variance of forecast error. The two models will be referred to as Holt-Corr1 and Holt-Corr2.

Some studies (Teunter and Sani, 2009; Syntetos and Boylan, 2010) attempted to derive theoretical computations of the variance of the forecasts for SBA and Croston. However, the derivations have not been empirically tested on real data and are considered to be computationally extensive compared to the other models. Nevertheless, this issue will be addressed in a following chapter as it might be rewarding to consider that theoretical derivations instead of the approach of relying on the MSE.

All of the models were initialized with the same initial amount of inventory on hand. The initial on hand inventory amount was computed by averaging the M_t computed by Holt-Corr2 and the current model which is the model currently employed by Company A. Three inventory metrics were considered to assess the performance of each forecasting-inventory model: average on-hand inventory, service level (SL), and the fill-rate (FR).

3.4.2. Inventory Model Performance on All SKUs

3.4.2.1. The Electronics Data Set

Results of the performance of each inventory model according to the average and standard deviation (STD) of on-hand inventory, service levels (SL), and fill rates (FR) are shown in Table 3.9.

Table 3.9: Averages and STDs of the Metrics for Each Model- Electronics Data Set

Forecasting-Inventory Model	On-Hand Inventory Means (STD)	Service Level Means (STD)	Fill Rate Means (STD)
Holt-Corr2	5.70 (2.26)	95.22 (5.72)	97.09 (4.54)
Holt-Corr1	4.18 (0.96)	92.14 (5.17)	95.16 (3.57)
Holt-MSE	4.15 (0.92)	92.36 (4.21)	95.24 (3.13)
Croston-MSE	3.90 (1.53)	90.23 (6.15)	93.32 (4.95)
SBA-MSE	3.41 (2.14)	89.07 (6.95)	92.66 (5.34)

The results show that the lowest on-hand inventory levels on average were achieved by SBA-MSE followed by Croston-MSE. However, carrying lower levels of inventory came at the expense of the service based performance metrics, as they achieved lower SL and FR. Nevertheless, a more detailed assessment of the results is deemed necessary to provide statistical evidence on the significance of the observed performance. To this purpose, a statistical comparison of means was conducted for each inventory performance measure. Again, since the sample size is large (n = 523), the Central Limit Theorem will be employed to assume the data is normal.

To evaluate the statistical significance of the on-hand inventory means, the hypothesis that there is no statistical difference between the means was tested. Based on Levene's statistics, the null hypothesis that the variances are equal was rejected at p-value of < 0.0001. Accordingly, the Welch's test was conducted, and the null hypothesis was again rejected at a p-value of <0.0001.

Since there is at least one mean that is different, the Tukey Kramer multi-comparison test was used to determine which methods were statistically different this showed that SBA-MSE achieved significantly lower on-hand inventory compared to all the other forecasting-inventory models at an $\alpha = 0.05$. On the contrary, Holt-Corr2 achieved statistically higher on-hand inventory amounts on average compared to all the other forecasting-inventory models at an $\alpha = 0.05$. No statistical difference was found between Croston-MSE, Holt-Corr1, and Holt-MSE.

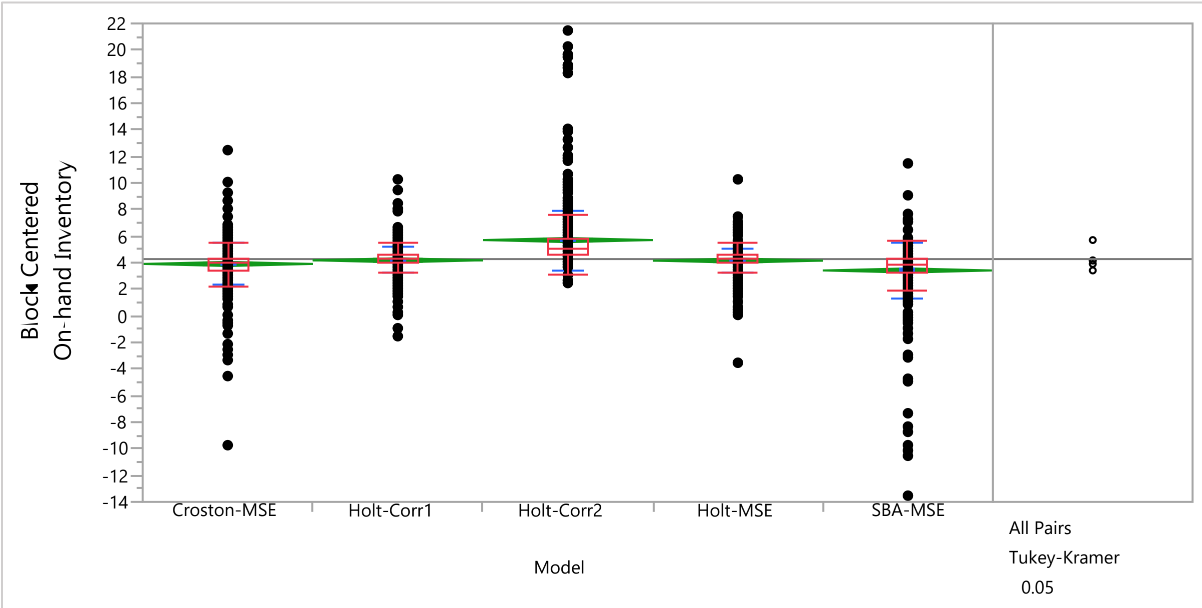

Figure 3-14: Box Plots of the "On-hand Inventory" Metric for Each Model- Electronics Data Set

Box plots of the on-hand inventory quantity across all the forecasting-inventory models are shown in Figure 3-14. A statistical comparison of means was also conducted for service level and fill rates. Box plots and statistical analysis for each can be found in Appendix. An overall summary of the results is shown in Table 3.10 where the letter A implies a higher result followed by B then C and so forth. The models that don't have overlapping in the letters are considered to be significantly different. In other words, models that are not connected by same letter are significantly different and their ranking can be interpreted from the letter, where A would be the largest in value.

Table 3.10: Summary of Statistical Results across the Metrics- Electronics Data Set

Inventory Measure	Statistical Difference?	Statistical Comparison		
		Level		**Mean**
Mean On-hand Inventory	YES	Holt-Corr2	A	5.70
		Holt-Corr1	B	4.18
		Holt-MSE	B	4.15
		Croston-MSE	B	3.90
		SBA-MSE	C	3.41
		Level		**Mean**
Mean Service Level	YES	Holt-Corr2	A	95.22
		Holt-MSE	B	92.36
		Holt-Corr1	B	92.14
		Croston-MSE	C	90.23
		SBA-MSE	D	89.07
		Level		**Mean**
Mean Fill Rate	YES	Holt-Corr2	A	97.09
		Holt-MSE	B	95.24
		Holt-Corr1	B	95.16
		Croston-MSE	C	93.32
		SBA-MSE	C	92.66

After reviewing both the initial results and the results of all the statistical analyses, one can make a general inference based on the statistical evidence. On one hand, the SBA-MSE tends to carry the lowest inventory levels, however that inflicts the lower service related performance, measured by service levels and fill rates. The initial results showed that both SBA-MSE and Croston-MSE achieved less than 95% service levels and fill rates. On the other hand, Holt-Corr2 and Holt-Corr1 tend to carry relatively more on-hand inventory, yet they also achieve much higher service levels and fill rates compared to SBA-MSE and Croston-MSE.

There is statistical evidence that Holt-MSE outperformed Croston-MSE. This holds true as there was no significant difference between the two models when comparing the on-hand inventory parameter, however, Holt-MSE achieved statistically higher service levels and fill rates. Moreover, no statistical difference was detected between Holt-MSE and Holt-Corr1 in terms of the on-hand inventory quantity, the service levels and fill rates. Holt-Corr2 was the only model that achieved service level and fill rate above 95% and 97%, respectively. So one conclusion is Holt-Corr2 achieved statistically higher on-hand inventory on average. However, this combination of forecast and inventory method was the only model that met a target of 95% service performance.

However, if the holding costs are very expensive then the company could save a lot by considering the 26% reduction of inventory amount on average between Holt-Corr2 and Holt-MSE. Nevertheless, this will pose the risk of achieving a service level that is less than 95% but is still relatively high. To this point, one can summarize that based on the results of this data set, if the prime concern is to achieve 95% target of service performance criteria then Holt-Corr2 would be the most suitable model to consider. On the other hand, if the prime concern is inventory cost reduction, then Holt-MSE would be the most suitable.

3.4.2.2. The Automotive Data Set

The performance results of the different inventory models according to the averages and standard deviations (STD) of the on-hand inventory, service levels, and fill rates are shown in Table 3.11. The results above show that the lowest on-hand inventory levels on average were achieved by SBA-MSE followed by Holt-MSE. SBA-MSE achieved the lowest service level and fill rate compared to the rest of the models. On the other hand, Holt-MSE tended to achieve a low on-hand level of inventory while maintaining a fill rate above 95%.

Table 3.11: Averages and STDs of the Metrics for Each Model- Automotive Data Set

Forecasting-Inventory Model	On-Hand Inventory Means (STD)	Service Level Means (STD)	Fill Rate Means (STD)
Holt-Corr2	15.57 (3.30)	94.96 (5.47)	97.21 (3.50)
Croston-MSE	13.64 (1.04)	91.90 (2.53)	95.20 (1.51)
Holt-Corr1	13.57 (1.32)	91.80 (3.05)	95.14 (1.82)
Holt-MSE	13.48 (1.13)	91.80 (2.72)	95.15 (1.54)
SBA-MSE	13.33 (1.40)	91.23 (3.17)	94.76 (1.96)

The results above show that the lowest on-hand inventory levels on average were achieved by SBA-MSE followed by Holt-MSE. SBA-MSE achieved the lowest service level and fill rate compared to the rest of the models. On the other hand, Holt-MSE tended to achieve a low on-hand level of inventory while maintaining a fill rate above 95%.

In accordance with the statistical analysis that was performed for the electronics data, the same analysis was conducted using the automotive data set. To this purpose, a statistical comparison of means was conducted for each inventory performance parameter. A statistical comparison of means was conducted for all the inventory parameters. Box plots and statistical analysis for each can be found in Appendix. An overall summary of the results is shown in Table 3.12.

Table 3.12: Summary of Statistical Results across the Metrics- Automotive Data Set

Inventory Measure	Statistical Difference?	Statistical Comparison		
		Level		**Mean**
Mean On-hand Inventory	YES	Holt-Corr2	A	15.57
		Croston-MSE	B	13.64
		Holt-Corr1	B C	13.57
		Holt-MSE	C	13.48
		SBA-MSE	D	13.33
		Level		**Mean**
Mean Service Level	YES	Holt-Corr2	A	94.96
		Croston-MSE	B	91.90
		Holt-Corr1	B	91.80
		Holt-MSE	B	91.80
		SBA-MSE	C	91.23
		Level		**Mean**
Mean Fill Rate	YES	Holt-Corr2	A	97.21
		Croston-MSE	B	95.20
		Holt-MSE	B	95.15
		Holt-Corr1	B	95.14
		SBA-MSE	C	94.76

By observing the results of the statistical analyses of all the inventory parameters considered in this study. One can claim that significant statistical evidence supports that SBA-MSE carries the lowest amount of inventory on average, however that negatively impacts their service level and fill rate performance.

There is statistical evidence to support that Holt-MSE outperformed Croston-MSE for these two data sets. In the electronics data set, no statistical difference was found between the models when comparing the on-hand inventory means, however, Holt-MSE achieved significantly higher service levels and fill rates. In the automotive data set, Holt-MSE achieved a significantly lower on-hand inventory level while maintaining relatively the same level of service and fill rate as Croston-MSE. In other words, in the latter case, Croston-MSE carried significantly higher on-hand inventory levels without improving any of its service parameters compared to Holt-MSE.

The interpretation of the results across the two different data sets seems to be consistent. Holt-MSE might be the most suitable forecasting-inventory model if the main concern is to carry less inventory on average at the expense of service performance measures, which could be ideal if the inventory holding costs are very high. However, if the emphasis is given to service performance measures then it is evident that Holt-Corr2 would be the most suitable model which achieves high service levels and fill rates that meet 95% target.

3.4.3. Inventory Model Performance Based on Each Demand Pattern Category

As seen in Table 3.3, the two industrial data sets are composed of four demand patterns. In spite of the consistency of the results of the different forecasting-inventory models across the two industrial data sets, the data sets will be further decomposed in terms of the four different demand patterns. Each demand pattern category will be analyzed in a manner identical to the previous analysis. To the best of our knowledge, no study has been conducted to assess all four categories of demand patterns according to inventory control performance rather than forecasting accuracy. Thus, in the following section, a detailed analysis of the forecasting-inventory models based on each demand pattern category will be conducted, and each model will be assessed based on on-hand inventory, service level, and fill rate.

3.4.3.1. The Electronics Data Set

3.4.3.1.1. Erratic Demand Pattern

The total number of SKUs categorized by having an erratic demand in the electronics data set is 43. Results of the performance of each inventory model according to the averages and STD of the on-hand inventory, service levels (SL) and fill rates (FR) are shown in Table 3.13.

Table 3.13: Averages and STDs of the Metrics for Erratic Demand Pattern - Electronics Data Set

Forecasting-Inventory Model	On-Hand Inventory Means (STD)	Service Level Means (STD)	Fill Rate Means (STD)
Holt-Corr2	8.33 (2.42)	84.53 (8.71)	90.05 (8.13)
Croston-MSE	6.09 (2.45)	75.59 (11.16)	80.72 (10.39)
Holt-Corr1	5.70 (1.61)	74.87 (10.71)	82.97 (8.19)
Holt-MSE	5.67 (1.39)	76.66 (7.06)	83.64 (6.23)
SBA-MSE	5.33 (2.45)	73.26 (11.38)	78.58 (10.44)

A statistical comparison of means was conducted for all the inventory parameters. Box plots and statistical analysis for each can be found in Appendix. An overall summary of the results is shown in Table 3.14. Based on the results of the comparative analysis for the category of erratic demand data, it can be concluded that Holt-Corr2 is the most suitable model. This holds true as all the models tended to achieve poor service performance results, and Holt-Corr2 was the only model that was significantly different in terms of both service levels and fill rates and it managed to achieve a fill rate above 90%.

Table 3.14: Statistical Results across the Metrics for Erratic Demand Pattern - Electronics Data Set

Inventory Measure	Statistical Difference?	Statistical Comparison		
		Level		**Mean**
Mean On-hand Inventory	YES	Holt-Corr2	A	8.33
		Croston-MSE	B	6.09
		Holt-Corr1	B	5.70
		Holt-MSE	B	5.67
		SBA-MSE	B	5.33
		Level		**Mean**
Mean Service Level	YES	Holt-Corr2	A	84.53
		Holt-MSE	B	76.66
		Croston-MSE	B	75.59
		Holt-Corr1	B	74.87
		SBA-MSE	B	73.26
		Level		**Mean**
Mean Fill Rate	YES	Holt-Corr2	A	90.05
		Holt-MSE	B	83.64
		Holt-Corr1	B	82.97
		Croston-MSE	B	80.72
		SBA-MSE	B	78.58

3.4.3.1.2. Intermittent Demand Pattern

The total number of SKUs categorized by having an intermittent demand in the electronics data set is 322. Results of the performance of each inventory model according to the averages and STD of the on-hand inventory, service levels (SL) and fill rates (FR) are shown in Table 3.15.

Table 3.15: Averages and STDs of the Metrics for Intermittent Demand Pattern - Electronics Data Set

Forecasting-Inventory Model	On-Hand Inventory Means (STD)	Service Level Means (STD)	Fill Rate Means (STD)
Holt-Corr2	3.34 (0.72)	97.22 (3.83)	98.29 (2.76)
Holt-Corr1	2.61 (0.40)	95.92 (2.84)	97.40 (1.86)
Holt-MSE	2.60 (0.40)	95.90 (2.89)	97.41 (1.85)
Croston-MSE	2.26 (0.59)	93.85 (4.07)	96.08 (2.82)
SBA-MSE	2.16 (0.59)	93.60 (4.43)	95.94 (3.06)

A statistical comparison of means was conducted for all the inventory parameters. Box plots and statistical analysis for each can be found in Appendix. An overall summary of the results is shown in Table 3.16.

Table 3.16: Statistical Results across the Metrics for Intermittent Demand Pattern-Electronics Data Set

Inventory Measure	Statistical Difference?	Statistical Comparison: Level				Mean
Mean On-hand Inventory	YES	Holt-Corr2	A			3.34
		Holt-Corr1		B		2.61
		Holt-MSE		B		2.60
		Croston-MSE			C	2.26
		SBA-MSE			C	2.16
Mean Service Level	YES	Holt-Corr2	A			97.22
		Holt-Corr1		B		95.92
		Holt-MSE		B		95.90
		Croston-MSE			C	93.85
		SBA-MSE			C	93.60
Mean Fill Rate	YES	Holt-Corr2	A			98.29
		Holt-MSE		B		97.41
		Holt-Corr1		B		97.40
		Croston-MSE			C	96.08
		SBA-MSE			C	95.94

After observing the results and their statistical significance, it could be concluded that if the goal is to achieve a fill rate of 95%, then either SBA-MSE or Croston-MSE would be the most suitable forecasting-inventory model for the intermittent demand. Both models gave an equivalent performance, and carried the lowest quantity of on-hand inventory on-average. However, if the goal is to achieve a 95% service level, then either Holt-MSE or Holt-Corr1 would be the most suitable forecasting-inventory model. No evidence of statistical difference was detected amongst Holt-MSE and Holt-Corr1.

3.4.3.1.3. Lumpy Demand Pattern

The total number of SKUs categorized by having a lumpy demand in the electronics data set is 80. Results of the performance of each inventory model according to the averages and STDs of the on-hand inventory, service levels (SL) and fill rates (FR) are shown in Table 3.17.

Table 3.17: Averages and STDs of the Metrics for Lumpy Demand Pattern - Electronics Data Set

Forecasting-Inventory Model	On-Hand Inventory Means (STD)	Service Level Means (STD)	Fill Rate Means (STD)
Holt-Corr2	5.83 (1.24)	94.57 (4.32)	96.83 (3.18)
Holt-MSE	4.20 (0.70)	92.45 (3.65)	95.55 (1.98)
Holt-Corr1	4.18 (0.67)	91.88 (3.16)	95.28 (2.21)
Croston-MSE	4.09 (0.95)	90.48 (4.32)	93.99 (3.21)
SBA-MSE	3.64 (1.05)	89.62 (4.88)	93.52 (3.54)

A statistical comparison of means was conducted for all the inventory parameters. Box plots and statistical analysis for each can be found in Appendix. An overall summary of the results is shown in Table 3.18.

Table 3.18: Statistical Results across the Metrics for Lumpy Demand Pattern-Electronics Data Set

Inventory Measure	Statistical Difference?	Statistical Comparison: Level		Mean
Mean On-hand Inventory	YES	Holt-Corr2	A	5.83
		Holt-MSE	B	4.20
		Holt-Corr1	B	4.18
		Croston-MSE	B C	4.09
		SBA-MSE	C	3.64
Mean Service Level	YES	Holt-Corr2	A	94.57
		Holt-MSE	B	92.45
		Holt-Corr1	B C	91.88
		Croston-MSE	C D	90.48
		SBA-MSE	D	89.62
Mean Fill Rate	YES	Holt-Corr2	A	96.83
		Holt-MSE	A B	95.55
		Holt-Corr1	B C	95.28
		Croston-MSE	C D	93.99
		SBA-MSE	D	93.52

After observing the results across all three inventory parameters and their statistical significance, it is evident that SBA-MSE tends to carry the lowest amount of on-hand inventory compared to Holt-MSE, Holt-Corr2 and Holt-Corr1, however, that comes at the expense of lowering the service performance of SBA-MSE. No statistical evidence was found to support that SBA-MSE outperforms Croston-MSE in terms of the considered inventory parameters.

There is statistical evidence that Holt-MSE outperformed Croston-MSE. This holds true as there was no significant difference between the two models when comparing the on-hand inventory parameter, however, Holt-MSE achieved statistically higher service levels and fill rates. Holt-Corr2 was the only model that achieved approximately 95% for both the service level and fill rate parameters.

From the results for the lumpy demand patterns, Holt-MSE would be the most suitable model if the main goal is to lower the on-average inventory levels and achieve a desired fill rate that is equal to 95%. However, if the prime concern is to maintain a service level that is equal to 95% while carrying a relatively higher amount of on-hand inventory, then the most suitable forecasting-inventory model would be Holt-Corr2. If the main key performance indicator is the fill rate, then Holt-MSE carried 28% less on-hand inventory compared to Holt-Corr2 while meeting the target rate of 95%.

3.4.3.1.4. Smooth Demand Pattern

The total number of SKUs categorized by having a smooth demand in the electronics data set is 78. Results of the performance of each inventory model according to the averages and STDs of the on-hand inventory, service levels (SL) and fill rates (FR) are shown in Table 3.19.

Table 3.19: Averages and STDs of the Metrics for Smooth Demand Pattern - Electronics Data Set

Forecasting-Inventory Model	On-Hand Inventory Means (STD)	Service Level Means (STD)	Fill Rate Means (STD)
Holt-Corr2	13.86 (4.40)	93.54 (7.51)	96.33 (6.04)
Holt-Corr1	9.82 (1.87)	86.35 (8.41)	92.55 (5.38)
Holt-MSE	9.69 (1.83)	86.30 (7.12)	92.32 (5.14)
Croston-MSE	9.28 (3.16)	83.09 (9.94)	88.18 (7.72)
SBA-MSE	7.28 (4.56)	78.55 (11.26)	85.99 (8.06)

A statistical comparison of means was conducted for all the inventory parameters. Box plots and statistical analysis for each can be found in Appendix. An overall summary of the results is shown in Table 3.20: Statistical Results across the Metrics for Smooth Demand Pattern-Electronics Data Set. After observing the results across all three inventory metrics including the statistical analysis, one can infer that both Holt-MSE and Holt-Corr1 outperform Croston-MSE. No statistical difference was found when comparing the on hand inventory means of the three models, however, both Holt-MSE and Holt-Corr1 achieved significantly higher fill rates compared to Croston-MSE. Also, SBA-MSE tends to carry significantly lower on hand inventory levels on average, however, that negatively impacts the performance with respect to service and fill rates.

On the contrary, Holt-Corr2 tended to carry relatively higher on hand inventory levels on average, but, achieved significantly higher service levels and fill rates. Moreover, Holt-Corr2 was the only model that achieved a service level higher than 90% and a fill rate higher than 95%. Therefore, Holt-Corr2 can be concluded to be the most suitable model as it is the only model that achieved significantly higher service level and fill rate compared to the rest of the models, and it managed to achieve satisfactory results for both service measures.

Table 3.20: Statistical Results across the Metrics for Smooth Demand Pattern-Electronics Data Set

<table>
<tr><th>Inventory Measure</th><th>Statistical Difference?</th><th colspan="3">Statistical Comparison</th></tr>
<tr><td rowspan="6">Mean On-hand Inventory</td><td rowspan="6">YES</td><td>Level</td><td></td><td>Mean</td></tr>
<tr><td>Holt-Corr2</td><td>A</td><td>13.86</td></tr>
<tr><td>Holt-Corr1</td><td>B</td><td>9.82</td></tr>
<tr><td>Holt-MSE</td><td>B</td><td>9.69</td></tr>
<tr><td>Croston-MSE</td><td>B</td><td>9.28</td></tr>
<tr><td>SBA-MSE</td><td>C</td><td>7.28</td></tr>
<tr><td rowspan="6">Mean Service Level</td><td rowspan="6">YES</td><td>Level</td><td></td><td>Mean</td></tr>
<tr><td>Holt-Corr2</td><td>A</td><td>93.54</td></tr>
<tr><td>Holt-Corr1</td><td>B</td><td>86.35</td></tr>
<tr><td>Holt-MSE</td><td>B</td><td>86.30</td></tr>
<tr><td>Croston-MSE</td><td>B</td><td>83.09</td></tr>
<tr><td>SBA-MSE</td><td>C</td><td>78.55</td></tr>
<tr><td rowspan="6">Mean Fill Rate</td><td rowspan="6">YES</td><td>Level</td><td></td><td>Mean</td></tr>
<tr><td>Holt-Corr2</td><td>A</td><td>96.33</td></tr>
<tr><td>Holt-Corr1</td><td>B</td><td>92.55</td></tr>
<tr><td>Holt-MSE</td><td>B</td><td>92.32</td></tr>
<tr><td>Croston-MSE</td><td>C</td><td>88.18</td></tr>
<tr><td>SBA-MSE</td><td>C</td><td>85.99</td></tr>
</table>

3.4.3.2. The Automotive Data Set

3.4.3.2.1. Erratic Demand Pattern

The total number of SKUs categorized by having an erratic demand in the automotive data set is 468. Results of the performance of each inventory model according to the averages and STDs of the on-hand inventory, service levels (SL) and fill rates (FR) are shown in Table 3.21.

Table 3.21: Averages and STDs of the Metrics for Erratic Demand Pattern-Automotive Data Set

Forecasting-Inventory Model	On-Hand Inventory Means (STD)	Service Level Means (STD)	Fill Rate Means (STD)
Holt-Corr2	29.03 (4.79)	92.57 (4.92)	95.29 (3.18)
Croston-MSE	25.75 (1.63)	90.12 (2.95)	93.58 (1.62)
Holt-Corr1	25.66 (1.82)	90.01 (3.01)	93.53 (3.18)
Holt-MSE	25.38 (1.91)	89.85 (2.89)	93.46 (1.72)
SBA-MSE	25.25 (2.10)	89.50 (3.02)	93.21 (1.96)

A statistical comparison of means was conducted for all the inventory parameters. Box plots and statistical analysis for each can be found in Appendix. An overall summary of the results is shown in Table 3.22.

Table 3.22: Statistical Results across the Metrics for Erratic Demand Pattern-Automotive Data Set

Inventory Measure	Statistical Difference?	Statistical Comparison: Level		Mean
Mean On-hand Inventory	YES	Holt-Corr2	A	29.03
		Croston-MSE	B	25.75
		Holt-Corr1	B	25.66
		Holt-MSE	B	25.38
		SBA-MSE	B	25.25
Mean Service Level	YES	Holt-Corr2	A	92.57
		Croston-MSE	B	90.12
		Holt-Corr1	B	90.01
		Holt-MSE	B	89.85
		SBA-MSE	B	89.50
Mean Fill Rate	YES	Holt-Corr2	A	95.29
		Croston-MSE	B	93.58
		Holt-Corr1	B	93.53
		Holt-MSE	B	93.46
		SBA-MSE	B	93.21

Looking at the results across all three inventory parameters and their statistical significance, it can be concluded that Holt-Corr2 is the most suitable model. This holds true as Holt-Corr2 was the only model that was significantly different in terms of both service levels and fill rates and it managed to achieve a service level above 90% and a fill rate above 95%. This conclusion is consistent with what was observed in the electronics data set for this demand pattern in Section 3.4.3.1.1.

3.4.3.2.2. Intermittent Demand Pattern

The total number of SKUs categorized by having an intermittent demand in the automotive data set is 941. Results of the performance of each inventory model according to the averages and STDs of the on-hand inventory, service levels (SL) and fill rates (FR) are shown Table 3.23.

Table 3.23: Averages and STDs of the Metrics for Intermittent Demand Pattern - Automotive Data Set

Forecasting-Inventory Model	On-Hand Inventory Means (STD)	Service Level Means (STD)	Fill Rate Means (STD)
Holt-Corr2	7.85 (2.91)	96.68 (5.12)	98.12 (3.23)
Croston-MSE	6.83 (0.63)	94.00 (2.38)	96.46 (1.50)
Holt-Corr1	6.77 (1.28)	93.92 (2.81)	96.36 (1.70)
Holt-MSE	6.73 (0.67)	93.96 (2.80)	96.37 (1.70)
SBA-MSE	6.72 (0.81)	93.60 (2.87)	96.19 (1.78)

The statistical comparison of means was conducted for all the inventory parameters, box plots and statistical results for each can be found in Appendix. An overall summary of the results is shown in Table 3.24. After observing the results, there is statistical evidence that Holt-Corr2 carried significantly higher levels of inventory but was the only model that achieved significantly higher service level and fill rate as compared to the rest of the models, as well as being the only model that achieved both a service level and fill rate above 95%. No evidence of a statistical difference was detected amongst the rest of the models across all three metrics.

Table 3.24: Statistical Results across the Metrics for Intermittent Demand Pattern-Automotive Data Set

Inventory Measure	Statistical Difference?	Statistical Comparison		
		Level		**Mean**
Mean On-hand Inventory	YES	Holt-Corr2	A	7.85
		Croston-MSE	B	6.83
		Holt-Corr1	B	6.77
		Holt-MSE	B	6.73
		SBA-MSE	B	6.72
		Level		**Mean**
Mean Service Level	YES	Holt-Corr2	A	96.68
		Croston-MSE	B	94.00
		Holt-MSE	B	93.96
		Holt-Corr1	B	93.92
		SBA-MSE	B	93.60
		Level		**Mean**
Mean Fill Rate	YES	Holt-Corr2	A	98.12
		Croston-MSE	B	96.46
		Holt-MSE	B	96.37
		Holt-Corr1	B	96.36
		SBA-MSE	B	96.19

3.4.3.2.3. Lumpy Demand Pattern

The total number of SKUs categorized by having a lumpy demand in the automotive data set is 286. Results of the performance of each inventory model according to the averages and STDs of the on-hand inventory, service levels (SL) and fill rates (FR) are shown in Table 3.25.

Table 3.25: Averages and STDs of the Metrics for Lumpy Demand Pattern - Automotive Data Set

Forecasting-Inventory Model	On-Hand Inventory Means (STD)	Service Level Means (STD)	Fill Rate Means (STD)
Holt-Corr2	19.15 (3.13)	91.00 (4.69)	94.94 (3.11)
Holt-Corr1	16.77 (1.18)	88.72 (2.28)	93.41 (1.56)
Croston-MSE	16.76 (1.14)	88.72 (1.80)	93.44 (1.27)
SBA-MSE	16.54 (1.27)	88.55 (2.04)	93.25 (1.59)
Holt-MSE	16.49 (1.45)	88.59 (1.92)	93.45 (1.30)

A statistical comparison of means was conducted for all the inventory parameters. Box plots and statistical analysis for each can be found in Appendix. An overall summary of the results is shown in Table 3.26.

Table 3.26: Statistical Results across the Metrics for Lumpy Demand Pattern-Automotive Data Set

Inventory Measure	Statistical Difference?	Statistical Comparison		
		Level		**Mean**
Mean On-hand Inventory	YES	Holt-Corr2	A	19.15
		Holt-Corr1	B	16.77
		Croston-MSE	B	16.76
		SBA-MSE	B	16.53
		Holt-MSE	B	16.49
		Level		**Mean**
Mean Service Level	YES	Holt-Corr2	A	91.00
		Croston-MSE	B	88.72
		Holt-Corr1	B	88.72
		Holt-MSE	B	88.59
		SBA-MSE	B	88.55
		Level		**Mean**
Mean Fill Rate	YES	Holt-Corr2	A	94.94
		Holt-MSE	B	93.45
		Croston-MSE	B	93.44
		Holt-Corr1	B	93.41
		SBA-MSE	B	93.25

After observing the results, there is statistical evidence that Holt-Corr2 carried significantly higher levels of inventory, but again is the only model that achieved a significantly higher service level and fill rate compared to the rest of the models. No evidence of statistical difference was detected amongst the rest of the models across all three parameters. This conclusion is in part similar to what was concluded for the electronics data set in Section 3.4.3.1.3.

3.4.3.2.4. Smooth Demand Pattern

The total number of SKUs categorized by having a smooth demand in the automotive data set is 1305. Results of the performance of each inventory model according to the averages and STDs of the on-hand inventory, service levels (SL) and fill rates (FR) are shown in Table 3.27.

Table 3.27: Averages and STDs of the Metrics for Smooth Demand Pattern - Automotive Data Set

Forecasting-Inventory Model	On-Hand Inventory Means (STD)	Service Level Means (STD)	Fill Rate Means (STD)
Holt-Corr2	15.53 (2.76)	95.44 (5.99)	97.74 (3.82)
Croston-MSE	13.53 (0.97)	91.73 (2.61)	95.26 (1.52)
Holt-Corr1	13.43 (1.16)	91.58 (3.35)	95.21 (1.89)
Holt-MSE	13.41 (0.86)	91.64 (2.74)	95.24 (1.39)
SBA-MSE	13.12 (1.41)	90.72 (3.56)	94.60 (2.12)

A statistical comparison of means was conducted for all the inventory parameters. Box plots and statistical analysis for each can be found in Appendix. An overall summary of the results is shown in Table 3.28.

Table 3.28: Statistical Results across the Metrics for Smooth Demand Pattern-Automotive Data Set

Inventory Measure	Statistical Difference?	Statistical Comparison				
		Level				**Mean**
Mean On-hand Inventory	YES	Holt-Corr2	A			15.53
		Croston-MSE		B		13.53
		Holt-Corr1		B		13.43
		Holt-MSE		B		13.41
		SBA-MSE			C	13.12
		Level				**Mean**
Mean Service Level	YES	Holt-Corr2	A			95.44
		Croston-MSE		B		91.73
		Holt-MSE		B		91.64
		Holt-Corr1		B		91.58
		SBA-MSE			C	90.72
		Level				**Mean**
Mean Fill Rate	YES	Holt-Corr2	A			97.74
		Croston-MSE		B		95.26
		Holt-MSE		B		95.24
		Holt-Corr1		B		95.21
		SBA-MSE			C	94.60

Looking at the results across all three inventory metrics and their statistical analysis, Holt-Corr2 tended to carry relatively higher on hand inventory levels on average, but, achieved significantly higher service levels and fill rates. Again, Holt-Corr2 was the only model that achieved a service level higher than 95%.

No statistical difference of the means was found when comparing Croston-MSE, Holt-MSE and Holt-Corr1 across all three inventory measures. Thus, no conclusive statement can be made with respect to which of the three models performed better. Therefore, Holt-Corr2 can be concluded to be the most suitable model since the model achieved significantly higher service level and fill rate compared to the rest of the models.

In the previous two sections, a number of in-depth analyses were conducted to assess the performance of the different forecasting-inventory models with respect to three metrics: level of on-hand inventory, service levels and fill rates. Furthermore, similar analyses were conducted for each of the four demand pattern categories: erratic, intermittent, lumpy and smooth and found in the Appendices.

The conducted analyses provide insights regarding the performance of not only the forecasting techniques but also the implications each forecasting-inventory combination had on stock control and service parameters which has been rarely considered in previous studies. The latter has been one of the documented research needs discussed in Chapter 2.

3.4.4. Exploring Regions of Superior Inventory Performance

This section will address the need of identifying superior regions of performance similar to the SBC pattern classification scheme (i.e., lumpy, erratic, intermittent, and smooth). Syntetos et al. (2005) have identified regions of superior performance by comparing SBA and Croston forecasting techniques. The identification was done based on the theoretical analysis MSE and was validated using a real data set. It was concluded that SBA was a more suitable forecasting technique for lumpy, erratic, and intermittent demand patterns and Croston performed well when demand is smooth.

However, this section will identify superior regions based on inventory stock control and service parameters rather than forecasting accuracy measures solely. To this end, this section will propose and identify superior regions of performance for the three forecasting-inventory combinations (i.e., SBA-MSE, Croston-MSE and Holt-MSE). The purpose of investigating and analyzing these three models is to determine which forecasting model outperform the others with respect to stock control and service parameters when dealing with each demand pattern category using the two real data sets. Only three forecasting-inventory models will be considered in this analysis; SBA-MSE, Croston-MSE and Holt-MSE. The analysis will follow the same steps as previous analyses conducted in this chapter.

3.4.4.1. The Electronics Data Set

3.4.4.1.1. Erratic Demand Pattern

A statistical comparison of means was conducted for all the inventory parameters. Box plots and statistical analysis for each can be found in Appendix. An overall summary of the results is shown in Table 3.29.

Table 3.29: Statistical Results for Erratic Demand Pattern (Three Models)-Electronics Data Set

Inventory Measure	Statistical Difference?	Statistical Comparison
Mean On-hand Inventory	NO	NONE
Mean Service Level	NO	NONE
Mean Fill Rate	YES	**Level** **Mean** Holt-MSE A 83.64 Croston-MSE A B 80.72 SBA-MSE B 78.58

Based on the observed results of the electronics data set and their statistical significance. Results showed that there is statistical evidence to support that Holt-MSE outperformed SBA-MSE for this demand category. Holt-MSE achieved a significantly higher fill rate compared to SBA-MSE, while no statistical difference was found between SBA-MSE and Holt-MSE in terms of the average on-hand inventory levels. No statistical difference was found when comparing Holt-MSE and Croston-MSE across all three criteria.

Consequently, Holt-MSE might be considered the most suitable model when dealing with erratic demand pattern. Given that it was the only model that yielded satisfactory results when considering the service performance parameters, and it maintained a comparably low on-hand inventory level.

3.4.4.1.2. Intermittent Demand Pattern

A statistical comparison of means was conducted for all the inventory parameters. Box plots and statistical analysis for each can be found in Appendix. An overall summary of the results is shown in Table 3.30

Table 3.30: Statistical Results for Intermittent Demand Pattern (Three Models) - Electronics Data Set

<table>
<tr><th>Inventory Measure</th><th>Statistical Difference?</th><th>Statistical Comparison</th></tr>
<tr><td>Mean On-hand Inventory</td><td>YES</td><td><table><tr><th>Level</th><th></th><th></th><th>Mean</th></tr><tr><td>Holt-MSE</td><td>A</td><td></td><td>2.60</td></tr><tr><td>Croston-MSE</td><td></td><td>B</td><td>2.26</td></tr><tr><td>SBA-MSE</td><td></td><td>B</td><td>2.16</td></tr></table></td></tr>
<tr><td>Mean Service Level</td><td>YES</td><td><table><tr><th>Level</th><th></th><th></th><th>Mean</th></tr><tr><td>Holt-MSE</td><td>A</td><td></td><td>95.90</td></tr><tr><td>Croston-MSE</td><td></td><td>B</td><td>93.85</td></tr><tr><td>SBA-MSE</td><td></td><td>B</td><td>93.60</td></tr></table></td></tr>
<tr><td>Mean Fill Rate</td><td>YES</td><td><table><tr><th>Level</th><th></th><th></th><th>Mean</th></tr><tr><td>Holt-MSE</td><td>A</td><td></td><td>97.41</td></tr><tr><td>Croston-MSE</td><td></td><td>B</td><td>96.08</td></tr><tr><td>SBA-MSE</td><td></td><td>B</td><td>95.94</td></tr></table></td></tr>
</table>

Based on the observed results of the electronics data set and the statistical analysis, there is no statistical evidence to support that SBA-MSE outperformed Croston-MSE. If the prime concern is to achieve a comparably low level of inventory while achieving a relatively high service level and fill rate then SBA-MSE would be suitable for this category. On the other hand, if the prime concern is to guarantee achieving a competitively high service level (above 95%) and fill rate while carrying relatively higher on-hand inventory level on average, then Holt-MSE would be suitable.

3.4.4.1.3. Lumpy Demand Pattern

The statistical comparison of means was conducted for all the inventory parameters, box plots and statistical results for each can be found in Appendix. An overall summary of the results is shown in Table 3.31.

Table 3.31: Statistical Results for Lumpy Demand Pattern (Three Models)-Electronics Data Set

Inventory Measure	Statistical Difference?	Statistical Comparison			
		Level			**Mean**
Mean On-hand Inventory	YES	Holt-MSE	A		4.20
		Croston-MSE	A		4.09
		SBA-MSE		B	3.64
		Level			**Mean**
Mean Service Level	YES	Holt-MSE	A		92.45
		Croston-MSE		B	90.48
		SBA-MSE		B	89.62
		Level			**Mean**
Mean Fill Rate	YES	Holt-MSE	A		95.55
		Croston-MSE		B	93.99
		SBA-MSE		B	93.52

Croston-MSE achieved higher levels of inventory compared to SBA-MSE with no statistical difference between SBA-MSE and Croston-MSE in terms of both service levels and fill rates. There is statistical evidence that Holt-MSE outperformed Croston-MSE with regard to service level and a fill rate but no statistical difference was captured when looking at the on-hand inventory criteria.

Therefore, if the prime concern is to guarantee achieving a competitively high service level and fill rate (i.e.,above 95%) while carrying relatively higher on-hand inventory level compared to the level achieved by SBA-MSE, then Holt-MSE would be suitable. If it is acceptable to achieve fill rates and service levels that are below 95% in an attempt to carry slightly lower on-hand inventory levels then SBA-MSE would be the suitable model. Chapter 4 will address this issue of comparing models based on two competing criteria.

3.4.4.1.4. Smooth Demand Pattern

A statistical comparison of means was conducted for all the inventory parameters. Box plots and statistical analysis for each can be found in Appendix. An overall summary of the results is shown in Table 3.32. It can be concluded that there is statistical evidence to support that Holt-MSE outperformed Croston-MSE as it tend to carry comparably close amounts of on-hand inventory while achieving statistically higher fill rates (above 90%). It can be recommended that Holt-MSE would be the most suitable model to consider.

Table 3.32: Statistical Results for Smooth Demand Pattern (Three Models)-Electronics Data Set

Inventory Measure	Statistical Difference?	Statistical Comparison			
		Level			**Mean**
Mean On-hand Inventory	YES	Holt-MSE	A		9.69
		Croston-MSE	A		9.28
		SBA-MSE		B	7.28
		Level			**Mean**
Mean Service Level	YES	Holt-MSE	A		86.30
		Croston-MSE	A		83.09
		SBA-MSE		B	78.55
		Level			**Mean**
Mean Fill Rate	YES	Holt-MSE	A		92.32
		Croston-MSE		B	88.18
		SBA-MSE		B	85.99

3.4.4.2. The Automotive Data Set

3.4.4.2.1. Erratic Demand Pattern

A statistical comparison of means was conducted for all the inventory parameters. Box plots and statistical analysis for each can be found in Appendix. An overall summary of the results is shown in Table 3.33.

Table 3.33: Statistical Results for Erratic Demand Pattern (Three Models)-Automotive Data Set

Inventory Measure	Statistical Difference?	Statistical Comparison			
		Level			**Mean**
Mean On-hand Inventory	YES	Croston-MSE	A		25.75
		Holt-MSE		B	25.38
		SBA-MSE		B	25.25
		Level			**Mean**
Mean Service Level	YES	Croston-MSE	A		90.12
		Holt-MSE	A	B	89.85
		SBA-MSE		B	89.50
		Level			**Mean**
Mean Fill Rate	YES	Croston-MSE	A		93.58
		Holt-MSE	A	B	93.46
		SBA-MSE		B	93.21

Based on the observed results of the automotive data set and their statistical significance, results showed that SBA-MSE tends to carry a lower level of inventory on average compared to Croston-MSE; nevertheless that comes at the expense of achieving lower levels of service and fill rates. There is statistical evidence to support that Holt-MSE outperformed Croston-MSE for this demand pattern. Statistical results showed that Holt-MSE achieved significantly lower on hand inventory while no statistical difference in service level and fill rate was found compared to Croston-MSE. Thus, Holt-MSE might be the most suitable for this erratic demand pattern to guarantee achieving a high fill rate (above 90%).

3.4.4.2.2. Intermittent Demand Pattern

A statistical comparison of means was conducted for all the inventory parameters. Box plots and statistical analysis for each can be found in Appendix. An overall summary of the results is shown in Table 3.34

Table 3.34: Statistical Results for Intermittent Demand Pattern (Three Models)- Automotive Data Set

Inventory Measure	Statistical Difference?	Statistical Comparison
Mean On-hand Inventory	YES	**Level** **Mean** Croston-MSE A 6.83 Holt-MSE B 6.73 SBA-MSE B 6.72
Mean Service Level	YES	**Level** **Mean** Croston-MSE A 94.00 Holt-MSE A 93.96 SBA-MSE B 93.60
Mean Fill Rate	YES	**Level** **Mean** Croston-MSE A 96.46 Holt-MSE A B 96.37 SBA-MSE B 96.19

Based on the statistical analysis of the automotive data set, Holt-MSE outperformed Croston-MSE in terms of mean on-hand inventory. Croston-MSE achieved statistically higher levels of inventory compared to Holt-MSE while no statistical difference between Holt-MSE and Croston-MSE in terms of both service level and fill rate. Holt-MSE also achieved a significantly higher service level compare to SBA-MSE while no statistical difference between Holt-MSE and SBA-MSE was found in terms of on-hand inventory level.

Therefore, if you knew your demand was going to be intermittent, Holt-MSE would be the most suitable model for this demand pattern.

3.4.4.2.3. Lumpy Demand Pattern

A statistical comparison of means was conducted for all the inventory parameters. Box plots and statistical analysis for each can be found in Appendix. An overall summary of the results is shown in Table 3.35.

Table 3.35: Statistical Results for Lumpy Demand Pattern (Three Models)-Automotive Data Set

Inventory Measure	Statistical Difference?	Statistical Comparison
Mean On-hand Inventory	YES	**Level** / **Mean** Croston-MSE A 16.76 SBA-MSE B 16.53 Holt-MSE B 16.49
Mean Service Level	NO	NONE
Mean Fill Rate	NO	NONE

Statistical Results showed that both SBA-MSE and Holt-MSE models achieved comparable performance across all three parameters. However, given that Holt-MSE achieved the lowest on-hand inventory on average while achieving the highest service level and fill rate, one can conclude that Holt-MSE would be the most suitable model for this demand pattern

3.4.4.2.4. Smooth Demand Pattern

A statistical comparison of means was conducted for all the inventory parameters. Box plots and statistical analysis for each can be found in Appendix. An overall summary of the results is shown in Table 3.36.

Table 3.36: Statistical Results for Smooth Demand Pattern (Three Models)-Automotive Data Set

Inventory Measure	Statistical Difference?	Statistical Comparison		
		Level		Mean
Mean On-hand Inventory	YES	Croston-MSE	A	13.53
		Holt-MSE	B	13.41
		SBA-MSE	C	13.12
Mean Service Level	YES	Croston-MSE	A	91.73
		Holt-MSE	A	91.64
		SBA-MSE	B	90.72
Mean Fill Rate	YES	Croston-MSE	A	95.26
		Holt-MSE	A	95.24
		SBA-MSE	B	94.60

SBA-MSE tends to carry lower levels of inventory on average statistically as compared to Holt-MSE and Croston-MSE, but, that comes at the expense of achieving lower levels of service and fill rates. Holt-MSE outperformed Croston-MSE since Holt-MSE achieved a significantly lower on hand inventory level with no statistical difference when comparing the means of service levels and fill rates between the two models. Thus, one can conclude that Holt-MSE would be the most suitable model for this demand pattern.

3.4.5. Case-Study Driven Analysis:

In this section, we will apply the same analysis conducted in the previous sections however we will additionally consider the model that is currently used by Company A. As mentioned earlier in Section 3.2.1, Company A is a global high tech company that offers a wide range of products including Personal Computers (PCs), laptops and tablets. The company typically provides 12-18 months of warranty for their commercialized products. Given the inherited complexity of service parts inventory management, the company has faced some challenges and sought to develop some improvements to their current method.

The company currently relies on a standard moving average (SMA) of 13 periods for forecasting and a simple periodic review inventory model. The company's goal is to maintain a seven weeks of inventory (WOI). During each review period an order is placed to raise the inventory level to the computed WOI.

Despite the simplicity of the model applied by Company A, there are some major drawbacks. The company reported that for some components, the model underestimates the required amount of inventory in order to meet their targeted service levels. On the contrary, for some other components, the model tends to overestimate the needed amount of inventory. Lastly, a key element that also had a drastic impact on the model performance was the different life cycle phases that each component follows. Each of the above mentioned situations has significant cost implications for the company in addition to the satisfacting their customers.

Hence, the company is considering altering their current approach in an attempt to address some of the challenges. Therefore, in this section, a comparative analysis will be conducted between Company A's model which will be referred to as "Current", and the rest of the models proposed earlier. The conclusions will be made according to what is in the best interest of the company.

3.4.5.1. Inventory Model Performance

Results of the performance of each inventory model according to the averages and STDs of the on-hand inventory, service levels (SL) and fill rates (FR) are shown in Table 3.37.

Table 3.37: Averages and STDs of the Metrics- Case Study

Forecasting-Inventory Model	On-Hand Inventory Means (STD)	Service Level Means (STD)	Fill Rate Means (STD)
Current	11.38 (16.7)	94.76 (5.40)	96.62 (3.63)
Holt-Corr2	5.70 (2.14)	95.22 (5.09)	97.09 (4.10)
Holt-Corr1	4.18 (3.46)	92.14 (5.30)	95.16 (3.56)
Holt-MSE	4.15 (3.51)	92.36 (4.25)	95.24 (3.07)
Croston-MSE	3.90 (3.90)	90.23 (6.45)	93.32 (5.23)
SBA-MSE	3.41 (5.05)	89.07 (7.44)	92.66 (5.71)

A statistical comparison of means was conducted for all the inventory parameters. Box plots and statistical analysis for each can be found in Appendix while Table 3.38 shows an overall summary of the results.

Table 3.38: Statistical Results across the Metrics - Case Study

Inventory Measure	Statistical Difference?	Statistical Comparison					
		Level					Mean
Mean On-hand Inventory	YES	Current	A				11.38
		Holt-Corr2		B			5.70
		Holt-Corr1			C		4.18
		Holt-MSE			C		4.15
		Croston-MSE			C		3.90
		SBA-MSE			C		3.41
		Level					Mean
Mean Service Level	YES	Holt-Corr2	A				95.22
		Current	A				94.76
		Holt-MSE		B			92.36
		Holt-Corr1		B			92.14
		Croston-MSE			C		90.23
		SBA-MSE				D	89.07
		Level					Mean
Mean Fill Rate	YES	Holt-Corr2	A				97.09
		Current	A				96.62
		Holt-MSE		B			95.24
		Holt-Corr1		B			95.16
		Croston-MSE			C		93.32
		SBA-MSE			C		92.66

After reviewing both the initial results and the results of all the statistical analyses, one can make a general inference based on the statistical evidence. On one hand, both SBA-MSE and Croston-MSE tend to carry lower inventory levels, however that negatively impacts on their service related performance measures. The initial results showed that both SBA-MSE and Croston-MSE achieved less than 95% service levels and fill rates. However, there is statistical evidence that Holt-Corr2 was the only model that achieved significantly lower levels of inventory while maintaining the same level of service and fill rate compared to "Current" model.

Based on the results, the most suitable model would be Holt-Corr2. If the company were to apply Holt-Corr2, a reduction of 50% of the average on-hand inventory quantity could be realized while maintaining the same level of service and fill rate as their "Current" approach. In the next section, the performance of the different models for each of the four demand patterns will be assessed and recommendations to what is in the best interest of the company will be provided as well.

3.4.5.2. Erratic Demand Pattern

Results of the performance of each inventory model according to the average on-hand inventory amount, service levels (SL) and fill rates (FR) are shown in Table 3.39.

Table 3.39: Averages and STDs for Erratic Demand Pattern - Case Study

Forecasting-Inventory Model	On-Hand Inventory Means (STD)	Service Level Means (STD)	Fill Rate Means (STD)
Current	16.81 (9.46)	87.03 (8.17)	89.66 (6.89)
Holt-Corr2	8.33 (2.55)	84.53 (7.80)	90.05 (7.49)
Croston-MSE	6.09 (2.76)	75.59 (11.56)	80.72 (10.74)
Holt-Corr1	5.70 (2.94)	74.87 (10.96)	82.97 (8.32)
Holt-MSE	5.67 (2.81)	76.66 (7.13)	83.64 (6.20)
SBA-MSE	5.33 (3.09)	73.26 (11.93)	78.58 (10.92)

A statistical comparison of means was conducted for all the inventory measures. Box plots and statistical analysis for each can be found in Appendix. An overall summary of the results is shown in Table 3.40. Based on the statistical analysis of the electronics data set, all of the models tended to carry significantly lower levels of inventory compared to the "Current" method used by the company. However, Holt-Corr2 was the only model that achieved a significantly lower on-hand inventory while maintaining the same level of service and fill rate compared to the "Current" method. Moreover, Holt-Corr2 was the only model that achieved a statistically higher service level and fill rate compared to Holt-Corr1, Holt-MSE, SBA-MSE, and Croston-MSE. Consequently, Holt-Corr2 can be recommended as the most suitable model when the demand pattern is erratic. In addition, only Holt-Corr2 was capable of achieving an overall fill rate higher than 90%.

Table 3.40: Statistical Results for Erratic Demand Pattern - Case Study

Inventory Measure	Statistical Difference?	Statistical Comparison
Mean On-hand Inventory	YES	**Level** **Mean** Current A 16.81 Holt-Corr2 B 8.33 Croston-MSE B 6.09 Holt-Corr1 B 5.70 Holt-MSE B 5.67 SBA-MSE B 5.33
Mean Service Level	YES	**Level** **Mean** Current A 87.03 Holt-Corr2 A 84.53 Holt-MSE B 76.66 Croston-MSE B 75.59 Holt-Corr1 B 74.87 SBA-MSE B 73.26
Mean Fill Rate	YES	**Level** **Mean** Holt-Corr2 A 90.05 Current A 89.66 Holt-MSE B 83.64 Holt-Corr1 B 82.97 Croston-MSE B 80.72 SBA-MSE B 78.58

3.4.5.3. Intermittent Demand Pattern

Results of the performance of each inventory model according to the averages and STDs of the on-hand inventory, service levels (SL) and fill rates (FR) are shown in Table 3.41.

Table 3.41: Averages and STDs for Intermittent Demand Pattern - Case Study

Forecasting-Inventory Model	On-Hand Inventory Means (STD)	Service Level Means (STD)	Fill Rate Means (STD)
Current	3.78 (2.22)	96.17 (2.97)	97.79 (1.99)
Holt-Corr2	3.34 (0.59)	97.22 (3.53)	98.29 (2.49)
Holt-Corr1	2.61 (0.66)	95.92 (2.77)	97.40 (1.80)
Holt-MSE	2.60 (0.68)	95.90 (2.81)	97.41 (1.78)
Croston-MSE	2.26 (0.75)	93.85 (4.35)	96.08 (3.04)
SBA-MSE	2.16 (0.84)	93.60 (4.69)	95.94 (3.29)

A statistical comparison of means was conducted for all the inventory parameters. Box plots and statistical analysis for each can be found in Appendix. An overall summary of the results is shown in Table 3.42.

Table 3.42: Statistical Results for Intermittent Demand Pattern - Case Study

Inventory Measure	Statistical Difference?	Statistical Comparison: Level	Groups	Mean
Mean On-hand Inventory	YES	Current	A	3.78
		Holt-Corr2	B	3.34
		Holt-Corr1	C	2.61
		Holt-MSE	C	2.60
		Croston-MSE	D	2.26
		SBA-MSE	D	2.16
Mean Service Level	YES	Holt-Corr2	A	97.22
		Current	B	96.17
		Holt-Corr1	B	95.92
		Holt-MSE	B	95.90
		Croston-MSE	C	93.85
		SBA-MSE	C	93.60
Mean Fill Rate	YES	Holt-Corr2	A	98.29
		Current	A B	97.79
		Holt-MSE	B	97.41
		Holt-Corr1	B	97.40
		Croston-MSE	C	96.08
		SBA-MSE	C	95.94

Based on the observed results of the electronics data set and their statistical significance. It can be concluded that there is statistical evidence to support that Holt-Corr2 was the only model that achieved a significantly lower on-hand inventory level while achieving a significantly higher service level compared to Current. Moreover, both Holt-MSE and Holt-Corr1 achieved significantly lower on-hand inventory levels while maintaining the same service level and fill rate compared to Current. Only the Holt-DES variants managed to achieve service levels above 95%.

If the company's prime concern is to cut costs while maintaining the same level of service and fill rate as their current approach then either Holt-MSE or Holt-Corr1 would be the recommended models. Either model would yield an approximate reduction of 30% in inventory levels. On the other hand, if the company's prime concern is to enhance their service performance parameters while generating savings from inventory reduction, then Holt-Corr2 would be the most suitable model. Holt-Corr2 would yield an approximate reduction of 11% in inventory costs.

3.4.5.4. Lumpy Demand Pattern

Results of the performance of each inventory model according to the average on-hand inventory amount, service levels (SL) and fill rates (FR) are shown in Table 3.43.

Table 3.43: Averages and STDs for Lumpy Demand Pattern– Case Study

Forecasting-Inventory Model	On-Hand Inventory Means (STD)	Service Level Means (STD)	Fill Rate Means (STD)
Croston-MSE	4.09 (1.65)	90.48 (4.30)	93.99 (3.23)
Current	9.66 (8.42)	93.03 (3.63)	95.87 (2.46)
Holt-Corr1	4.18 (2.07)	91.88 (3.50)	95.28 (2.40)
Holt-Corr2	5.83 (1.47)	94.57 (4.43)	96.83 (3.04)
Holt-MSE	4.20 (2.20)	92.45 (2.87)	95.55 (2.10)
SBA-MSE	3.64 (2.16)	89.62 (5.04)	93.52 (3.62)

A statistical comparison of means was conducted for all the inventory parameters. Box plots and statistical analysis for each can be found in Appendix. An overall summary of the results is shown in Table 3.44. Based on the statistical analysis of the electronics data, Holt-Corr2 would be recommended if the prime concern is to achieve a service level of approximately 95% while reducing the inventory on-hand level by 40% when compared to the "Current" model. However, if the prime concern is to generate savings by inventory reduction then either Holt-MSE or Holt-Corr1 would yield an approximate reduction of 55% while maintaining the same level of service and fill rate on average compared to “Current” model.

Table 3.44: Statistical Results for Lumpy Demand Pattern - Case Study

Inventory Measure	Statistical Difference?	Statistical Comparison					
		Level					**Mean**
Mean On-hand Inventory	YES	Current	A				9.66
		Holt-Corr2		B			5.83
		Holt-MSE		B	C		4.20
		Holt-Corr1		B	C		4.18
		Croston-MSE		B	C		4.09
		SBA-MSE			C		3.64
		Level					**Mean**
Mean Service Level	YES	Holt-Corr2	A				94.57
		Current	A	B			93.03
		Holt-MSE		B	C		92.45
		Holt-Corr1		B	C		91.88
		Croston-MSE			C	D	90.48
		SBA-MSE				D	89.62
		Level					**Mean**
Mean Fill Rate	YES	Holt-Corr2	A				96.83
		Current	A	B			95.87
		Holt-MSE	A	B			95.55
		Holt-Corr1		B	C		95.28
		Croston-MSE			C	D	93.99
		SBA-MSE				D	93.52

3.4.5.5. Smooth Demand Pattern

Results of the performance of each inventory model according to the average on-hand inventory amount, service levels (SL) and fill rates (FR) are shown in Table 3.45.

Table 3.45: Averages and STDs for Smooth Demand Pattern– Case Study

Forecasting-Inventory Model	On-Hand Inventory Means (STD)	Service Level Means (STD)	Fill Rate Means (STD)
Current	41.51 (34.94)	94.97 (6.91)	96.40 (4.46)
Holt-Corr2	13.86 (4.54)	93.54 (6.91)	96.33 (5.55)
Holt-Corr1	9.82 (6.86)	86.35 (8.43)	92.55 (5.23)
Holt-MSE	9.69 (6.95)	86.30 (7.03)	92.32 (4.97)
Croston-MSE	9.28 (8.35)	83.09 (10.28)	88.18 (8.07)
SBA-MSE	7.28 (10.74)	78.55 (11.08)	88.99 (8.50)

A statistical comparison of means was conducted for all the inventory parameters. Box plots and statistical analysis for each can be found in Appendix. An overall summary of the results is shown in Table 3.46. Based on the observed results of the electronics data set and their statistical significance, it can be recommended that Holt-Corr2 would be suitable for this demand pattern. Holt-Corr2 was the only model that managed to achieve a significantly lower on-hand inventory level while achieving the same levels of service and fill rates compared to the "Current" model.

Table 3.46: Statistical Results for Smooth Demand Pattern - Case Study

Inventory Measure	Statistical Difference?	Statistical Comparison
Mean On-hand Inventory	YES	**Level** / **Mean** Current A 41.51 Holt-Corr2 B 13.86 Holt-Corr1 B 9.82 Holt-MSE B 9.69 Croston-MSE B 9.28 SBA-MSE B 7.28
Mean Service Level	YES	**Level** / **Mean** Current A 94.97 Holt-Corr2 A 93.54 Holt-Corr1 B 86.35 Holt-MSE B 86.30 Croston-MSE B 83.09 SBA-MSE C 78.55
Mean Fill Rate	YES	**Level** / **Mean** Current A 96.40 Holt-Corr2 A 96.33 Holt-Corr1 B 92.55 Holt-MSE B 92.32 Croston-MSE C 88.18 SBA-MSE C 85.99

3.5. Conclusion

This chapter presented a number of comparative analyses of different forecasting-inventory models. Two empirical data sets were used for the analyses; an electronics data set and an automotive data set. Each data set has its own characteristics that aided in providing different insights and observations. An overall summary of the achieved performance of the proposed forecasting-inventory model is shown in Table 3.47 through Table 3.51.

Each table represents the final conclusion for each analysis section after conducting the statistical analysis. The conclusions are made with respect to the three inventory parameters and the performance of each model under each demand pattern. The final conclusion was made considering the observed results and statistical analysis of means across all the three inventory parameters considered. It also takes into account whether a company is considering the service level or the fill rate as its KPI (key performance indicator) for inventory.

For example in Table 3.47, for the lumpy demand pattern for this data set, the results showed that Holt-MSE would be the most suitable model in terms of carrying lower levels of inventory (OH) while achieving a high Fill Rate (FR) (i.e., above 95%) compared to the rest of the models. However, if the KPI used is Service Levels (SL) then Holt-Corr2 would be the most suitable model to consider.

The conclusions for Section 3.4.5 is based on a case study and it was compared according to the company's applied model. Thus the conclusions are a little bit different as we intended to select the most suitable model under the assumption that the company would not be willing to decrease its service levels and fill rates. Thus the inventory reductions were welcomed as long as the same or better levels of service and fill rates were achieved by the models.

Table 3.47: Conclusions According to Analyses Conducted in Section 3.4.3.1-Electronics Data Set

ADI = 1.32

CV^2 =0.49	***"Erratic"*** Holt-Corr2	***"Lumpy"*** *SL: Holt-Corr2* *FR: Holt-MSE*
	"Smooth" Holt-Corr2	***"Intermittent"*** *SL: Holt-MSE or Holt-Corr1* *FR: SBA-MSE or Croston-MSE*

Table 3.48: Conclusions According to Analyses Conducted in Section 3.4.3.2 Automotive Data Set

ADI = 1.32

CV^2 =0.49	***"Erratic"*** Holt-Corr2	***"Lumpy"*** SL: Holt-Corr2 FR: Holt-MSE
	"Smooth" SL: Holt-Corr2 FR: SBA-MSE	***"Intermittent"*** SL: Holt-Corr2 FR: SBA-MSE

Table 3.49: Conclusions According to Analyses in Section 3.4.4.1-3 models-Electronics Data Set

ADI = 1.32

CV^2 =0.49

"Erratic" Holt-MSE	***"Lumpy"*** Holt-MSE
"Smooth" Holt-MSE	***"Intermittent"*** SL: Holt-MSE FR: SBA-MSE

Table 3.50: Conclusions According to Analyses in Section 3.4.4.2-3 models -Automotive Data Set

ADI = 1.32

CV^2 =0.49

"Erratic" Holt-MSE	***"Lumpy"*** Holt-MSE
"Smooth" Holt-MSE	***"Intermittent"*** Holt-MSE

Table 3.51: Conclusions According to Analyses Conducted in Section 3.4.5–Case Study

ADI = 1.32

CV^2 =0.49

"Erratic" Holt-Corr2	***"Lumpy"*** *Holt's Variants*
"Smooth" Holt-Corr2	***"Intermittent"*** *Holt's Variants*

This chapter aimed to address some of the highlighted research gaps; one of which is the lack of studies that use real data sets to assess the different forecasting models for service parts inventory management. Moreover, this chapter contributed to bridge the gap between research and practitioners by proposing a number of easily applicable forecasting-inventory models. Unlike the majority of the previous studies in the literature, the performance assessment of the mentioned models relied on their impact on inventory parameters rather than relying solely on forecasting accuracy. Holt-DES was selected for the comparative study for a number of plausible reasons as mentioned earlier in Section 3.3.1. Only a few papers considered Holt-DES for dealing with service parts inventory management. However, the results showed that Holt-DES has a promising and competitive performance compared to the commonly used methods; SBA and Croston.

Given the different demand patterns that are commonly found in the service parts management field, the selected models were analyzed for each of the four demand patterns. To the best of our knowledge, no study has previously considered the performance of forecasting-inventory models with respect to all four demand patterns.

Also, this chapter attempted to define regions of superior performance similar to what was proposed by the SBC classification scheme in Section 3.4.4. However, in this study Holt-DES was also considered and the classification was proposed based on the model's empirical inventory performance with respect to three parameters: on-hand inventory level, service level and fill rate. To the best of our knowledge this is the first study to propose such classification with an inventory performance criteria.

This chapter has provided some diverse insights regarding the performance of each considered model. However when attempting to answer one question you will find more questions to address. One significant and influential difference between the electronics data set and the automotive data set is the different life cycle phases. The SKUs of the electronics data set can be segmented according to the current life cycle phase whether that is introduction (“Ramp”), regular (“Stable”) or drop (“decline”) phase. This characteristic is not found in the automotive data set and to the best of our knowledge no study has previously attempted to investigate the performance of the models for each life cycle phase. This observation and a number of other assumptions will be further discussed and analyzed in future chapters.

Chapter 4

New Forecasting Methods

4.1. Introduction

This chapter aims to develop and test newly proposed techniques for spare parts demand forecasting. To address some of the main research needs discussed in Chapter 2 and deploy some of the valuable insights gained through experimental analyses in Chapter 3.

The literature discussed in Chapter 2 advocated for developing more robust forecasting techniques that take into consideration the life cycle (LC) process and transitions from one stage to another as well as integrating the installed base information and the risk of obsolescence (Babai, M.Z et al., 2017; Hu et al., 2018; Van der Auweraer et al., 2019). Another key suggestion was to try to identify points in the life cycle phase where installed base information could enhance the performance of forecasting techniques and inventory models (Van der Auweraer et al., 2019).

The experiments in Chapter 3 demonstrated that there is a potential advantage in enhancing the performance level and prediction accuracy of the forecast when considering a trend based approach (e.g. Holt). However, the accuracy of SBA, Croston, and Holt drops when demand exhibits a sudden sustained upward or downward trends. For the instance of a downward trend, SBA and Croston mainly struggled as they were not developed to capture trend nor update their demand estimates unless a non-zero demand occurred. Holt, on the other hand, was able to capture the trend in these cases but progressively continued to underestimate the demand owing to the continuous drop of the volume in demand. The inaccuracy of estimates generated by both SBA and Croston resulted in overestimation and over carrying of inventory levels to meet demand, while Holt underestimated and struggled to meet demand.

These scenarios occur frequently when dealing with spare parts forecasting, particularly as the product transitions through the different phases of the life cycle. Despite the fact that numerous studies have been conducted for forecasting intermittent demand, only a limited number of studies have addressed the trend element in the demand (Altay *et al.* 2008; Lindsey and Pavur 2005; Ghobbar and Friend 2003;Snyder 2002), some of which attributed the trend to the different life cycle (LC) stages of products. However, none of the previous studies attempted to incorporate the life cycle into the forecasting models. After studying the electronics data set, these LC trends are quite prevalent. For instance, many SKUs exhibit a clear increasing trend in demand during their early LC phase, which later shifts to a more constant followed by a decreasing trend, as the LC phase transitions from growth to maturity then decline. On a similar note, a direct relation between the installed base curve of a product and its components' demand curves exists, and they both tend to follow a regular product life cycle curve with three distinct phases (i.e., growth, maturity and decline) (Dekker et al., 2013). The shape of the components' demand curve is similar to the installed base curve of products but with a lag.

Moreover, the severity of the sudden shifts in trend and demand volume is closely linked to the industry considered. For example when dealing with short life, high tech products, the shifts tend to be more sudden, as opposed to other serviceable products with longer life spans. A very valid consideration is that the nature of the industry and products ought to be handled differently from one another. From Chapter 2, there were several papers that conducted different empirical investigations using and comparing data sets from the aircraft, automotive, and electronics industries. The papers attempted to derive general conclusions without considering the different nature of the industries (e.g., warranty periods, failure rates, and product life cycle). Given that the product's life cycle and warranty period have a direct impact on the resulting demand for spare parts, the suitability of the forecasting techniques ought to be tested and/or developed with the targeted industry sector in mind.

Four forecasting techniques will be developed, namely M1, M2, M3 and M4. Each method will deploy a different level of information, which will be discussed in great detail in Section 4.3. The proposed methods combine the findings and insights of both Chapters 2 and 3, to help ensure that the findings of this study is significant to this research area.

4.2. Defining LC phases

The LC phases of products and the transition between phases are very important aspects to consider and investigate when dealing with spare parts management (Babai, M.Z., *et al*., 2017; Hu *et al*., 2018; Van der Auweraer *et al*., 2019). Most studies in the literature that have investigated product life cycle aspects mainly addressed the issue of LC prediction, particularly the prediction of the obsolescence phase using sales volumes (Solomon *et al*., 2000; Sandborn *et al*., 2007; Ma and Kim, 2016; Jennings *et al*., 2016). For instance, Solomon *et al*. (2000) predicted the obsolescence period with the assumption of normality of the product life cycle (PLC) curve, where each LC stage was defined with respect to the distance from the mean (μ) measured in standard deviations (σ). The study used the sales volumes to plot the LC curve and then fitted a normal distribution, such that μ represented the sales peak. Ma and Kim (2016) deployed time series modelling to predict obsolescence in a PLC using sales data, where Jennings et al. (2016) utilized machine learning approaches to predict and label whether a product was active or obsolete. However, the latter two studies did not investigate or propose approaches to define each life cycle phase. Although Solomon *et al*. (2000) mainly focused on the prediction of obsolescence using sales data, they provided a method to classify and distinguish between the different LC phases. The main shortcoming was the normality assumption of the sales curve (Jennings *et al.,* 2016).

A practical approach to define and distinguish between different life cycle phases using the installed base values is developed. Three major life cycle phases were considered: ramp, regular (reg.), and drop. The ramp phase combines the introduction and growth stages in a product life cycle (PLC) featuring a clear upward trend. The reg. phase represents the maturity phase where demand stabilizes in a PLC, while the drop phase reflects the decline stage in a PLC, featuring a clear downward trend.

Instead of assuming normality of the sales curve or generating assumptions and predictions pertaining to the estimated peak sale μ and how the data deviates from μ, our approach relied on computing the period to period change R_t in the installed base values and the maximum installed base value each period up until period *t* IB_t^{Max}. The change rate R_t in the values of the installed base will be computed using Equation (4.1

$$R_t = \frac{IB_t}{IB_{t-n}} \qquad \text{Equation (4.1)}$$

where $IB_t$the install base at time *t* and *n* is the number of periods prior to *t*. After computing R_t, a growth percentage *GP* is selected based on the nature of the industry and the product. The LC phases are then categorized as follows: If $R_t \geq$ (1+ *GP)* then the LC cycle phase is ramp, as this indicates growth magnitude that is either greater than or equal to *GP*. However, if $R_t <$ (1+ *GP)*, then IB_t is then compared to the maximum install base value up until period *t* (IB_t^{Max}). If $\frac{IB_t^{Max} - IB_t}{IB_t^{Max}} < GP$ then the LC phase is reg. If $\frac{IB_t^{Max} - IB_t}{IB_t^{Max}} \geq GP$, then the LC phase is drop.

For example, assuming *GP = 0.2*, then if $R_t \geq 1.2$, the LC cycle phase is the ramp phase which indicates a growth magnitude that is either greater than or equal to 20%. However, if $R_t <$ 1.2, then the IB_t is then compared to the maximum install base value up until period *t* (IB_t^{Max}). If

$\frac{IB_t^{Max} - IB_t}{IB_t^{Max}} < 0.2$ then the LC phase will be considered in the Reg. phase. If $\frac{IB_t^{Max} - IB_t}{IB_t^{Max}} \geq 0.2$ this would indicate the Drop LC phase.

4.3. Developing New Forecasting Techniques for Spare Parts Demand

Four different prediction methods will be presented where the distinction between each one is linked with the level of information the method utilizes to generate the demand estimates. The first method (M1) will use only the observed demand information, while the second method (M2) will use both the observed demand and the LC phase information. The third method (M3) will utilize both the observed demand and the installed base information. The last method (M4) combines all the levels of information and will be referred to as M4. The type of information involved and how it is deployed by each method will be discussed below.

4.3.1. Method One – M1

Method one solely relies on the observed demand to generate the forecast estimate using three main elements: level, trend, and demand probability which are shown in Equation 4.2 through Equation 4.4 respectively. Each element is updated during each period whether or not the observed demand was zero or non-zero, which differs from both SBA and Croston where estimates are only updated if a non-zero demand occurs. Three distinct smoothing constants, α, β and γ, are used to update the estimates of the forecasting elements where l_t is the level estimate at period *t* and is updated with the smoothing constant α, T_t is the trend element that is updated with the smoothing constant β, and d_t is the demand observed at time *t.* The method follows the same assumptions as Croston and SBA, that demand is independent and identically distributed.

$$l_t = \alpha d_t + (1-\alpha)(l_{t-1} + T_{t-1}) \qquad \text{Equation 4.2}$$

$$T_t = \beta\,(l_t - l_{t-1}) + (1-\beta)\,T_{t-1} \qquad \text{Equation 4.3}$$

The probability of demand occurrence p_t gets updated each period using

Equation 4.4, where p'_t is the demand occurrence indicator, meaning that when $p'_t = 0$ the observed d_t is zero, and when $p'_t = 1$, a positive (non-zero) demand was observed. The equations below are calculated and updated similar to a simple exponential smoothing approach in the error form with smoothing a constant γ.

$$p_t = \begin{Bmatrix} if\ \ p'_t = 0 & p_t = p_{t-1} + \gamma(0 - p_{t-1}) \\ if\ \ p'_t = 1 & p_t = p_{t-1} + \gamma(1 - p_{t-1}) \end{Bmatrix} \qquad \text{Equation 4.4}$$

Using Equation 4.5, the forecast (f_t) at period t can be computed.

$$f_t = (l_t + T_t)\,p_t \qquad \text{Equation 4.5}$$

The TSB method discussed in Section 1.7.1.1 of Chapter 2, utilized the concept of calculating and updating the demand probability after each time period and used separate smoothing constants for demand probability and demand size. The TSB approach was proposed mainly to address the high risk of obsolescence which is inherent in the nature of service parts management. However, M1 combines the trend element to compute the demand size, in addition to calculating and updating the demand probability. The main goal is to account for both the underlying change in trend as well as to aid in accounting for the risk of obsolescence. Method 1 utilizes the information related to observed demand with the goal of being robust with respect to handling periods with zero demand as TSB, SBA and Croston intends to do, while also incorporating the trend estimate which relates to the LC phases.

When discussing the LC process, the approach of computing the trend in Equation 4.3 may be successful in capturing an ongoing upward or downward trend, which takes place during the ramp and drop phases, respectively. However, considering just the trend element may not result in the level of responsiveness desired when dealing with parts throughout the entire LC as they transition from one phase to the next. Forecasting method one only relies on local changes in demand which might cause the method to lag behind, resulting in less accurate performance. This will be addressed in the other methods.

4.3.2. Method Two- M2

Method Two closely resembles Method One in terms of the elements used to generate the prediction estimates, which are the level, trend, and demand probability. However, Method Two additionally utilizes the LC phase information to alter the process of updating the probability of demand occurrence (p_t) shown in

Equation 4.6. The values used for the smoothing constant γ vary depending on the LC stage ($\gamma^{\boldsymbol{LC}}$). Secondly, to help the forecasting technique deal better with the transition between LC phases, the model forces a one-time probability estimate (e.g., probabilities (p_t) of 1, 0.9, and 0.6 for ramp, reg., and drop respectively). The two alterations proposed in M2 are mainly implemented to overcome the shortcomings of M1 and to better handle the transition from one LC phase to another, where the forecast estimate is then computed using Equation 4.5.

$$p_t = \begin{cases} if\ \ p'_t = 0 & p_t = p_{t-1} + \gamma^{LC}(0 - p_{t-1}) \\ if\ \ p'_t = 1 & p_t = p_{t-1} + \gamma^{LC}(1 - p_{t-1}) \end{cases} \qquad \text{Equation 4.6}$$

4.3.3. Method Three- M3

This method investigates the potential of utilizing the observed demand data in addition to incorporating the rate at which the installed values change (R_t). This relates to the observation highlighted by Dekker (2013) that the demand curve for parts follow the curve of the PLC. Method three relies on three elements to generate demand estimates; level (Equation 4.2), trend (Equation

4.3), and global level (Equation 4.7). The global level (GL_t) attempts to update the level l_{t-1} using a change rate (R_t) in the values of installed base as seen in Equation 4.7, while the demand estimate at period *t* is then computed using Equation 4.8.

$$GL_t = l_{t-1} + \alpha(d_t - l_{t-1})(R_t) \qquad \text{Equation 4.7}$$

$$f_t = (GL_t + T_t) \qquad \text{Equation 4.8}$$

4.3.4. Method Four- M4

Finally, method four combines all three levels of information; the observed demand, the installed base values, and the LC phase. M1, M2, and M3 will be integrated to estimate the demand. The elements used to generate the demand estimate are the global level (GL_t), trend and demand probability. The three equations used to calculate the demand estimate are Equation 4.7, Equation 4.9, and Equation 4.6. The assumptions regarding the demand probability updates follow the ones made for M2, while the demand estimate at period *t* is then computed using Equation 4.10.

$$T_t = \beta\,(GL_t - GL_{t-1}) + (1-\beta)\,T_{t-1} \qquad \text{Equation 4.9}$$

$$f_t = (GL_t + T_t) * p_t \qquad \text{Equation 4.10}$$

4.4. Numerical Investigation

To evaluate and compare the accuracy level of each of the four proposed forecasting techniques, an extensive numerical investigation will be performed. Three sets of data were generated to test the validity of the assumptions made for each forecasting method. The investigation examined the performance of the four proposed methods, SBA, Croston, and Holt. The numerical investigation will assess the forecast accuracy of each technique with respect to each LC phase and how well it adapts in the transition from one LC phase to another.

The data sets that are generated depict three different scenarios associated with the level of zero occurrences in demand observations. Studies in the literature have argued that the main hurdle when forecasting spare parts demand is dealing with the zero occurrences (Croston, 1972; Syntetos, 2001; Prestwich et al., 2014). Therefore, the data sets were created to have different degrees of intermittency by varying the failure rates.

To generate a data set that closely resembles real life scenarios, three elements were considered: a sales curve, in-warranty (IW) installed base, and a component's failures. The sales curve was defined using a Bass-diffusion model, which is one of the most widely used and accepted theories for estimating sales curves (Bass, 2004; Guo, 2013; Lee et al., 2014; Kim and Hong, 2015). The Bass diffusion model relies on three parameters: r, q and m, which represent the coefficient of innovation, coefficient of imitation and the market size, respectively. Using the Bass model, sales at each period t, Sales S_t was computed using Equation 4.11 where $Y(t)$ is the cumulative adopters at period t. To compute the installed base IB_t at period t, sales S_t at period t are added to the installed base at period $t-1$ (IB_{t-1}), and then both the sum of all the failures at time t and the number of products that come out of warranty at time t are subtracted. For a warranty length of w, S_{t-w}^{NF} products come out of warranty at time t, where S_{t-w}^{NF} equals the number of sales that occurred in ($t-w$) that have not failed by time t. the computation of IB_t is shown in Equation 4.12. The number of failures at time t (f_t) was generated by using a binomial process with a fixed failure probability (p) and a number of trials equal to IB_{t-1}.

$$S_t = rm + (q-r)Y(t)-(q/m)[Y(t)]^2 \qquad \text{Equation 4.11}$$

$$IB_t = S_t + IB_{t-1} - \sum f_t - S_{t-w}^{\mathrm{NF}} \qquad \text{Equation 4.12}$$

The three data sets generated followed the exact same assumptions. The only parameter that varied was the probability of failure, in order to examine different levels of intermittency. The data periods represented weeks, while the span of the sales curve covered 145 weeks, and the warranty period was assumed to be 52 weeks. The values of Bass diffusion model parameters *r*, *q*, and *m* were 0.0004, 0.09, and 11,000, respectively. The selection of these parameters served the purpose of generating a wide centered spread from the sales curve. Some studies have addressed the topic of estimating and optimizing the values of the Bass model parameters (Srinivasan and Mason, 1986; Sultan et al., 2000; Massiani and Gohs, 2015), however, this is beyond the scope of this research. The data sets will be referred to as slightly, moderately and highly intermittent with fixed failure probabilities of 0.0002, 0.0009 and 0.00007, respectively. For each scenario, 600 different SKUs were generated.

4.4.1. **Comparative Analysis of the Accuracy of Forecasting Techniques: FLC**

The accuracy of the forecasting techniques will be measured by the mean square error (MSE) and the mean error (ME). The analyses conducted will explore parts throughout the full life cycle (i.e., Ramp, Reg., and Drop). For each SKU, the parameters for the forecasting techniques were optimized by minimizing the MSE of the first 13 data points ("In-Sample points"). Given the presence of random zeros in the data, the 13 point range starts with the first non-zero demand point. The points that are not included for the optimization process are referred to as "Out of Sample" points and all the results reported in this chapter were computed using these points. To ease the comparison across all of the different methods and data sets, the constant initial values used for the newly introduced methods M1, M2, and M4 were the same across all three scenarios. However, parametric analyses were conducted and the results of using different values for the parameters of the new methods can be found in sections 6.2.B.10 through 6.2.B.13 of the appendix. The insights and observations regarding using different values for the forecasting methods will be discussed later in this chapter. For M1, the initialization of the demand probability was set to one with a smoothing constant γ of 0.02. For both M2 and M4, the one-time probability estimate values that are applied according to the LC phases are 1.0, 0.9, and 0.6 for the Ramp, Reg., and Drop phases respectively. The smoothing constant γ values of 0.001, 0.001, and 0.02 were used to update the probability of occurrence for Ramp, Reg, and Drop respectively. The computations and related equations of each of the mentioned methods are discussed in detail in sections 4.3.1, 4.3.2 and 4.3.4.

4.4.1.1. Data Set One (DS1): Slightly Intermittent (FLC)

The first data set represents the case where there are very few intermittent data (i.e., zero points). An overview of DS1 characteristics can be found in Table 4.1. Figure 4-1 shows an example of the demand generated for parts in data set one.

Table 4.1: Summary of DS1 Data Characteristics

	Demand	***ADI***	CV^2
Min	438.0	1.31	0.35
Max	589.0	1.78	0.66
Average	497.4	1.49	0.48
Median	497.0	1.49	0.48
25%ile	483.0	1.43	0.45
75%ile	483.0	1.55	0.52

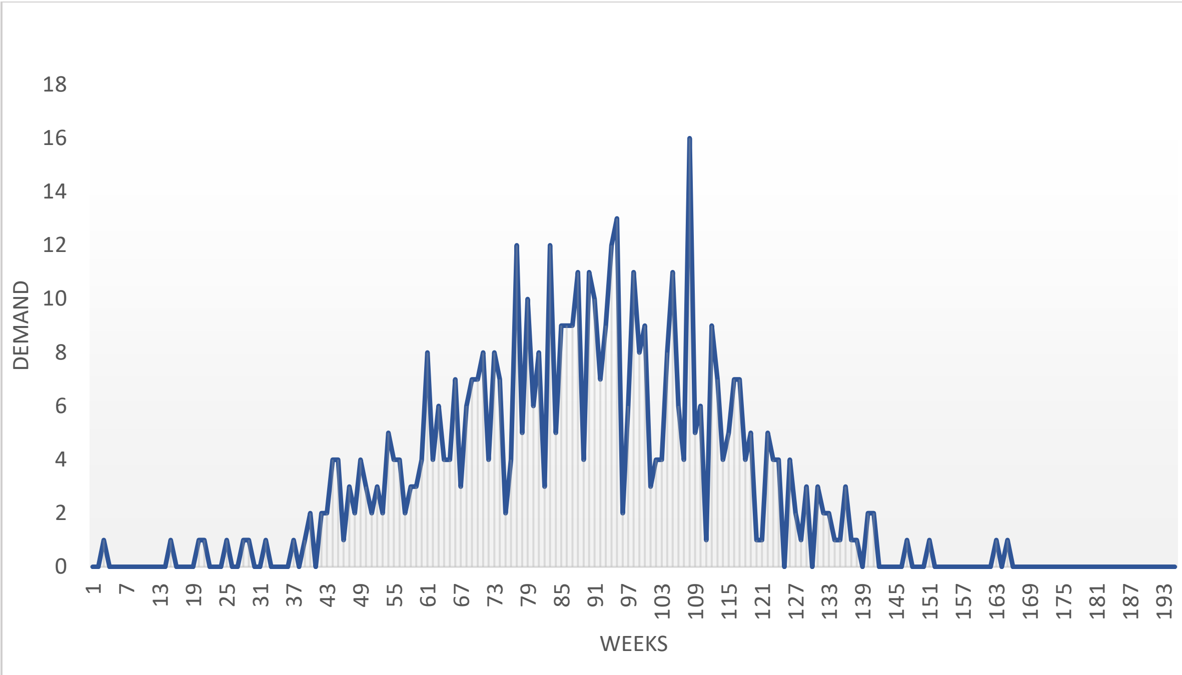

Figure 4-1: Example of an Intermittent Demand Data- DS1 SKU

Table 4.2 shows the average and standard deviations of both the MSE and ME for all four new methods as well as Croston, SBA, and Holt. This demonstrates that the M2 and M4 methods are better in terms of MSE. The overall results showed that the most accurate forecasting technique when considering the MSE error metric was M4 followed by M2. From Table 4.2 and Figure 4-1, the M2 and M4 methods have less variability as compared to the rest of the techniques. The box plots are shown in Figure 4-2 blocking on part numbers.

Statistical analysis was conducted to compare the MSE performance means of the forecast models Croston, SBA, Holt, and the four new methods. Since there are 600 part numbers for each forecasting method, the Central Limit Theorem can be used to state that the distribution of the means is normally distributed. Next based on Levene's statistic seen in Figure 4-3, we reject the null hypothesis that the variances are equal and conclude they are not equal. Therefore, Welch's means test, instead of standard ANOVA, is used to reject the null hypothesis, that the means of the MSE for all methods are equal, based on a p-value of <0.0001.

Table 4.2: Averages and STDs of ME and MSE - Data Set One (FLC)

Forecasting Technique	ME Means (STD)	MSE Means (STD)
Croston	-0.14 (0.05)	6.12 (1.07)
SBA	-0.07 (0.05)	6.03 (0.99)
Holt	0.01 (0.07)	4.00 (0.47)
M1	0.30 (0.09)	4.06 (0.41)
M3	-0.02 (0.08)	4.16 (0.55)
M2	0.17 (0.03)	3.71 (0.27)
M4	0.14 (0.02)	3.68 (0.27)

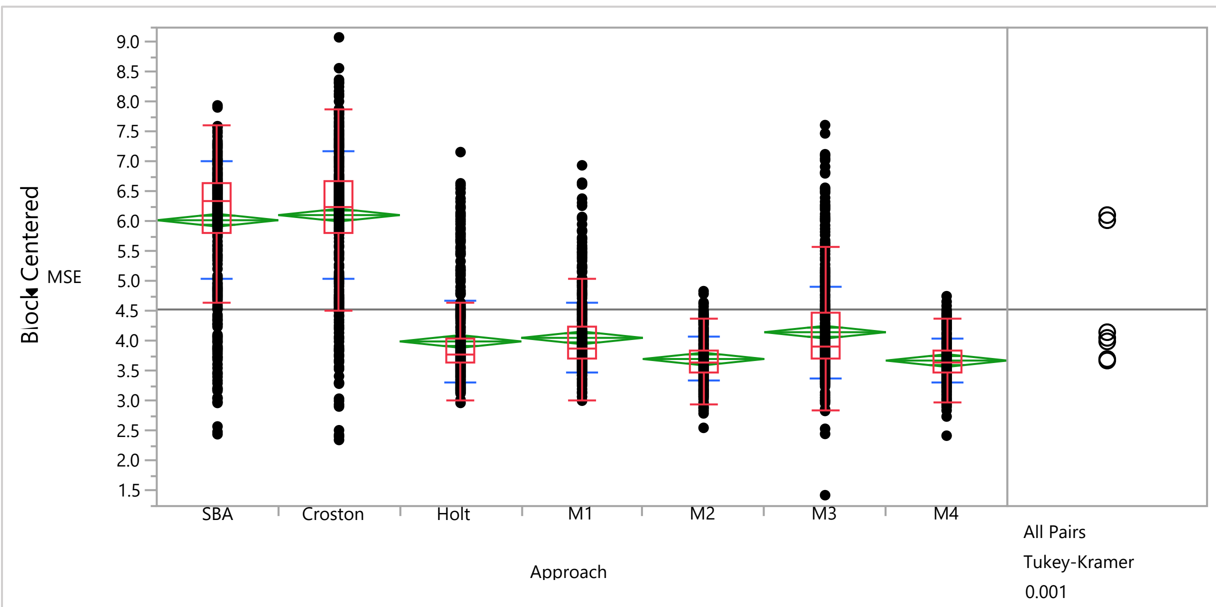

Figure 4-2: Box Plots of MSE - DS1 (FLC)

Test	F Ratio	DFNum	DFDen	Prob > F
O'Brien[.5]	60.4370	6	4193	<.0001*
Brown-Forsythe	67.6723	6	4193	<.0001*
Levene	102.7720	6	4193	<.0001*
Bartlett	201.3814	6	.	<.0001*

Welch's Test

Welch Anova testing Means Equal, allowing Std Devs Not Equal

F Ratio	DFNum	DFDen	Prob > F
957.9808	6	1831.2	<.0001 *

Figure 4-3: Levene's Test for Equal Variances and Welch's Test for MSE FLC

Since at least one mean is different, the Tukey Kramer multi-means comparison test is applied to determine which methods are statistically different. The results are shown in Table 4.3. Owing to there being 600 data points per group, an alpha level of 0.001 will be used to avoid detecting insignificant MSE levels. Since each letter represents a statistically different group, both Croston and SBA achieved a significantly higher MSE compared to Holt, M1, and M3, which are statistically higher than M2 and M4. No statistical difference was found between M2 and M4. The full analysis and the individual comparisons of the new methods with Holt, SBA and Croston can be found in section 6.2.B.1 of the appendix.

Table 4.3: Tukey-Kramer's Comparison of Accuracy Measures for FLC Data Set 1

Methods	Levels			MSE
Croston	A			6.12
SBA	A			6.03
M3		B		4.16
M1		B		4.06
Holt		B		4.00
M2			C	3.71
M4			C	3.68

4.4.1.2. Data Set Two (DS2): Moderately Intermittent (FLC)

Table 4.4 displays an overview of the DS2 characteristics. This shows that the average demand is less than DS1, owing to the more intermittent data. Figure 4-4 shows an example of the demand generated for parts in data set two. Table 4.5 shows the average and standard deviations of both the MSE and ME for all four new methods, as well as Croston, SBA, and Holt. The overall results showed that the most accurate forecasting technique when considering the MSE as the error metric was M4 followed by M2 and M3. The results of the ME metric showed that for this data set Croston, SBA, and Holt had negative bias on average (i.e., overestimates demand), while the rest of the models had positive bias. From Table 4.5 and Figure 4-5, SBA and Croston have more variability as compared to the rest of the techniques based on MSE.

Table 4.4: Summary of DS2 Data Characteristics

	Demand	*ADI*	CV^2
Min	79.00	1.83	0.18
Max	145.00	3.07	0.62
Average	113.02	2.33	0.33
Median	113.00	2.32	0.32
25%ile	106.00	2.18	0.28
75%ile	120.00	2.47	0.36

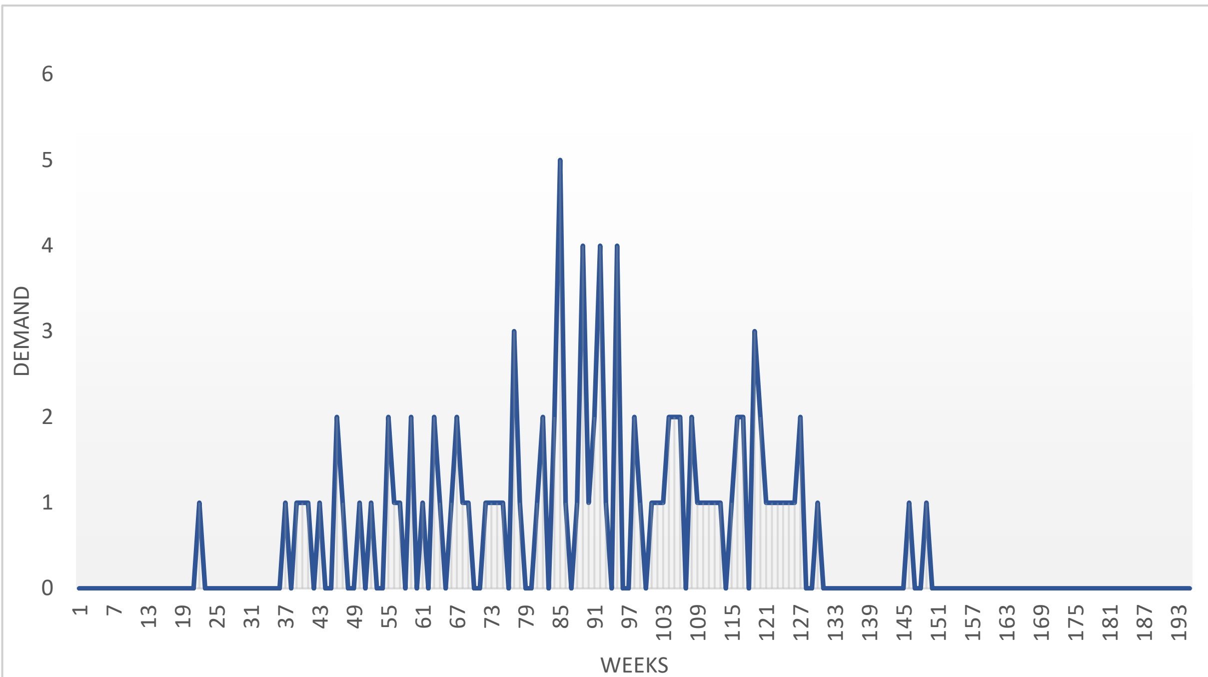

Figure 4-4: Example of an Intermittent Demand Data- DS2 SKU

Table 4.5: Averages and STDs of ME and MSE - Data Set Two (FLC)

Forecasting Technique	ME Means (STD)	MSE Means (STD)
Croston	-0.17 (0.06)	0.99 (0.080)
SBA	-0.06 (0.05)	0.93 (0.040)
Holt	-0.14 (0.10)	0.84 (0.025)
M1	0.20 (0.05)	0.85 (0.020)
M3	0.00 (0.02)	0.82 (0.024)
M2	0.06 (0.01)	0.82 (0.025)
M4	0.01 (0.02)	0.80 (0.025)

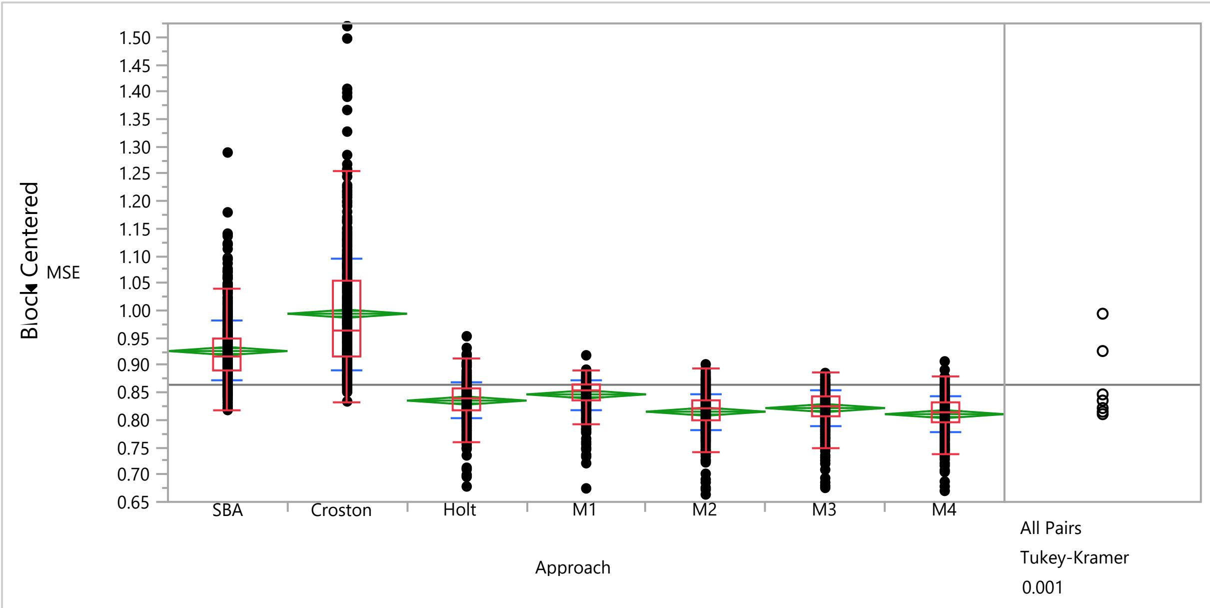

Figure 4-5: Box Plots of MSE – DS2 (FLC)

Statistical analysis was conducted for this data set following the same assumptions and steps described in section 4.4.1.1. The results of Tukey's test conducted at a *p*-value of 0.001 in Table 4.6 demonstrate that Croston achieved significantly higher average MSE compared to SBA which was statistically higher than all the other methods. M2, M3, and M4 had a statistically lower MSE compared to all the methods but were not different among themselves. The full analysis and the individual comparisons of the new methods with Holt, SBA and Croston can be found in section 6.2.B.2 of the appendix.

Table 4.6: Tukey-Kramer's Comparison of Accuracy Measures for FLC Data Set 2

Method	Levels				MSE
Croston	A				0.99
SBA		B			0.93
M1			C		0.85
Holt			C		0.84
M3				D	0.82
M2				D	0.82
M4				D	0.81

4.4.1.3. Data Set Three (DS3): Highly Intermittent (FLC)

An overview of DS3 characteristics can be found in Table 4.7, while Figure 4-6 shows an example of the demand generated for parts in data set three. Table 4.8 shows the average and standard deviations of both MSE and ME for all four new methods, as well as Croston, SBA, and Holt. Table 4.8 demonstrates that all of the proposed methods had a smaller MSE compared to Holt, SBA and Croston. The results of the ME metric showed that for this data only Croston and SBA had negative bias on average, while the rest of the models had positive bias.

Table 4.7: Summary of DS3 Data Characteristics

	Demand	***ADI***	CV^2
Min	22.00	3.07	0.03
Max	58.00	7.68	0.39
Average	39.39	4.48	0.16
Median	39.00	4.42	0.16
25%ile	35.00	4.00	0.11
75%ile	43.00	4.87	0.20

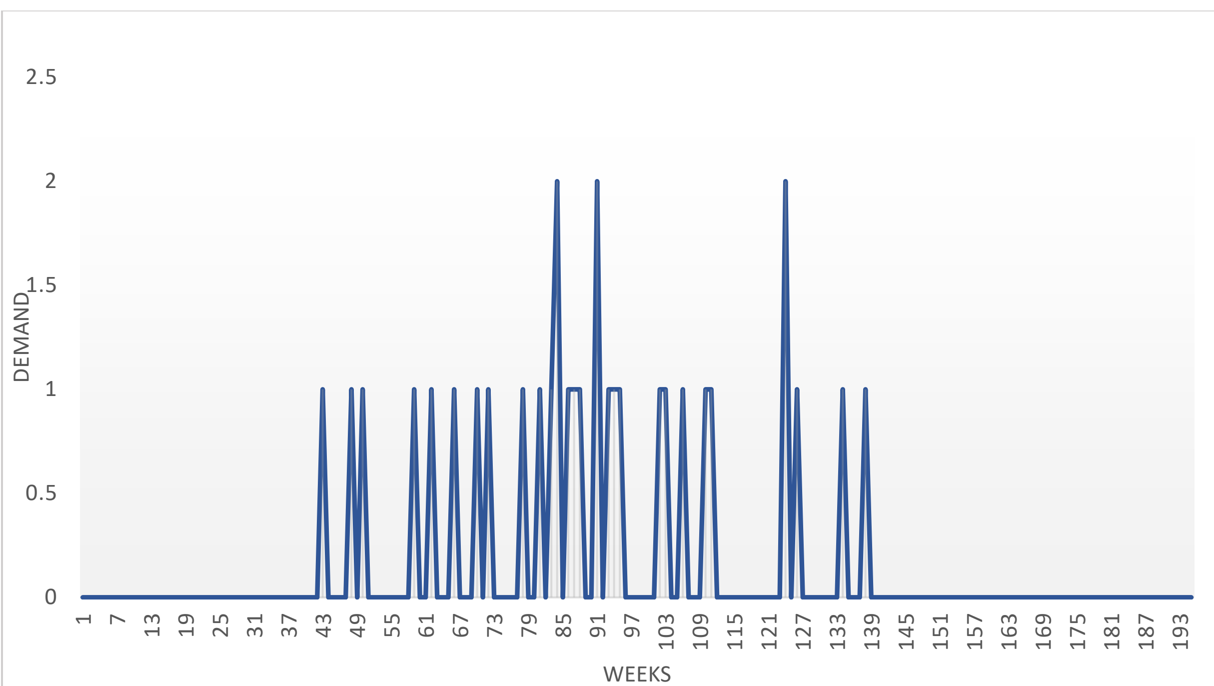

Figure 4-6: Example of an Intermittent Demand Data- DS3 SKU

Table 4.8: Averages and STDs of ME and MSE - Data Set Three (FLC)

Forecasting Technique	ME Means (STD)	MSE Means (STD)
Croston	-0.17 (0.04)	0.33 (0.035)
SBA	-0.10 (0.03)	0.31 (0.025)
Holt	0.02 (0.03)	0.30 (0.013)
M1	0.12 (0.03)	0.29 (0.011)
M3	0.01 (0.01)	0.29 (0.013)
M2	0.04 (0.00)	0.29 (0.012)
M4	0.02 (0.01)	0.29 (0.014)

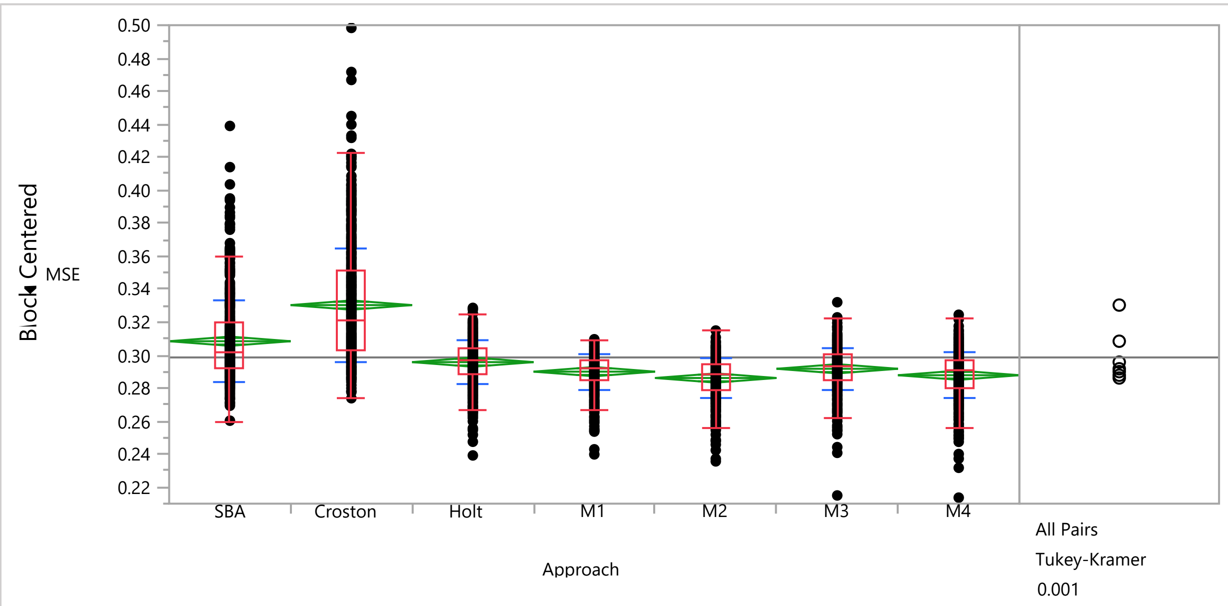

Figure 4-7: Box Plots of MSE – DS2 (FLC)

A statistical analysis was conducted for this data set following the same assumptions and steps described in section 4.4.1.1. The results of Tukey's test conducted at a p-value of 0.001 are shown in Table 4.9. The results showed that M4, M2 and M1 achieved significantly lower MSE compared to Croston, SBA and Holt. Both Holt and M3 achieved significantly lower MSE compared to Croston, SBA. Croston achieved the highest MSE followed by SBA and Holt. The full analysis and the individual comparisons of the new methods with Holt, SBA and Croston can be found in section 6.2.B.3 of the appendix.

Table 4.9: Tukey-Kramer's Comparison of Accuracy Measures for FLC Data Set 3

Method	Levels					MSE
Croston	A					0.330
SBA		B				0.308
Holt			C			0.296
M3			C	D		0.292
\M1				D	E	0.290
M4				D	E	0.288
M2					E	0.286

Owing to the very large variations of Croston and SBA compared to the rest of the methods which can cause some confounding, Tukey-Kramer test was repeated where Croston and SBA have been removed. The results in Table 4.10 show that all of the methods were significantly different than one another except for M2 and M4 which performed similarly and achieved the lowest MSE values.

Table 4.10: Tukey's Comparison Accuracy for FLC Data Set 3 with Croston and SBA Removed

Method	Levels				MSE
Holt	A				0.296
M3		B			0.292
M1			C		0.290
M4				D	0.288
M2				D	0.286

4.4.2. Comparative Analysis of the Accuracy of Forecasting Techniques: Ramp-Reg.

The previous analysis was performed on the full life cycle while this section will evaluate only the ramp phase followed by the regular phase of the life cycle to determine if certain forecasting methods work better in the Ramp-Reg. phase. The analyses will investigate the accuracy of the forecasting techniques only on the first 103 points of the generated demand data which represent the ramp through regular phases only (i.e., the install base is increasing owing to being in the introduction phase of a PLC, which correlates to service demand potentially increasing).

4.4.2.1. Data Set One (DS1): Slightly Intermittent (Ramp-Reg.)

Table 4.11 shows the average and standard deviations of both the MSE and ME for all four new methods as well as Croston, SBA, and Holt. The results of the ME metric demonstrate that for this data, all of the models had positive bias, which lead to higher MSE values. M2 and M4 had the lowest MSE compared to the rest of the models.

Table 4.11: Averages and STDs of ME and MSE - Data Set One (Ramp-Reg)

Forecasting Technique	ME Means (STD)	MSE Means (STD)
Croston	1.51 (0.26)	8.50 (1.26)
SBA	1.75 (0.27)	9.27 (1.05)
Holt	0.10 (0.27)	6.01 (0.47)
M1	0.73 (0.23)	6.37 (0.53)
M3	0.19 (0.19)	6.02 (0.47)
M2	0.32 (0.07)	5.85 (0.48)
M4	0.34 (0.06)	5.86 (0.45)

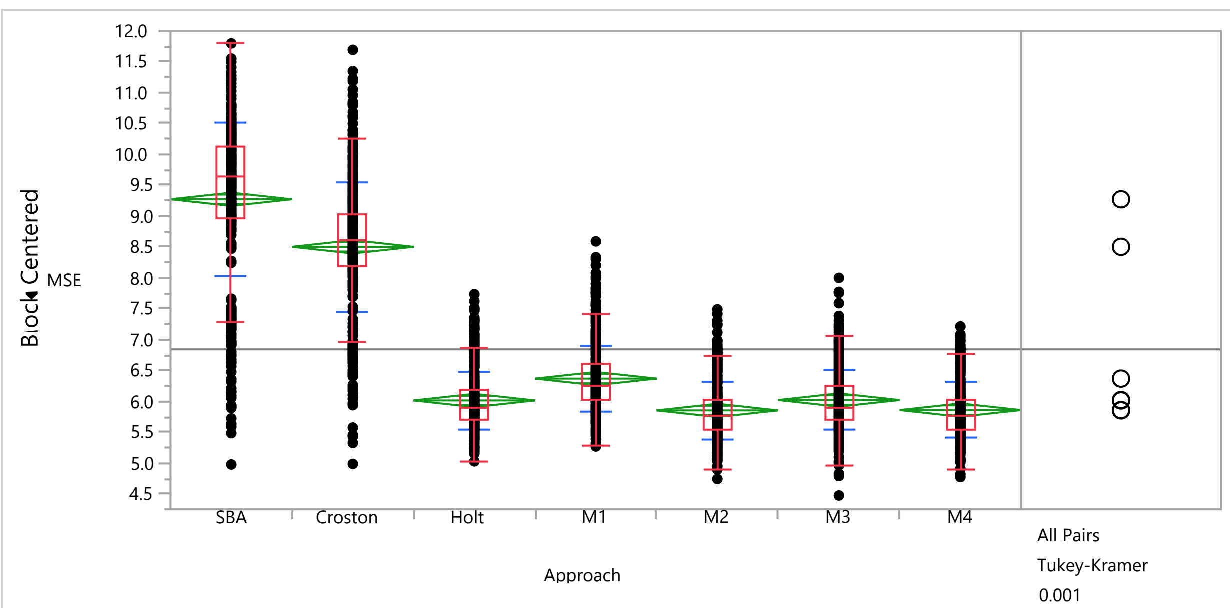

Figure 4-8: Box Plots of MSE – DS1 (Ramp-Reg)

A statistical analysis was conducted for this data set following the same assumptions and steps described in section 4.4.1.1. The results of Tukey's test conducted at a p-value of 0.001 are shown in Table 4.12. The results showed that M2, M4, Holt, and M3 achieved a significantly lower MSE compared to M1, Croston and SBA. The highest MSE was achieved by SBA followed by Croston then M1. The full analysis and the individual comparisons of the new methods with Holt, SBA and Croston can be found in section 6.2.B.46.2.B.3 of the appendix.

Table 4.12: Tukey-Kramer's Comparison of Accuracy Measures for Ramp-Reg Data Set 1

Method	Level				MSE
SBA	A				9.27
Croston		B			8.50
M1			C		6.37
M3				D	6.02
Holt				D	6.01
M4				D	5.86
M2				D	5.85

Since the variations associated with SBA and Croston are almost three times as much as the other methods, the overall confounding of the last four methods could be attributed to the large difference in variation. Therefore, Table 4.13 shows the results of the Tukey comparison test when Croston and SBA are removed. It demonstrates that M2 and M4 are statistically less than M3 and Holt, which are statistically less than M1.

Table 4.13: Tukey-Kramer's Comparison of Accuracy Measures for Ramp-Reg DS1 with Croston and SBA Removed

Method	Level			MSE
M1	A			6.37
M3		B		6.02
Holt		B		6.01
M4			C	5.86
M2			C	5.85

4.4.2.2. Data Set Two (DS2): Moderately Intermittent (Ramp-Reg.)

Table 4.14 shows the average and standard deviations of both the MSE and ME for all four new methods as well as Croston, SBA, and Holt. The results showed that M4 and M2 achieved the lowest MSE followed by M3. The results of the ME metric showed that for this data all of the models had positive bias.

Table 4.14: Averages and STDs of ME and MSE - Data Set Two (Ramp-Reg)

Forecasting Technique	ME Means (STD)	MSE Means (STD)
Croston	0.32 (0.05)	1.50 (0.092)
SBA	0.39 (0.06)	1.53 (0.066)
Holt	0.04 (0.06)	1.47 (0.032)
M1	0.38 (0.06)	1.53 (0.027)
M3	0.06 (0.03)	1.45 (0.035)
M2	0.10 (0.02)	1.44 (0.038)
M4	0.09 (0.01)	1.44 (0.034)

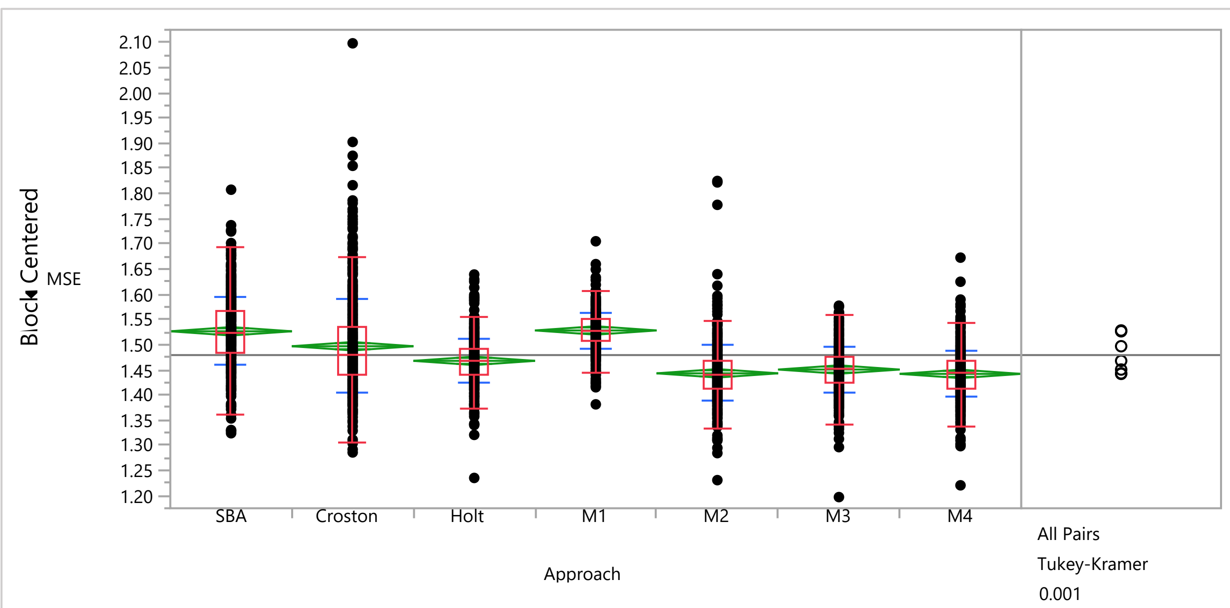

Figure 4-9: Box Plots of MSE – DS2 (Ramp-Reg)

Table 4.15 displays the results of Tukey's test conducted at a *p*-value of 0.001. The results showed that M2, M4, and M3 achieved statistically lower MSE compared to M1, Croston, Holt, and SBA. Holt achieved significantly lower MSE compared to M1, Croston, and SBA. M1 and

SBA then Croston achieved the highest MSE. The full analysis and the individual comparison of the new methods with Holt, SBA and Croston can be found in section 6.2.B.5 of the appendix.

Table 4.15: Tukey-Kramer's Comparison of Accuracy Measures for Ramp-Reg Data Set 2

Method	Level				MSE
M1	A				1.53
SBA	A				1.53
Croston		B			1.50
Holt			C		1.47
M3				D	1.45
M2				D	1.44
M4				D	1.44

4.4.2.3. Data Set Three (DS3): Highly Intermittent (Ramp-Reg.)

Table 4.16 shows the average and standard deviations of both the MSE and ME for all four new methods, as well as Croston, SBA, and Holt. The results showed that both Croston and SBA achieved the lowest MSE followed by the new methods and Holt. The results of the ME metric showed that for this data, all of the models had positive bias, except for Croston. However, as seen in Figure 4-10, the variations of Croston and SBA are still much larger than the other methods.

Table 4.16: Averages and STDs of ME and MSE - Data Set Three (Ramp-Reg)

Forecasting Technique	ME Means (STD)	MSE Means (STD)
Croston	-0.00 (0.06)	0.548 (0.065)
SBA	0.08 (0.04)	0.546 (0.051)
Holt	0.05 (0.05)	0.577 (0.032)
M1	0.22 (0.02)	0.578 (0.027)
M3	0.05 (0.01)	0.572 (0.035)
M2	0.06 (0.01)	0.563 (0.038)
M4	0.07 (0.01)	0.560 (0.046)

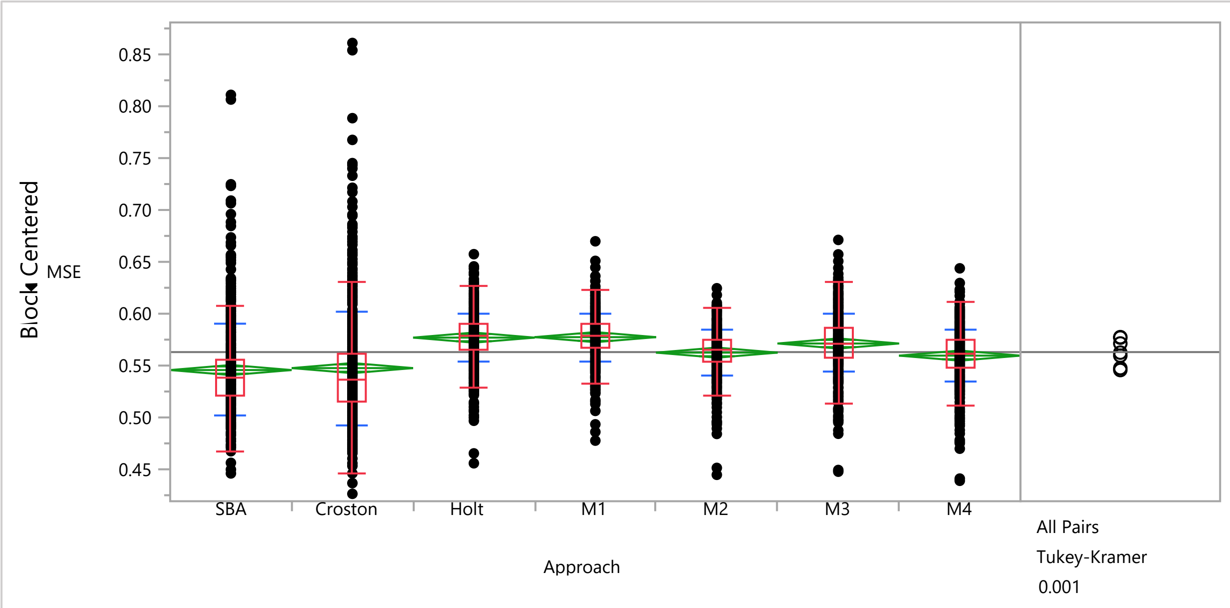

Figure 4-10: Box Plots of MSE – DS3 (Ramp-Reg)

Table 4.17 displays the results of Tukey's test conducted at a p-value of 0.001. The results showed that both SBA and Croston achieved statistically lower MSE compared to all the models. M4 and M2 achieved statistically lower MSE compared to Holt, M1, and M3. The full analysis and the individual comparison of the new methods with Holt, SBA and Croston can be found in section 6.2.B.6 of the appendix.

Table 4.17: Tukey-Kramer's Comparison of Accuracy Measures for Ramp-Reg Data Set 3

Method	Level			MSE
M1	A			0.578
Holt	A			0.577
M3	A			0.572
M2		B		0.563
M4		B		0.560
Croston			C	0.548
SBA			C	0.546

4.4.3. Comparative Analysis of the Accuracy of Forecasting Techniques: Reg.-Drop

This section will evaluate the situation where the regular phase is followed by the drop phase of the life cycle, to determine if certain forecasting methods work better during the end of the product life cycle. In this section, the accuracy of the forecasting techniques using only the last 118 points of demand data will be investigated.

4.4.3.1. Data Set One (DS1): Slightly Intermittent (Reg.-Drop)

Table 4.18 shows the average and standard deviations of both the MSE and ME for all four new methods, as well as Croston, SBA, and Holt. The results showed that M4 achieved the lowest MSE, followed by Holt. The results of the ME metric showed that for this data, Croston, SBA and M3 had negative bias on average, while the rest of the models had positive bias. As seen in Figure 4-11, Croston and SBA continued to have higher variation during this LC phase as well.

Table 4.18: Averages and STDs of ME and MSE - Data Set One (Reg-Drop)

Forecasting Technique	ME Means (STD)	MSE Means (STD)
Croston	-1.17 (0.27)	4.22 (0.80)
SBA	-1.00 (0.25)	3.87 (0.56)
Holt	0.07 (0.27)	2.69 (0.91)
M1	0.08 (0.20)	2.82 (0.16)
M3	-0.10 (0.08)	3.12 (0.47)
M2	0.13 (0.12)	2.90 (0.22)
M4	0.02 (0.09)	2.65 (0.31)

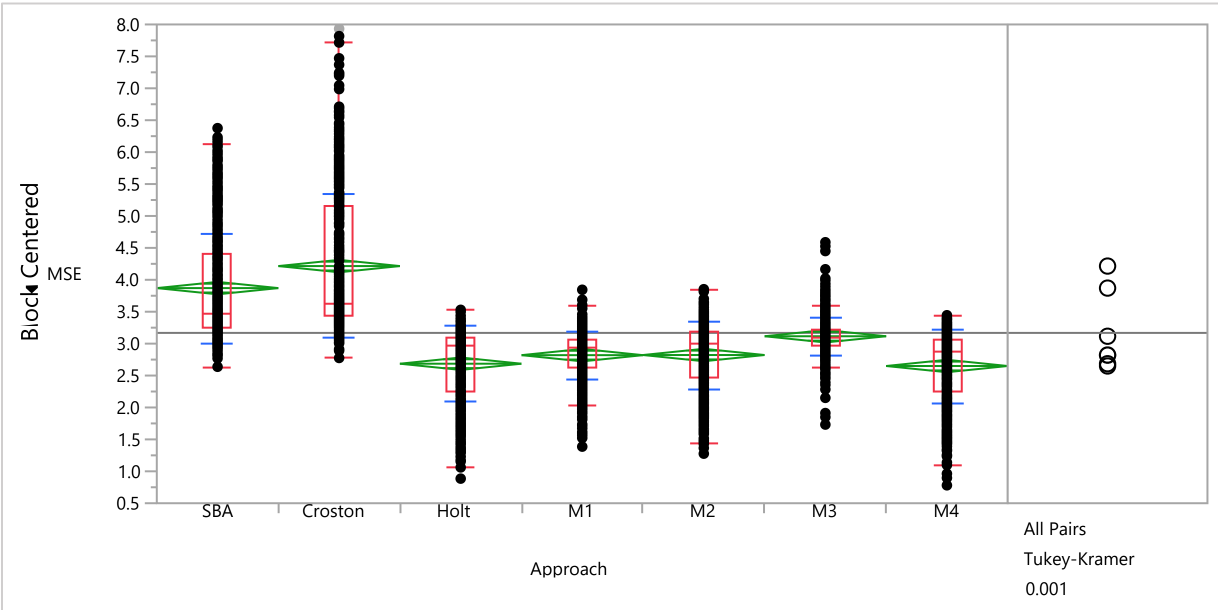

Figure 4-11: Box Plots for MSE - Data Set One (Reg-Drop)

The results of Tukey's test conducted at a p-value of 0.001 are shown in Table 4.19. The results showed that M4 statistically achieved the lowest MSE compared to all the models excluding Holt. M2, M3, SBA and Croston were significantly different than one another where Croston achieved the highest MSE, followed by SBA. Owing to the high variability of SBA and Croston, Tukey's test was repeated excluding both methods. The results in Table 4.20 show M4 and Holt performed similarly and achieved significantly lower MSE compared to M1, M2 and M3.The full analysis and the individual comparisons of the new methods with Holt, SBA and Croston can be found in section 6.2.B.7 of the appendix.

Table 4.19: Tukey-Kramer's Comparison of Accuracy Measures for Reg-Drop DS1

Method	Levels					MSE
Croston	A					4.22
SBA		B				3.87
M3			C			3.12
M2				D		2.82
M1				D		2.82
Holt				D	E	2.69
M4					E	2.65

Table 4.20: Tukey's Comparison Accuracy for Reg-Drop DS1with Croston and SBA Removed

Method	Levels			MSE
M3	A			3.12
M2		B		2.82
M1		B		2.82
Holt			C	2.69
M4			C	2.65

4.4.3.2. Data Set Two (DS2): Moderately Intermittent (Reg.-Drop)

Table 4.21 shows the average and standard deviations of both MSE and ME for all four new methods, as well as Croston, SBA, and Holt. The results showed that the lowest MSE was achieved by M1, M2, and M4 as seen in Figure 4-12. The results of the ME metric showed that for this data, Croston, SBA and M3 had negative bias on average, while the rest of the models had positive bias.

Table 4.21: Averages and STDs of ME and MSE - Data Set Two (Reg-Drop)

Forecasting Technique	ME Means (STD)	MSE Means (STD)
Croston	-0.50 (0.08)	0.83 (0.14)
SBA	-0.43 (0.08)	0.78 (0.13)
Holt	0.00 (0.08)	0.62 (0.05)
M1	0.061 (0.01)	0.57 (0.06)
M3	-0.016 (0.03)	0.61 (0.05)
M2	0.084 (0.01)	0.56 (0.07)
M4	0.076 (0.02)	0.55 (0.06)

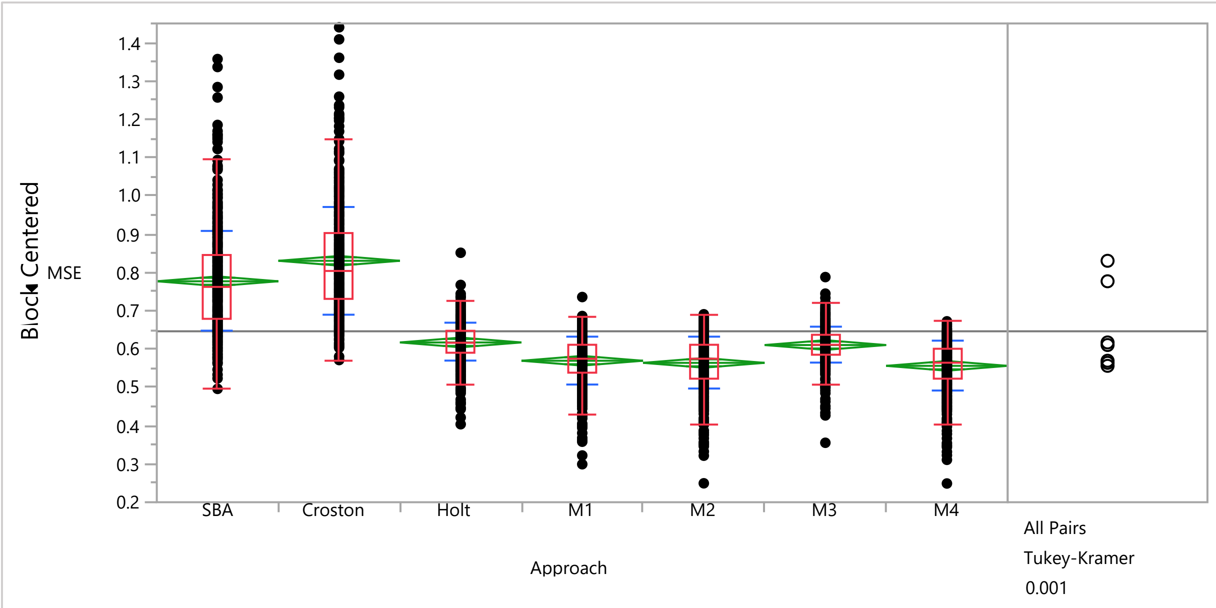

Figure 4-12: Box Plots for MSE - Data Set Two (Reg-Drop)

A statistical analysis was conducted for this data set following the same assumptions and steps described in Section 4.4.1.1. The results of Tukey's test conducted using a *p*-value of 0.001 are shown in Table 4.22. The results showed that M4, M2, and M1 achieved statistically lower MSE compared to the rest of the methods. Croston achieved the highest MSE, followed by SBA and there was no statistical difference captured between Holt and M3. The full analysis and the individual comparisons of the new methods with Holt, SBA and Croston can be found in Section 6.2.B.8 of the appendix.

Table 4.22: Tukey-Kramer's Comparison of Accuracy Measures for Reg-Drop DS2

Method	Levels				MSE
Croston	A				0.83
SBA		B			0.78
Holt			C		0.62
M3			C		0.61
M1				D	0.57
M2				D	0.56
M4				D	0.55

4.4.3.3. Data Set Three (DS3): Highly Intermittent (Reg.-Drop)

Table 4.23 shows the average and standard deviations of both the MSE and ME for all four new methods, as well as Croston, SBA, and Holt. The results showed that M4, M2 and M1 achieved the lowest MSE. Croston achieved the highest MSE compared to all of the models, followed by SBA. The results of the ME metric showed that for this data, Croston and SBA had negative bias on average, while the rest of the models had positive bias.

Table 4.23: Averages and STDs of ME and MSE - Data Set Three (Reg-Drop)

Forecasting Technique	ME Means (STD)	MSE Means (STD)
Croston	-0.27 (0.05)	0.26 (0.051)
SBA	-0.23 (0.05)	0.24 (0.045)
Holt	0.03 (0.05)	0.20 (0.018)
M1	0.06 (0.01)	0.19 (0.021)
M3	0.02 (0.01)	0.20 (0.017)
M2	0.00 (0.02)	0.19 (0.021)
M4	0.05 (0.02)	0.19 (0.020)

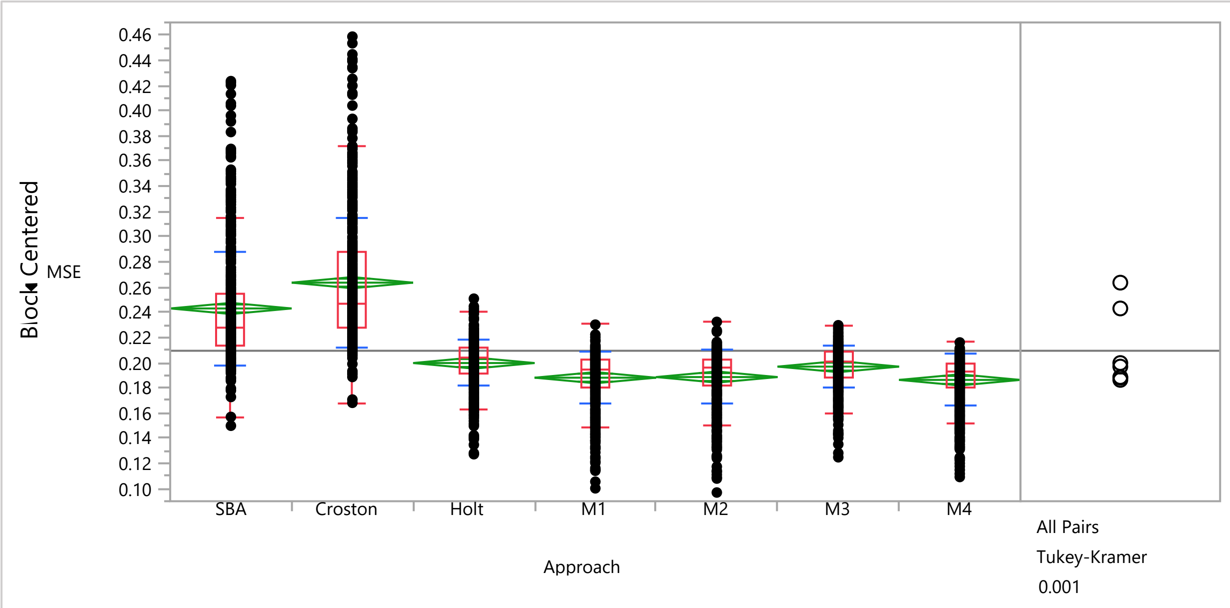

Figure 4-13: Box Plots for MSE - Data Set Three (Reg-Drop)

A statistical analysis was conducted for this data set following the same assumptions and steps described in section 4.4.1.1. The results of Tukey's test conducted at a p-value of 0.001 are shown in Table 4.24. The results showed that M4, M2 and M1 achieved significantly lower MSE compared to all the models. Croston achieved significantly higher MSE compared to all the methods. Holt and M3 achieved significantly lower MSE compared to both Croston and SBA. Even when using a *p*-value of 0.0001, the statistical groups do not change. The full analysis and the individual comparisons of the new methods with Holt, SBA and Croston can be found in section 6.2.B.9 of the appendix.

Table 4.24: Tukey-Kramer's Comparison of Accuracy Measures for Reg-Drop DS3

Method	Level				MSE
Croston	A				0.26
SBA		B			0.24
Holt			C		0.20
M3			C		0.20
M1				D	0.19
M2				D	0.19
M4				D	0.19

4.5. Conclusion

The four new forecasting methods created incorporate different levels of information and a comparative analysis investigated the accuracy of the new methods with respect to the MSE and ME metrics for different phases of the life cycle. The results across all three levels of intermittent demand and all three different life cycle analyses reveal that Croston and SBA consistently had more variation than the other methods.

The results also showed that when considering the FLC phase across all three data sets, M4 and M2 consistently achieved higher levels of accuracy with respect to the MSE metric. M1 showed superior performance compared to Holt, Croston, and SBA during the FLC phase only when the demand data was highly intermittent (i.e., data set three). Furthermore, the results showed that on average, SBA and Croston had negative bias for the FLC phase across all data sets. When considering the MSE metric, the performance of Holt showed promise when demand was slightly and moderately intermittent.

For the Ramp-Reg LC phases, M2 and M4 achieved a high level of accuracy when demand was slightly or moderately intermittent. On the contrary, when the data set was highly intermittent SBA and Croston achieved the highest levels of accuracy compared to the rest of the models during this LC phase but they had twice as much as variation. All of the methods were very similar owing to the lower demands. Furthermore, the results showed that on average all of the models exhibited positive bias during this phase, except for Croston in data set three. This implies that the method had a difficulty in picking up the ramping trend. Lastly, the results of the Reg-Drop LC phases showed that M4 consistently achieved higher levels of accuracy with respect to the MSE metric followed by M2. M1 showed superior performance compared to Holt's, Croston and SBA when demand was moderately or highly intermittent. The performance of M1 was more accurate in the Reg-Drop phases as opposed to the FLC and Ramp-Reg phases.

Based on the overall results, utilizing the LC phase in a short-term forecasting method can yield higher levels of accuracy in almost all of the scenarios and in the few other scenarios the methods performed similarly to the most accurate method. The ramp-reg. phase is the most challenging phase to forecast. This is expected due to the limited number of data points. M1, M2 and M4 performed well during the Reg-Drop phases particularly when demand is moderately or highly intermittent. This highlights the importance of incorporating the probability of demand occurrence and the LC phase to the forecasting approach, as it enables the methods to better handle demand prediction and lower the risks of obsolescence associated with this phase. Even though Croston and SBA were designed for highly intermittent service demand data, they performed poorly in all of the scenarios and hardly managed to outperform M2 and M4 in only one scenario (i.e., ramp-reg. data set three).

To ease the comparison between all of the different methods and data sets, constant initial values were used for the newly introduced methods M1, M2, and M4 throughout this chapter (see section 4.4.1). However, parametric analyses were conducted and the results of using different values for the parameters of the new methods can be found in sections 6.2.B.10 through 6.2.B.13 of the appendix. The analyses showed that M2 and M4 consistently achieved the lowest MSE when the smoothing constant γ of 0.001, 0.001, and 0.02 were used to update the probability of occurrence for Ramp, Reg, and Drop respectively. M1 seemed to generally perform better using a smoothing constant γ of 0.001. In Chapter five, the performance of an inventory model when incorporating the different forecasting methods will be investigated.

Chapter 5

New Forecasting Methods and Inventory Model

Chapter 4 introduced four new forecasting techniques that include different levels of information and outperformed the accuracy of SBA, Croston, and Holts under most of the considered conditions. Using one of the inventory models discussed in Chapter 3, the performance of the new forecasting techniques versus SBA, Croston, and Holts will be compared for both the generated and the electronics data sets across each lifecycle phase. In Chapter 3, comparing the inventory scenarios was difficult owing to the methods achieving different fill rates. Therefore, for each scenario, the *K* safety stock value is adjusted in order to meet an average overall target fill rate of 95%, to enable a direct inventory level comparison.

Two recent literature review studies emphasized the importance of integrating different levels of information into the decision making process of spare parts management (Hu et al., 2018; Van der Auweraer et al., 2019). Hu *et al*. (2018) mentioned the need to incorporate the life cycle process into the demand forecasting and inventory planning decisions. On a similar note, Van der Auweraer *et al*. (2019) emphasized the need for studies that integrate installed base information with commonly used forecasting techniques. They also suggested identifying the points in the life cycle phases where the installed base information could enhance the performance of forecasting techniques and inventory models. Moreover, future research ought to consider developing new forecasting methods that capture the risk of obsolescence by having frequent and timely updates of demand estimates (Babai, M.Z., et al., 2017).

5.1. Inventory Model

In this chapter, only the first inventory model (see Equation5.1) discussed in Chapter 3 will be utilized, which was considered mainly as all the statistical derivations documented in literature for the forecasting techniques were derived with the assumption of having a single smoothing parameter (Teunter and Sani, 2009; Syntetos and Boylan, 2010). To the best of our knowledge, no study has been conducted to compute the statistical derivations when having two distinct values for the smoothing parameters. Deriving the statistical properties of the forecasting techniques is a promising avenue for further research but remains beyond the scope of this study. Thus, to ensure an adequate comparison between the model's performances, Equation5.1 is used to compute the order-up-to quantity at each period.

$$M_{t_{\mathrm{MSE}}} = (L+1)\widehat{D} + K\sqrt{(L+1)MSE} \qquad \textbf{Equation5.1}$$

To reach the target fill rate (FR) of 95% across all of the models, the *K* safety factor in Equation5.1 will be changed (i.e., increased or decreased) until an overall average FR of 95% across all SKUs is reached. The process starts with an initial value of 1 for *K* and then depending on the yielded FR, the value for *K* is changed until the target is met. For instance, if the original *K* value of 1, yields an FR of 93%, then the value of *K* will be increased until an average FR of 95% is reached. Results and observations pertaining to the values of *K* associated with each forecasting technique and LC phase will be discussed in the following sections.

Babai *et al*. (2017) applied different values for the *K* safety factor when dealing with service parts inventory management. However, in their study, they assumed four fixed values for *K* (i.e., 1, 2, 3, and 4) without any iteration to reach a desired service measure. Efficiency tradeoff curves with the different values of *K* were plotted between holding volumes and backordering volumes for each of the forecasting techniques (i.e., SBA, Croston, modified SBA, SES and TSB) (Babai

M.Z. *et al*., 2017). To perform the analysis, Babai *et al.* (2017) used a data set of 84 observations for 5000 SKUs from the aircraft industry and a data set of 24 observations from the automotive industry. The results showed that for the automotive data set, Croston's method outperformed the other methods, and for the aircraft data set, all models performed similarly. They have also conducted the same analyses on the automotive and aircraft data sets using only the SKUs with decreasing mean demand. The results for the SKUs with decreasing demand patterns showed that the modified SBA and Croston methods outperformed the rest of the methods for the aircraft data set. However, for the automotive data set, the TSB method clearly outperformed all of the other methods.

In this research, the same three generated data sets described in Chapter 4 will be used in addition to the electronics data set. The electronics data set is composed of SKUs in different life cycle phases, including spare parts demand for some newly introduced. For SKUs early in their life cycle stage, the beginning of the 112 data points might include consecutive zeros until the first demand occurs. To better deal with this issue, the initial 21 points following a demand occurrence were excluded from the results of the inventory performance measures. Those points provide a warm up period for the model prior to collecting the inventory performance measures. The remaining points were regarded as the out-of-sample set and were used to compute the inventory performance measures discussed below.

5.2. Inventory Model Performance on SKUS with FLC Phase: The Generated Data Sets

In this section, all of the SKU's data points are used to assess the performance of the inventory measures yielded by the models, except for the initial 21 points used for the warm-up period. The analyses are conducted for each of the three generated data sets with the purpose of evaluating the performance of the models throughout the SKU's FLC (Ramp, Reg., and Drop phases). A total of

195 demand data points were included in the analysis, the characteristics of each data set and the generated demand can be found in Chapter 4.

5.2.1. Data Set One (DS1): Slightly Intermittent FLC)

The inventory performance measures are compared and analyzed for the slightly intermittent data set. Table 5.1 includes the mean and standard deviation (STD) of on-hand inventory, service levels (SL), and fill rates (FR) as well as *K* values while Figure 5-1 shows the on-hand inventory box-plots for all the models. In Chapter 4, it was shown that both M2 and M4 have less variability compared to all of the other method. The same holds true when considering M2-MSE and M4-MSE. The *K* values are higher for Croston and SBA in order to force them to carry enough inventory to meet the overall average 95% fill rates. Overall, the *K*-values ranged between 1.19 and 2.01 with an average of 1.51.

Table 5.1: Results of all Inventory Performance Measures- DS1 (FLC)

Forecasting-Inventory Model	On-Hand Inventory Means (STD)	Service Level Means (STD)	Fill Rate Means (STD)	K-Values
Croston-MSE	9.74 (1.16)	90.86 (1.66)	95.00 (1.06)	1.88
SBA-MSE	9.70 (1.18)	90.92 (1.71)	95.00 (1.09)	2.01
Holt-MSE	5.19 (0.66)	90.88 (1.67)	95.00 (0.86)	1.19
M1-MSE	5.63 (1.07)	90.86 (1.12)	95.00 (0.61)	1.60
M3-MSE	5.47 (0.94)	90.89 (1.85)	95.00 (1.13)	1.20
M2-MSE	4.60 (0.47)	90.68 (1.03)	95.00 (0.60)	1.37
M4-MSE	4.42 (0.47)	90.47 (1.10)	95.00 (0.69)	1.29

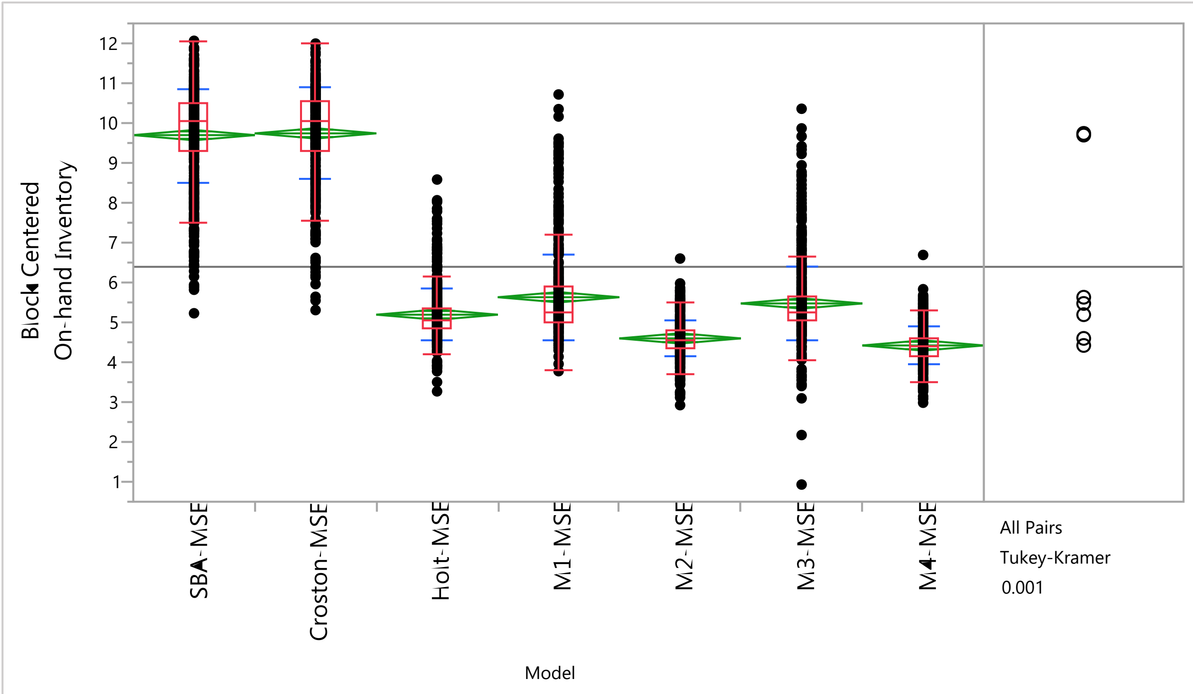

Figure 5-1: Box-Plots Comparison of On-Hand Inventory- DS1 (FLC)

The first analysis compares the on-hand inventory performance means of Croston, SBA, Holt, and the four new methods. Figure 5-1 shows the box plots of the on-hand inventory means. Since there are 600 data points for each forecasting method, the Central Limit Theorem can be used to state that the distribution of the means is normally distributed. For the remaining analysis, if we reject the null hypothesis that the variances are equal based on the Levene's test, then the analysis uses the Welch's test instead of the standard ANOVA to test the hypothesis that the on-hand inventory means are equal. If the null hypothesis that the means of the inventory for all methods are not equal is rejected owing to a *p*-value of <0.001 then the Tukey-Kramer multi-means comparison method will be used. From the results in Table 5.2, M2-MSE and M4-MSE are statistically better than all of the other methods but cannot be distinguished from one another while Holt-MSE is better than M1-MSE and M3-MSE, which are better than Croston-MSE, and SBA-MSE.

Table 5.2: Tukey-Kramer for Slightly Intermittent- FLC (p-value < 0.001)

Model	Levels				On-Hand Avg.
Croston-MSE	A				9.74
SBA-MSE	A				9.70
M1-MSE		B			5.63
M3-MSE		B			5.47
Holt-MSE			C		5.19
M2-MSE				D	4.60
M4-MSE				D	4.42

After reviewing both the initial results and the results of the statistical analysis, Croston-MSE and SBA-MSE achieved significantly higher inventory levels compared to all of the models. M4-MSE and M2-MSE outperformed all of the considered models. Holt-MSE outperformed M1-MSE and M3-MSE. See Section 6.2.C.1 of the appendix for the full analysis and the individual comparison of the new methods with Holt, SBA and Croston.

5.2.2. Data Set Two (DS2): Moderately Intermittent (FLC)

Table 5.3 shows the mean and standard deviation for all the inventory performance measures. Figure 5-2 displays the boxplots for the on-hand inventory when the demand is moderately intermittent. The boxplots reveal that the inventory models of the newly proposed methods have lower variation than Croston-MSE and SBA-MSE. The results showed that when considering an overall average fill rate of 95%, the lowest on-hand inventory levels were achieved by M4-MSE followed by M3-MSE and M2-MSE. Overall, the K-values ranged between 0.54 and 1.30 with an average of 0.90.

Table 5.3: Results of all Inventory Performance Measures- DS2 (FLC)

Forecasting-Inventory Model	On-Hand Inventory Means (STD)	Service Level Means (STD)	Fill Rate Means (STD)	K-Values
Croston-MSE	3.18 (0.23)	92.66 (1.26)	95.00 (0.89)	1.14
SBA-MSE	2.93 (0.18)	92.65 (1.10)	95.00 (0.75)	1.30
Holt-MSE	2.33 (0.15)	92.55 (0.99)	95.00 (0.69)	0.65
M1-MSE	2.41 (0.16)	92.57 (0.87)	95.00 (0.60)	1.18
M3-MSE	2.14 (0.14)	92.55 (0.86)	95.00 (0.59)	0.54
M2-MSE	2.16 (0.15)	92.50 (0.88)	95.00 (0.59)	0.76
M4-MSE	2.08 (0.15)	92.48 (0.92)	95.00 (0.61)	0.75

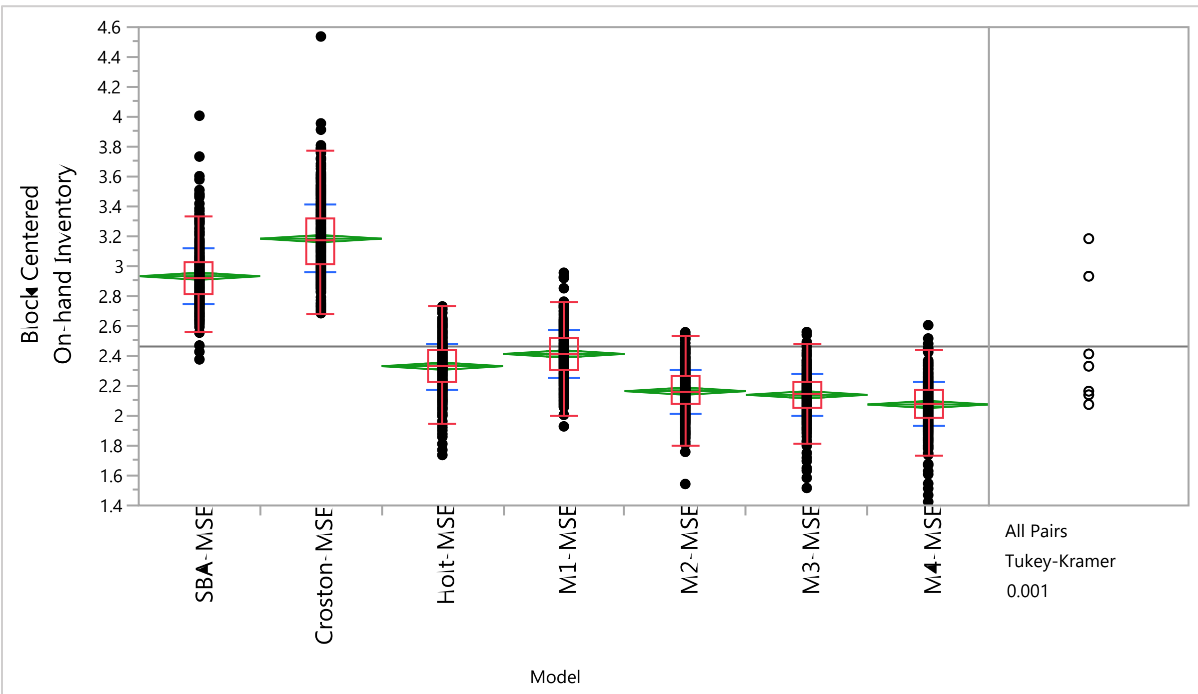

Figure 5-2: Box-Plots Comparison of On-Hand Inventory- DS2 (FLC)

Table 5.4: Tukey-Kramer for Moderately Intermittent- FLC (p-value < 0.001)

Model	Levels						On-Hand Avg.
Croston-MSE	A						3.18
SBA-MSE		B					2.93
M1-MSE			C				2.41
Holt-MSE				D			2.33
M2-MSE					E		2.16
M3-MSE					E		2.14
M4-MSE						F	2.08

After reviewing both the initial results and the results of the statistical analysis (see Table 5.4), Croston-MSE achieved significantly higher inventory levels compared to all of the models followed by SBA-MSE. M4-MSE, M3-MSE and M2-MSE outperformed Holt-MSE, Croston-MSE and SBA-MSE. Moreover, statistically M4-MSE achieved the lowest on-hand inventory level compared to all of the models while Holt-MSE outperformed M1-MSE. See Section 6.2.C.2 of the appendix for the full analysis and the individual comparison of the new methods with Holt, SBA and Croston.

5.2.3. Data Set Three (DS3): Highly Intermittent (FLC)

Table 5.5 shows the mean and standard deviation for all the inventory performance measures, while Figure 5-3 displays the boxplots for the on-hand inventory when the demand is highly intermittent. Similar to what has been observed for both DS1 and DS2, the inventory models of the newly proposed methods have lower variation than Croston-MSE and SBA-MSE.

Table 5.5: Inventory Results for Highly Intermittent Data for FLC

Forecasting-Inventory Model	On-Hand Inventory Means (STD)	Service Level Means (STD)	Fill Rate Means (STD)	K-Values
Croston-MSE	1.54 (0.18)	93.48 (1.46)	96.00 (0.92)	0.38
SBA-MSE	1.52 (0.17)	93.57 (1.36)	96.00 (0.87)	0.55
Holt-MSE	1.40 (0.15)	93.49 (1.06)	96.00 (0.65)	0.05
M1-MSE	1.30 (0.12)	93.16 (1.00)	96.00 (0.60)	0.64
M3-MSE	1.31 (0.12)	93.69 (1.19)	96.00 (0.71)	0.0001
M2-MSE	1.30 (0.12)	93.25 (1.01)	96.00 (0.60)	0.10
M4-MSE	1.23 (0.12)	93.37 (1.10)	96.00 (0.61)	0.0001

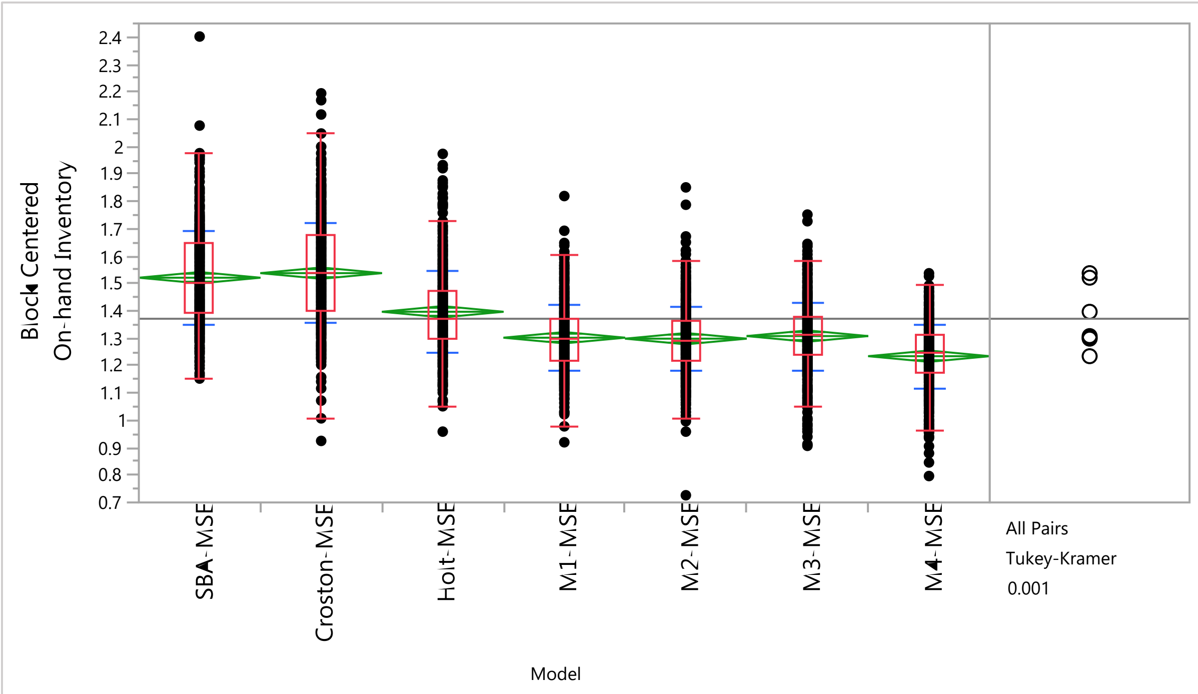

Figure 5-3: Box-Plots Comparison of On-Hand Inventory- DS3 (FLC)

After reviewing both the initial results for achieving an overall average 95% fill rate and the results of the statistical analysis (see Table 5.6), Croston-MSE and SBA-MSE achieved statistically higher inventory levels compared to all the models at an alpha level of 0.001. All of the new methods outperformed Holt-MSE, Croston-MSE and SBA-MSE. M4-MSE achieved the lowest on-hand inventory levels compared to all of the models while no difference was detected between M1-MSE and M3-MSE as well as M3-MSE and M2-MSE. See Section 6.2.C.3 of the appendix for the full analysis and the individual comparison of the new methods with Holt, SBA and Croston.

Table 5.6: Tukey-Kramer for Highly Intermittent- FLC (p-value < 0.001)

Model	Levels				On-Hand Avg.
Croston-MSE	A				1.54
SBA-MSE	A				1.52
Holt-MSE		B			1.40
M3-MSE			C		1.31
M1-MSE			C		1.30
M2-MSE			C		1.30
M4-MSE				D	1.23

5.3. Inventory Performance on SKUS with Ramp-Reg. Phase: The Generated Data Sets

In this section, the demand data points of SKU's in the Ramp-Reg phase were used to assess the performance of the inventory measures yielded by the models. The analyses were conducted for each of the three generated data sets with the purpose of evaluating the performance of the models throughout SKU's Ramp-Reg. phases. Recall that all of the methods had a more difficult time in forecasting the demand during this LC phase. A total of 103 demand data points were included in this analysis.

5.3.1. Data Set One (DS1): Slightly Intermittent (Ramp-Reg.)

The inventory performance measures were compared and analyzed for this data set considering only the demand during the Ramp-Reg. phases. Table 5.7 shows the mean and standard deviation for all the inventory performance measures. Figure 5-4 displays the boxplots for the on-hand inventory when the demand is slightly intermittent. The results showed that when considering an overall average fill rate of 95%, the lowest on-hand inventory levels were achieved by M4-MSE followed by M2-MSE. Moreover, the *K*-values ranged between 1.92 and 2.75 with an average of 2.21, which makes sense since the MSE errors were higher and the ME had a positive bias.

Table 5.7: Results of all Inventory Performance Measures- DS1 (Ramp-Reg.)

Forecasting-Inventory Model	On-Hand Inventory Means (STD)	Service Level Means (STD)	Fill Rate Means (STD)	K-Values
Croston-MSE	7.10 (0.48)	90.03 (2.23)	95.00 (1.24)	2.57
SBA-MSE	7.07 (0.47)	90.07 (2.28)	95.00 (1.24)	2.75
Holt-MSE	7.33 (0.37)	90.36 (1.78)	95.00 (0.93)	1.94
M1-MSE	7.21 (0.34)	90.17 (1.42)	95.00 (0.72)	2.34
M3-MSE	7.20 (0.47)	90.08 (2.50)	95.00 (1.27)	1.97
M2-MSE	6.91 (0.29)	90.12 (1.50)	95.00 (0.73)	2.01
M4-MSE	6.64 (0.33)	89.73 (1.95)	95.00 (1.05)	1.92

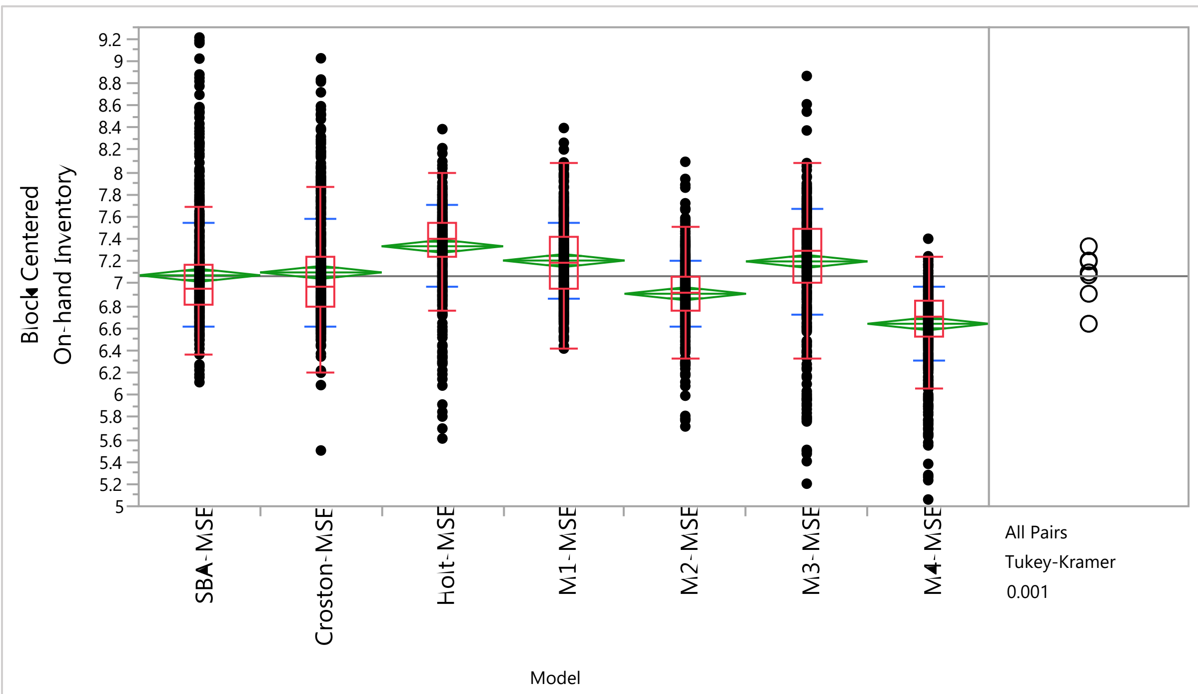

Figure 5-4: Box-Plots Comparison of On-Hand Inventory- DS1 (Ramp-Reg.)

After reviewing both the initial results for achieving an overall average 95% fill rate and the results of the statistical analysis for Ramp-Reg phases (see Table 5.8), Holt-MSE achieved significantly higher on-hand inventory level compared to all of the models, while M4-MSE achieved the lowest followed by M2-MSE. The overall results in Table 5.7 and Table 5.8 are different from the results when comparing just the forecast accuracy in Section 4.1.2.1. SBA-MSE and Croston-MSE, achieved lower on-hand levels compared to M1-MSE. No difference can be detected between SBA-MSE and Croston-MSE nor between Croston-MSE and M3-MSE. See Section 6.2.C.4 of the appendix for the full analysis and the individual comparison of the new methods with Holt, SBA and Croston.

Table 5.8: Tukey-Kramer for Slightly Intermittent- Ramp-Reg (p-value < 0.001)

Model	Levels						On-hand Avg.
Holt-MSE	A						7.33
M1-MSE		B					7.21
M3-MSE		B	C				7.20
Croston-MSE			C	D			7.10
SBA-MSE				D			7.07
M2-MSE					E		6.91
M4-MSE						F	6.64

5.3.2. Data Set Two (DS2): Moderately Intermittent (Ramp-Reg.)

The inventory performance measures were compared and analyzed for this data set considering only the demand during the Ramp-Reg. phases. Table 5.9 shows the mean and standard deviation for all the inventory performance measures. Figure 5-5 displays the boxplots for the on-hand inventory when the demand is moderately intermittent. The results showed that when considering an overall average fill rate of 95%, the lowest on-hand inventory levels were achieved by SBA-MSE followed by Croston-MSE. Overall, the *K*-values range between 1.27 and 1.98 with an average of 1.60.

Table 5.9: Results of all Inventory Performance Measures- DS2 (Ramp-Reg.)

Forecasting-Inventory Model	On-Hand Inventory Means (STD)	Service Level Means (STD)	Fill Rate Means (STD)	K-Values
Croston-MSE	3.26 (0.24)	92.08 (1.95)	95.00 (1.31)	1.88
SBA-MSE	3.24 (0.22)	92.10 (1.77)	95.00 (1.21)	1.98
Holt-MSE	3.37 (0.16)	92.16 (1.61)	95.00 (1.06)	1.34
M1-MSE	3.32 (0.21)	92.16 (1.53)	95.00 (0.97)	1.87
M3-MSE	3.29 (0.17)	92.20 (1.48)	95.00 (0.96)	1.27
M2-MSE	3.37 (0.15)	92.25 (1.54)	95.00 (1.01)	1.48
M4-MSE	3.29 (0.14)	92.22 (1.48)	95.00 (0.98)	1.35

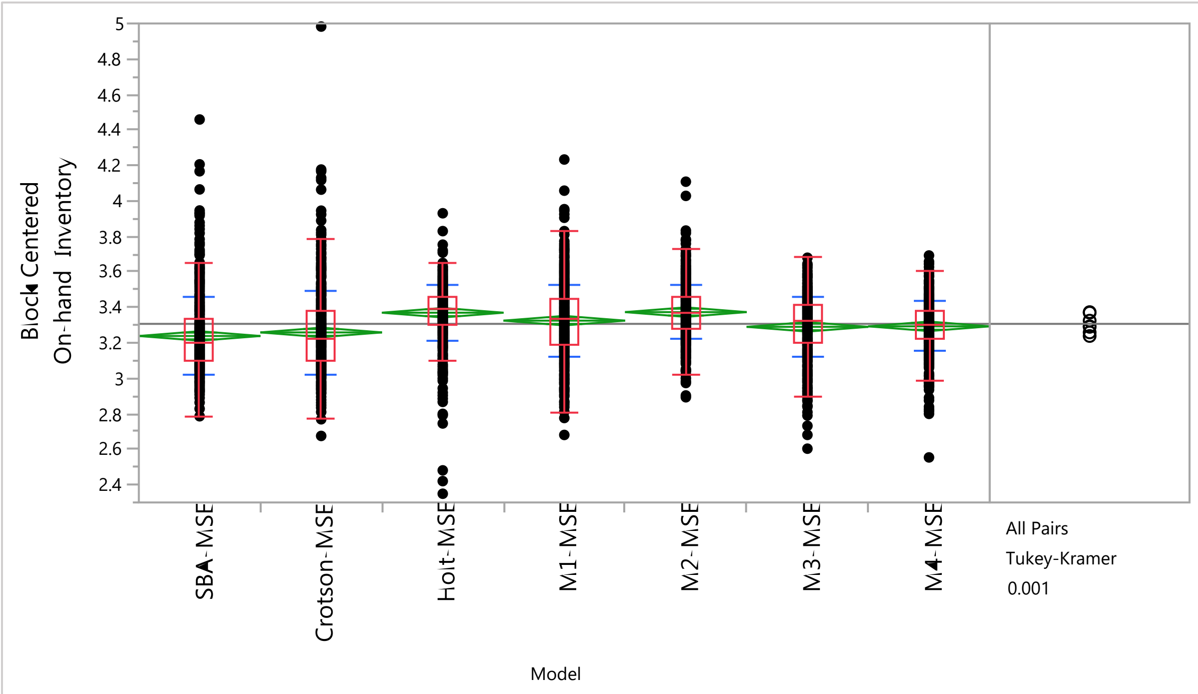

Figure 5-5: Box-Plots Comparison of On-Hand Inventory- DS2 (Ramp-Reg.)

After reviewing both the initial results for achieving an overall average 95% fill rate and the results of the statistical analysis for the Ramp-Reg phases (see Table 5.10Table 5.8), M2-MSE achieves significantly higher on-hand inventory levels compared to all of the models except Holt-MSE. On the contrary, SBA-MSE achieved significantly lower on-hand inventory levels compared to all the models except Croston-MSE. The Croston-MSE inventory level is not statistically different from the ones achieved by SBA-MSE, M3-MSE and M4-MSE. Holt-MSE carried more inventory compared to Croston-MSE, SBA-MSE, M3-MSE and M4-MSE. See Section 6.2.C.5 of the appendix for the full analysis and the individual comparison of the new methods with Holt, SBA and Croston.

Table 5.10: Tukey-Kramer for Moderately Intermittent- Ramp-Reg (p-value < 0.001)

Model	Levels					On-hand Avg.
M2-MSE	A					3.37
Holt-MSE	A	B				3.37
M1-MSE		B	C			3.32
M4-MSE			C	D		3.29
M3-MSE			C	D		3.29
Crotson-MSE				D	E	3.26
SBA-MSE					E	3.24

5.3.3. Data Set Three (DS3): Highly Intermittent (Ramp-Reg.)

The inventory performance measures were compared and analyzed for this data set considering only the demand during the Ramp-Reg. phases. Table 5.11 shows the mean and standard deviation for all the inventory performance measures. Figure 5-6 displays the boxplots for the on-hand inventory when the demand is highly intermittent.

Table 5.11: Results of all Inventory Performance Measures- DS3 (Ramp-Reg.)

Forecasting-Inventory Model	On-Hand Inventory Means (STD)	Service Level Means (STD)	Fill Rate Means (STD)	K-Values
Croston-MSE	1.89 (0.23)	92.45 (2.34)	95.00 (1.57)	1.07
SBA-MSE	1.89 (0.21)	92.42 (2.30)	95.00 (1.50)	1.24
Holt-MSE	1.95 (0.14)	92.44 (1.70)	95.00 (1.17)	0.70
M1-MSE	1.91 (0.15)	92.48 (1.54)	95.00 (1.04)	1.24
M3-MSE	1.92 (0.15)	92.43 (1.79)	95.00 (1.16)	0.58
M2-MSE	1.95 (0.14)	92.44 (1.55)	95.00 (1.05)	0.77
M4-MSE	1.93 (0.15)	92.43 (1.84)	95.00 (1.23)	0.66

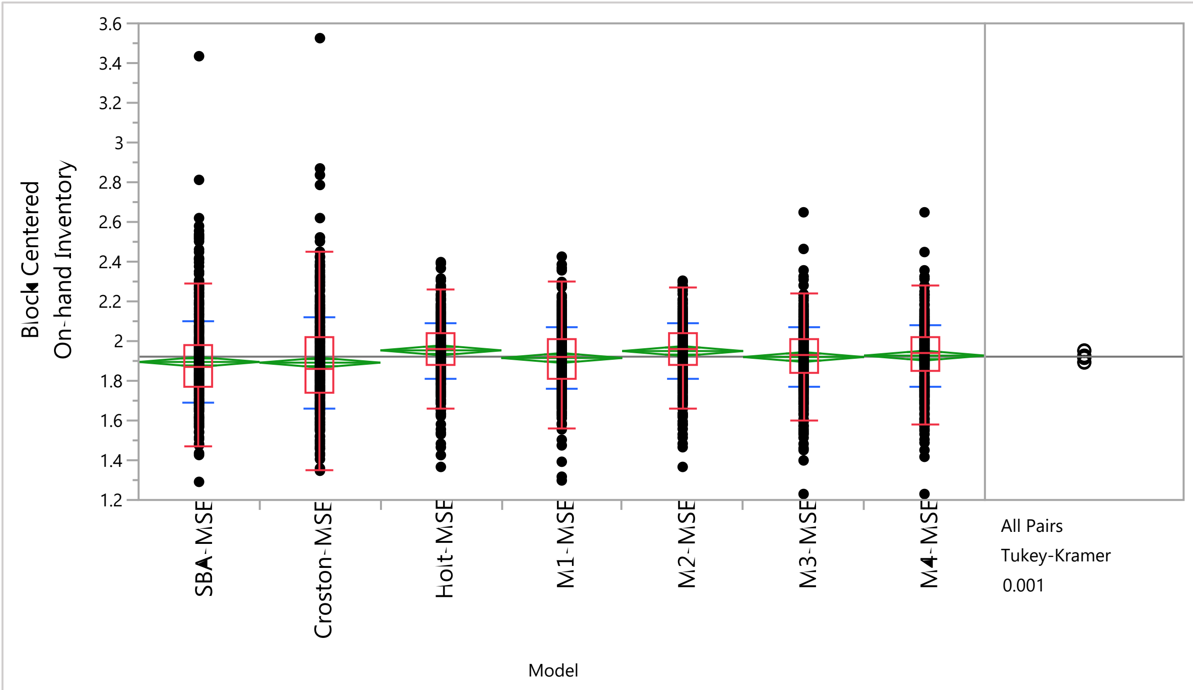

Figure 5-6: Box-Plots Comparison of On-Hand Inventory- DS3 (Ramp-Reg.)

The results showed that when considering an overall average fill rate of 95%, the lowest on-hand inventory levels were achieved by SBA-MSE and Croston-MSE. Moreover, it can be observed that the *K*-values ranged between 0.58 and 1.24, with an average of 0.89. After reviewing both the initial results for achieving an overall average 95% fill rate and the results of the statistical analysis for Ramp-Reg phases (Table 5.12Table 5.8), it can be concluded that, under the considered inventory, model SBA-MSE and Croston-MSE performed similarly and achieved the lowest on-hand levels compared to both Holt-MSE and M2-MSE. No statistical difference was found between M1-MSE, M3-MSE and M4-MSE and the rest of the models. See Section 6.2.C.6 of the appendix for the full analysis and the individual comparison of the new methods with Holt, SBA and Croston.

Table 5.12: Tukey-Kramer for Highly Intermittent- Ramp-Reg (p-value < 0.001)

Method	Levels		Mean
Holt-MSE	A		1.95
M2-MSE	A		1.95
M4-MSE	A	B	1.93
M3-MSE	A	B	1.92
M1-MSE	A	B	1.91
SBA-MSE		B	1.89
Croston-MSE		B	1.89

5.4. Inventory Performance on SKUS with Reg-Drop Phase: The Generated Data Sets

In this section, the demand points in the Reg-Drop phases were used to assess the performance of the inventory measures yielded by the models. The analyses were conducted for each of the three generated data sets with the purpose of evaluating the performance of the models throughout SKU's Reg-Drop phases. A total of 118 demand data points were included in the analysis.

An interesting observation was made when analyzing the performance of inventory measures for the Reg.-Drop LC phases. It was noticed that both Croston and SBA struggled to provide accurate forecast estimates owing to the fact that this phase exhibits a downward trend with frequent zero demands. This performance is expected because both Croston and SBA do not update their forecasts when zero demands occur and therefore overestimate the demand. For example, forecasting for a SKU whose demand average and sum are equal to 0.68 and 80, respectively, Croston's generated forecast had an average and sum equal to 1.10 and 129, respectively while SBA yielded an average and sum equal to 0.86 and 100, respectively.

On the contrary, M1's generated forecast had an average and sum equal to 0.60 and 69, respectively for the same considered SKU. This showed that incorporating a method that updates promptly to demand changes is crucially needed for the Reg-Drop phases to avoid the overestimation of demand that will potentially impose a high risk of obsolescence. Thus, the FR of the Croston-MSE model could not be lowered to 95% using the considered inventory model, even when applying very low values of k. Consequently, in this section only the lowest FR that could be achieved by Croston-MSE was considered for all of the other models.

5.4.1. Data Set One (DS1): Slightly Intermittent (Reg.-Drop)

The inventory performance measures were compared and analyzed for this data set considering only the demand during the Reg.-Drop phases. Table 5.13 shows the mean and standard deviation for all of the inventory performance measures. Figure 5-7 displays the boxplots for the on-hand inventory when the demand is slightly intermittent. The results showed that when considering an overall average fill rate of 98%, the lowest on-hand inventory levels were achieved by Holt-MSE followed by M4-MSE, while the highest was achieved by SBA-MSE.

Table 5.13: Results of all Inventory Performance Measures- DS1 (Reg.-Drop)

Forecasting-Inventory Model	On-Hand Inventory Means (STD)	Service Level Means (STD)	Fill Rate Means (STD)	K-Values
Croston-MSE	4.71 (1.03)	94.86 (3.09)	98 (1.13)	0.0000001
SBA-MSE	4.89 (1.13)	94.90 (3.28)	98 (1.21)	0.18
Holt-MSE	3.73 (0.71)	95.48 (2.30)	98 (0.82)	0.82
M1-MSE	4.07 (0.62)	93.00 (7.23)	98 (1.16)	0.99
M3-MSE	4.07 (0.70)	92.69 (7.27)	98 (1.38)	0.72
M2-MSE	3.94 (0.73)	95.20 (2.48)	98 (0.87)	1.40
M4-MSE	3.85 (0.72)	95.32 (2.38)	98 (0.86)	1.40

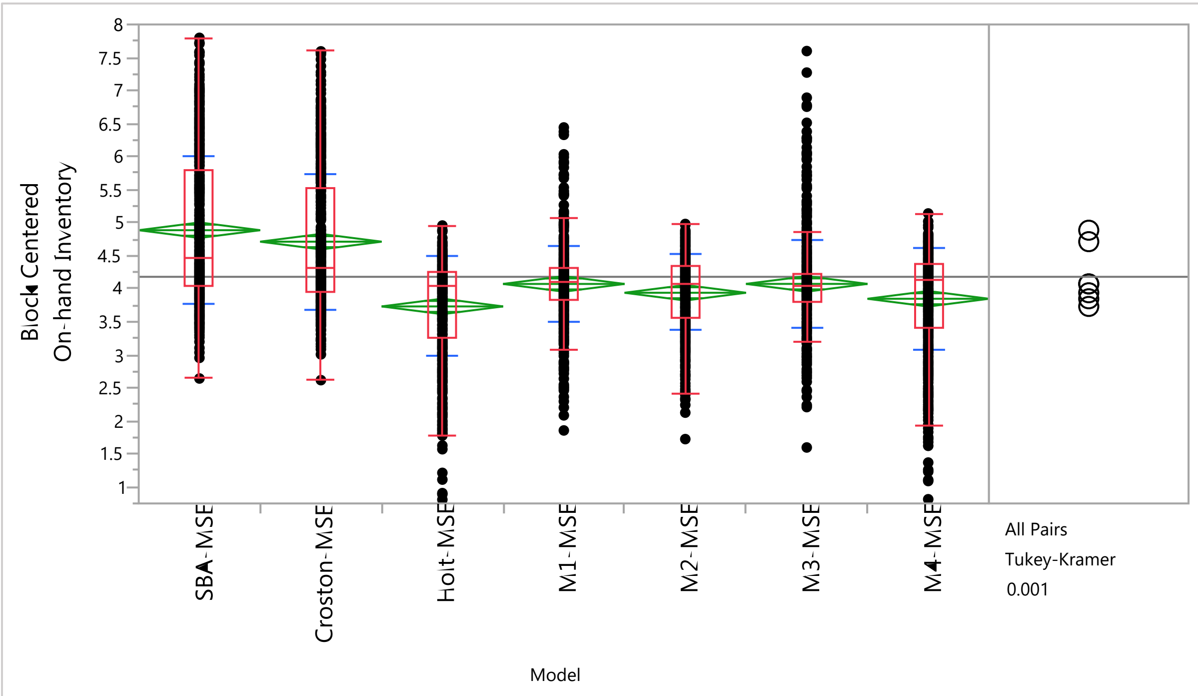

Figure 5-7: Box-Plots Comparison of On-Hand Inventory- DS1 (Reg.-Drop)

After reviewing both the initial results and the results of the statistical analysis for Reg.-Drop phases (Table 5.14). SBA-MSE and Croston-MSE performed similarly and achieved the highest inventory levels compared to all of the other models. Holt-MSE achieved lower levels of inventory compared to all the models excluding M4-MSE. M4-MSE achieved lower levels of inventory compared to all the models excluding M2-MSE, while no statistical difference exists when comparing M2-MSE to M3-MSE and M1-MSE. See Section 6.2.C.7 of the appendix for the full analysis and the individual comparison of the new methods with Holt, SBA and Croston.

Table 5.14: Tukey-Kramer for Slightly Intermittent-Reg-Drop (p-value < 0.001)

Level					Mean
SBA-MSE	A				4.89
Croston-MSE	A				4.71
M3-MSE		B			4.07
M1-MSE		B			4.07
M2-MSE		B	C		3.94
M4-MSE			C	D	3.85
Holt-MSE				D	3.73

5.4.2. Data Set Two (DS2): Moderately Intermittent (Reg.-Drop)

The inventory performance measures were compared and analyzed for this data set considering only the demand during the Reg.-Drop phases. Table 5.15 shows the mean and standard deviation for all of the inventory performance measures. Figure 5-8 displays the boxplots for the on-hand inventory when the demand is moderately intermittent. The results showed that when considering an overall average fill rate of 97%, the lowest on-hand inventory levels were achieved by M4-MSE followed by M2-MSE.

Table 5.15: Results of all Inventory Performance Measures- DS2 (Reg.-Drop)

Forecasting-Inventory Model	On-Hand Inventory Means (STD)	Service Level Means (STD)	Fill Rate Means (STD)	K-Values
Croston-MSE	2.22 (0.35)	95.33 (1.78)	97 (1.19)	0.0000001
SBA-MSE	2.23 (0.36)	95.26 (1.68)	97 (1.10)	0.14
Holt-MSE	1.81 (0.26)	95.00 (1.56)	97 (0.80)	0.30
M1-MSE	1.78 (0.20)	95.13 (1.10)	97 (0.67)	0.60
M3-MSE	1.77 (0.26)	95.03 (1.45)	97 (0.77)	0.28
M2-MSE	1.72 (0.18)	95.12 (1.12)	97 (0.74)	0.68
M4-MSE	1.68 (0.18)	95.06 (1.13)	97 (0.74)	0.65

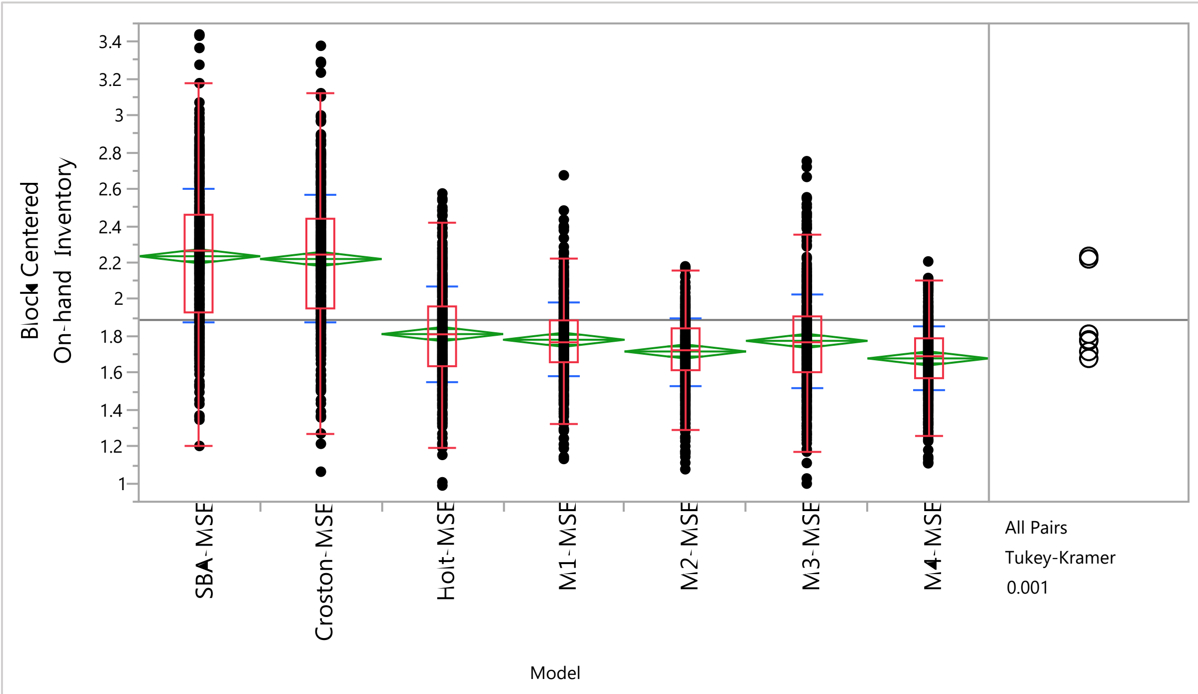

Figure 5-8: Box-Plots Comparison of On-Hand Inventory- DS2 (Reg.-Drop)

After reviewing both the initial results and the results of the statistical analysis for Reg.-Drop phases (Table 5.16Table 5.8), it can be concluded that under the considered inventory model M4-MSE statistically achieved the lowest on-hand levels compared to all of the other models excluding M2-MSE. Both SBA-MSE and Croston performed similarly and achieved significantly higher on-hand levels compared to all the models. No difference was found between Holt-MSE, M3-MSE and M1-MSE. No statistical difference was found when compared M2-MSE with M3-MSE and M4-MSE. See Section 6.2.C.8 of the appendix for the full analysis and the individual comparison of the new methods with Holt, SBA and Croston.

Table 5.16: Tukey-Kramer for Moderately Intermittent-Reg-Drop (p-value < 0.001)

Model	Levels				On-Hand Avg.
SBA-MSE	A				2.23
Croston-MSE	A				2.22
Holt-MSE		B			1.81
M1-MSE		B	C		1.78
M3-MSE		B	C		1.77
M2-MSE			C	D	1.72
M4-MSE				D	1.68

5.4.3. Data Set Three (DS3): Highly Intermittent (Reg.-Drop)

The inventory performance measures were compared and analyzed for this data set considering only the demand during the Reg.-Drop phases. Table 5.17 shows the mean and standard deviation for all the inventory performance measures. Figure 5-9 displays the boxplots for the on-hand inventory when the demand is highly intermittent. The results showed that when considering an overall average fill rate of 98%, the lowest on-hand inventory levels were achieved by M4-MSE followed by M2-MSE.

Table 5.17: Results of all Inventory Performance Measures- DS3 (Reg.-Drop)

Forecasting-Inventory Model	On-Hand Inventory Means (STD)	Service Level Means (STD)	Fill Rate Means (STD)	K-Values
Croston-MSE	1.37 (0.27)	97.00 (1.24)	98 (0.73)	0.0000001
SBA-MSE	1.35 (0.27)	96.84 (1.25)	98 (0.73)	0.10
Holt-MSE	1.32 (0.23)	96.75 (1.01)	98 (0.55)	0.18
M1-MSE	1.24 (0.15)	96.80 (0.80)	98 (0.47)	0.47
M3-MSE	1.27 (0.21)	96.67 (0.96)	98 (0.50)	0.15
M2-MSE	1.20 (0.15)	96.66 (0.95)	98 (0.52)	0.43
M4-MSE	1.17 (0.15)	96.65 (0.95)	98 (0.53)	0.41

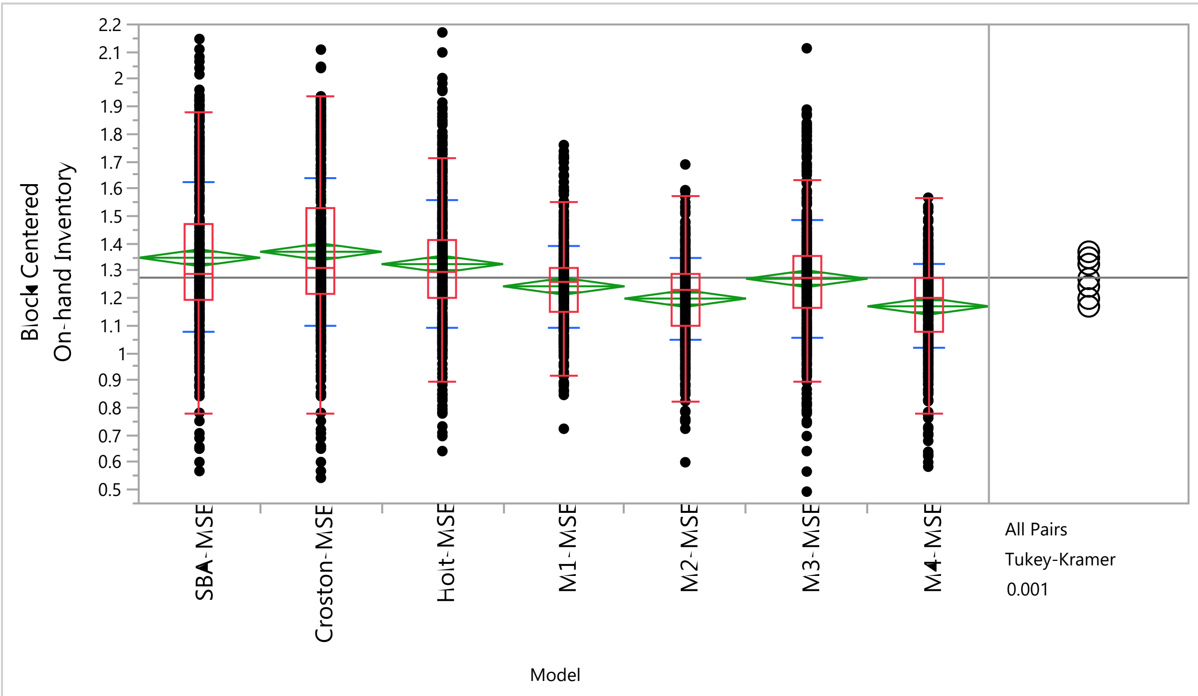

Figure 5-9: Box-Plots Comparison of On-Hand Inventory- DS3 (Reg.-Drop)

After reviewing both the initial results and the results of the statistical analysis for Reg.-Drop phases (Table 5.18Table 5.8), it can be concluded that, under the considered inventory model, M4 statistically achieved the lowest on-hand inventory level compared to all of the models excluding M2-MSE. Croston-MSE and SBA-MSE performed similarly and achieved significantly higher inventory levels compared to the models of the newly proposed forecasting techniques. See Section 6.2.C.9 of the appendix for the full analysis and the individual comparison of the new methods with Holt, SBA and Croston.

Table 5.18: Tukey-Kramer for Highly Intermittent-Reg-Drop (p-value < 0.001)

Model	Levels					On-hand Avg.
Croston-MSE	A					1.37
SBA-MSE	A					1.35
Holt-MSE	A	B				1.32
M3-MSE		B	C			1.27
M1-MSE			C	D		1.24
M2-MSE				D	E	1.20
M4-MSE					E	1.17

5.5. Inventory Model Performance: The Electronics Data Set

The previous sections explored the new forecast methods with inventory analysis on the generated data sets. Next, the new forecasting methods will be compared to the SBA, Croston, and Holt methods on the industrial electronics data set utilized in Chapter 3.

5.5.1. Inventory Model Performance on All SKUs

The inventory performance measures were compared and analyzed for this data set considering all of the SKUs, irrespective of their LC phases. Table 5.19 shows the mean and standard deviation for all of the inventory performance measures, while Figure 5-10 shows the on-hand inventory box-plots for all the models. The results showed that when considering an overall average fill rate of 95%, the lowest on-hand inventory levels were achieved by M4-MSE followed by M2-MSE**.** Moreover, it can be observed that the *K*-values ranged between 0.98 and 1.27 with an average of 1.15.

Table 5.19: Inventory Performance Measures- the Electronics Data Set (All SKUs)

Forecasting-Inventory Model	On-Hand Inventory Means (STD)	Service Level Means (STD)	Fill Rate Means (STD)	K-Values
Croston-MSE	5.37 (1.94)	91.86 (3.73)	95.00 (2.65)	1.12
SBA-MSE	5.10 (1.62)	91.78 (3.40)	95.00 (2.52)	1.27
Holt-MSE	5.04 (1.30)	91.72 (2.90)	95.00 (2.02)	0.98
M1-MSE	4.92 (1.50)	91.80 (2.27)	95.00 (1.35)	1.25
M3-MSE	4.92 (1.32)	91.69 (2.41)	95.00 (1.48)	0.98
M2-MSE	4.46 (1.16)	91.55 (2.26)	95.00 (1.60)	1.22
M4-MSE	4.28 (1.99)	91.49 (2.22)	95.00 (1.53)	1.22

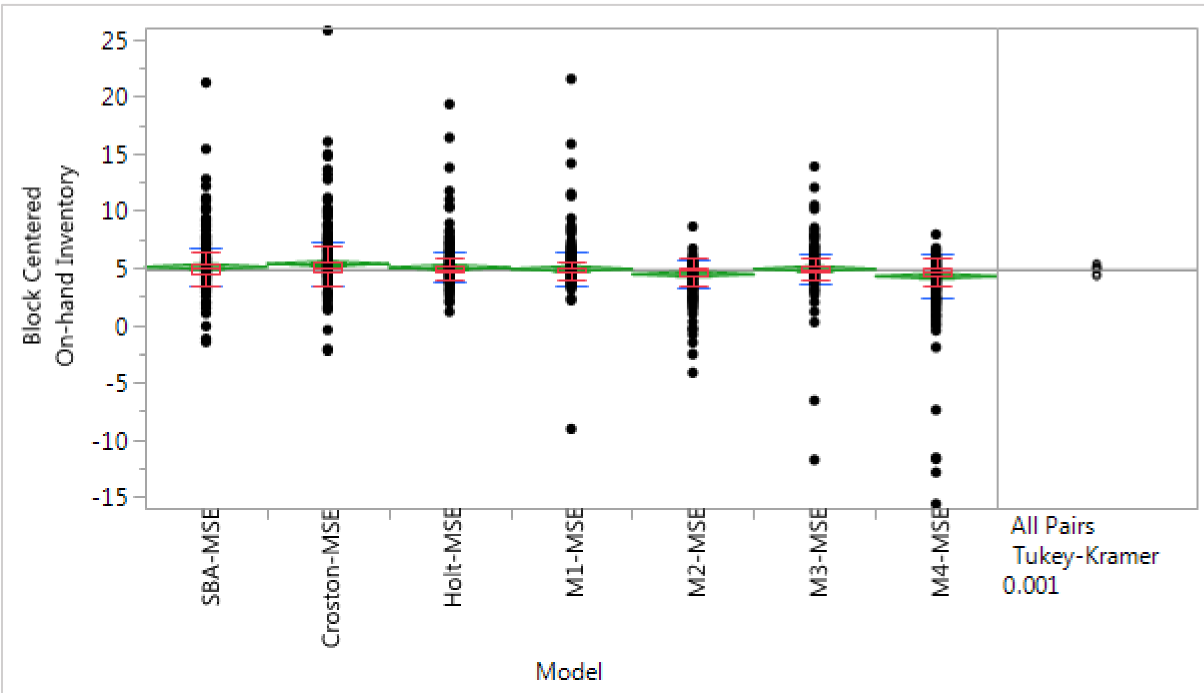

Figure 5-10: Box Plots for All 467 SKUs of the Electronics Data

After reviewing both the initial results and the results of the statistical analysis (Table 5.20Table 5.8), the inventory models M4-MSE and M2-MSE achieved significantly lower on-hand levels compared to all of the other models, while there is no statistical difference amongst the rest of the models at an alpha level of 0.001. See Section 6.2.C.10 of the appendix for the full analysis and the individual comparison of the new methods with Holt, SBA and Croston.

Table 5.20: Tukey-Kramer for the Electronics Data Set (All SKUs) (p-value < 0.001)

Model	Levels		Mean
Croston-MSE	A		5.37
SBA-MSE	A		5.10
Holt-MSE	A		5.04
M3-MSE	A		4.92
M1-MSE	A		4.92
M2-MSE		B	4.46
M4-MSE		B	4.28

5.5.2. Inventory Model Performance on SKUS with FLC Phases

The inventory performance measures were compared and analyzed considering only the SKUs having all three phases (Ramp, Reg and Drop). Table 5.21 shows the mean and standard deviation for all of the inventory performance measures of the 357 SKUs with the FLC phases. Figure 5-11 shows the on-hand inventory box-plots for all the models. The results showed that when considering an overall average fill rate of 95%, the lowest on-hand inventory levels were achieved by M2-MSE followed by M4-MSE**.** Moreover, it can be observed that the *K*-values ranged between 0.80 and 1.09, with an average of 0.96.

Table 5.21: Inventory Performance Measures- the Electronics Data Set (FLC)

Forecasting-Inventory Model	On-Hand Inventory Means (STD)	Service Level Means (STD)	Fill Rate Means (STD)	K-Values
Croston-MSE	5.01 (1.61)	91.70 (4.00)	95.00 (2.89)	0.94
SBA-MSE	4.78 (1.32)	91.64 (3.60)	95.00 (2.66)	1.08
Holt-MSE	4.89 (1.27)	91.55 (2.68)	95.00 (1.69)	0.80
M1-MSE	4.80 (1.17)	91.60 (2.70)	95.00 (1.70)	0.86
M3-MSE	4.79 (1.52)	91.63 (2.34)	95.00 (1.53)	0.82
M2-MSE	4.37 (1.06)	91.50 (2.35)	95.00 (1.56)	1.09
M4-MSE	4.38 (1.10)	91.49 (2.49)	95.00 (1.59)	1.08

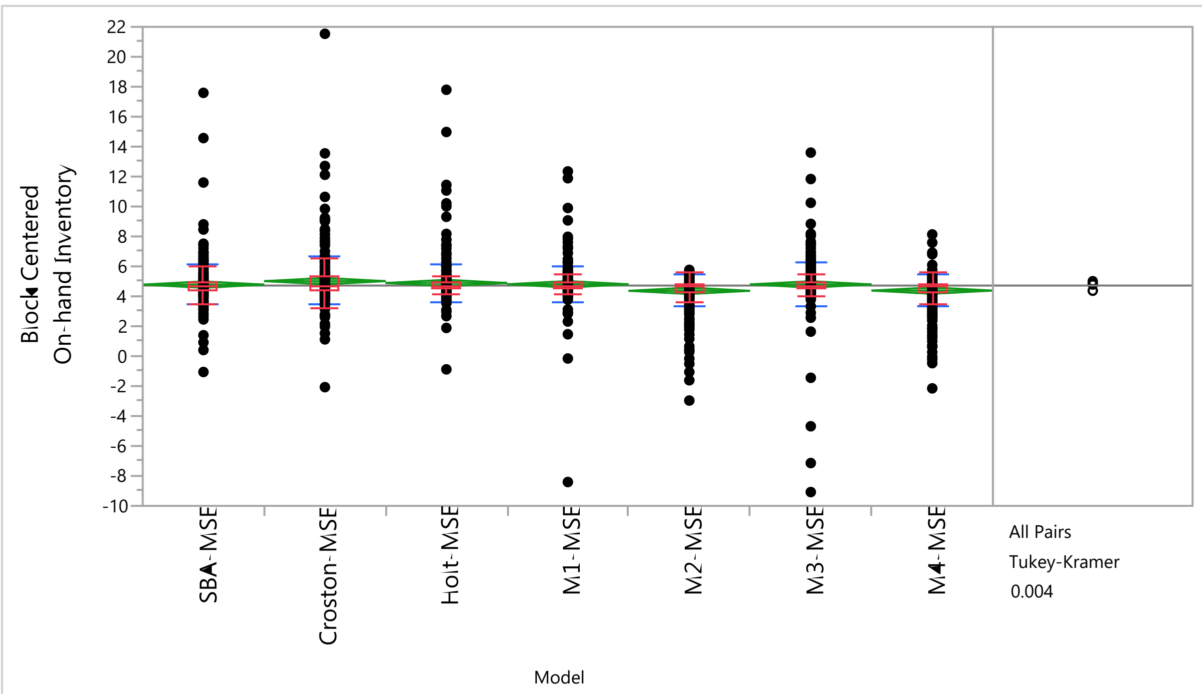

Figure 5-11: Box Plots for the Electronics Data Set (FLC)

Since there are only 357 data points, an alpha level of 0.004 will be utilized to ensure that the power of the test is similar to when there were 600 data points. After reviewing both the initial results and the results of the statistical analysis (Table 5.22Table 5.8), it can be concluded that the inventory models M4-MSE and M2-MSE achieved significantly lower on-hand levels compared to all of the other models, while there is no statistical difference amongst the rest of the models at an alpha level of 0.004. See Section 6.2.C.11 of the appendix for the full analysis and the individual comparison of the new methods with Holt, SBA and Croston.

Table 5.22: Tukey-Kramer for the Electronics Data Set (FLC) (*p*-value < 0.004)

Model	Levels		On-hand Avg.
Croston-MSE	A		5.01
Holt-MSE	A		4.89
M1-MSE	A		4.80
M3-MSE	A		4.79
SBA-MSE	A		4.78
M4-MSE		B	4.38
M2-MSE		B	4.37

5.5.3. Inventory Model Performance on SKUS with Ramp-Reg Phases

The inventory performance measures were compared and analyzed considering only the SKUs having the phases (Ramp and Reg.) Table 5.23 shows the mean and standard deviation for all of the inventory performance measures of the 71 SKUs with Ramp-Reg phases, while Figure 5-12 shows the on-hand inventory box-plots for all of the models. The results showed that when considering an overall average fill rate of 95%, the lowest on-hand inventory levels were achieved by M4-MSE followed by the rest of the newly proposed methods. Moreover, it can be observed that the *K*-values ranged between 1.77 and 2.36, with an average of 1.97.

Table 5.23: Inventory Performance Measures- the Electronics Data Set (Ramp-Reg.)

Forecasting-Inventory Model	On-Hand Inventory Means (STD)	Service Level Means (STD)	Fill Rate Means (STD)	K-Values
Croston-MSE	7.89 (1.30)	90.95 (3.03)	95.00 (1.92)	2.20
SBA-MSE	7.87 (1.12)	90.88 (3.40)	95.00 (2.32)	2.36
Holt-MSE	7.84 (1.09)	90.44 (2.46)	95.00 (1.63)	1.88
M1-MSE	7.81 (1.11)	90.53 (2.59)	95.00 (1.51)	1.91
M3-MSE	7.69 (1.07)	90.60 (2.14)	95.00 (0.96)	1.77
M2-MSE	7.53 (0.95)	90.78 (2.58)	95.00 (1.45)	1.93
M4-MSE	7.21 (1.73)	89.99 (2.29)	95.00 (1.48)	1.77

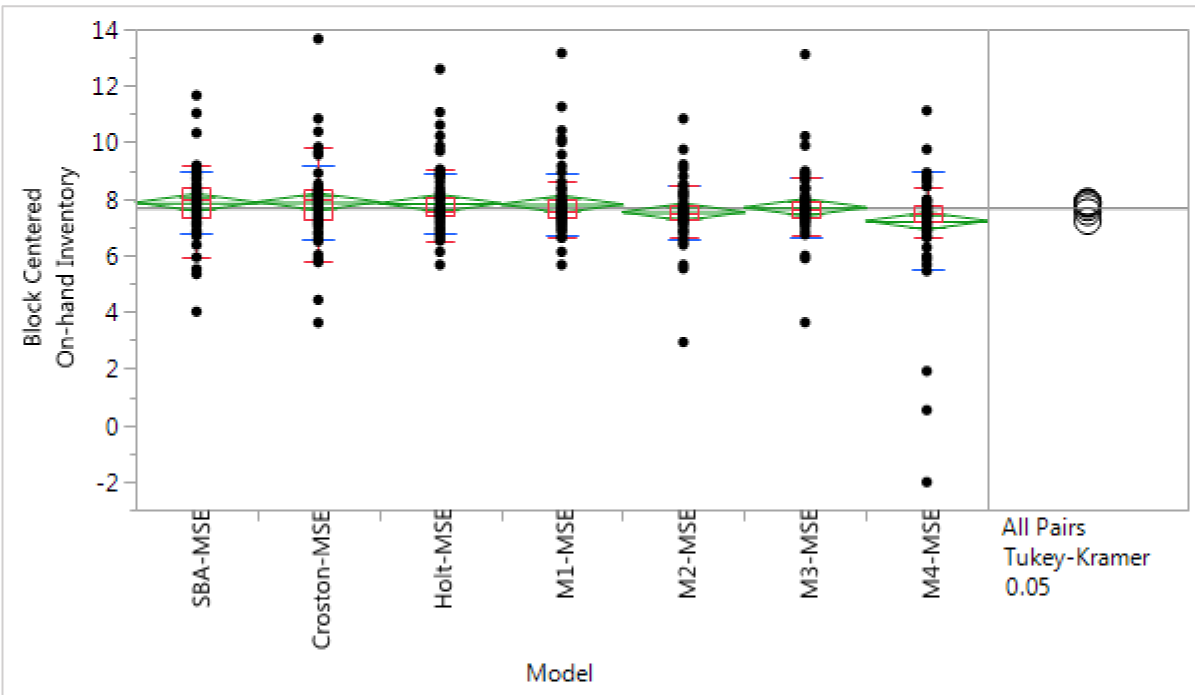

Figure 5-12: Box Plots for the Electronics Data Set (Ramp-Reg.)

Since there are only 71 data points, an alpha level of 0.05 will be utilized to ensure that the power of the test is similar to when there was 600 data points. The results of the statistical analysis (Table 5.24) shows that only M4-MSE achieved significantly lower on-hand levels compared to both SBA-MSE and Croston-MSE, while there is no statistical difference amongst the rest of the models at an alpha level of 0.05. See Section 6.2.C.12 of the appendix for the full analysis and the individual comparison of the new methods with Holt, SBA and Croston.

Table 5.24: Tukey-Kramer for the Electronics Data Set (Ramp-Reg.) (p-value < 0.05)

Model	Level		On-hand
Croston-MSE	A		7.89
SBA-MSE	A		7.87
Holt-MSE	A	B	7.84
M1-MSE	A	B	7.81
M3-MSE	A	B	7.69
M2-MSE	A	B	7.53
M4-MSE		B	7.21

5.5.4. Inventory Model Performance on SKUS with Reg-Drop Phases

The inventory performance measures were compared and analyzed considering only 48 SKUs which have the phases (Reg. and Drop). It was noticed that since demand tends to shift and drop significantly for this LC phase, SBA-MSE model was not able to lower its FR to 95%, even when applying very low values of *k*. This observation indicated that the mean estimate of the per period demand of both SBA and Croston methods tended to very large. This is similar to what has been observed with the generated data sets in Section 5.4. Consequently, the *k* values were selected such that all of the models will achieve a FR of 98.8%, in order to be able to compare SBA and Croston with the rest of the models. Table 5.25 shows the mean and standard deviation for all the inventory performance measures while Figure 5-13 shows the on-hand inventory box-plots for all of the models. The results showed that when considering an overall average fill rate of 98.8%, the lowest on-hand inventory levels were achieved by M1-MSE followed by the rest of the newly proposed methods.

Table 5.25: Inventory Performance Measures- the Electronics Data Set (Reg.-Drop)

Forecasting-Inventory Model	On-Hand Inventory Means (STD)	Service Level Means (STD)	Fill Rate Means (STD)	K-Values
Croston-MSE	4.54 (1.32)	98.03 (2.16)	98.8 (1.49)	0.1
SBA-MSE	4.45 (1.03)	97.96 (2.12)	98.8 (1.36)	0.00001
Holt-MSE	5.89 (2.96)	98.07 (2.08)	98.8 (1.43)	1.85
M1-MSE	3.89 (0.86)	97.90 (0.90)	98.8 (0.45)	1.1
M3-MSE	3.92 (0.96)	97.93 (1.10)	98.8 (0.62)	0.96
M2-MSE	3.93 (1.05)	98.02 (0.94)	98.8 (0.51)	1.2
M4-MSE	3.91 (1.04)	98.02 (1.16)	98.8 (0.60)	1.7

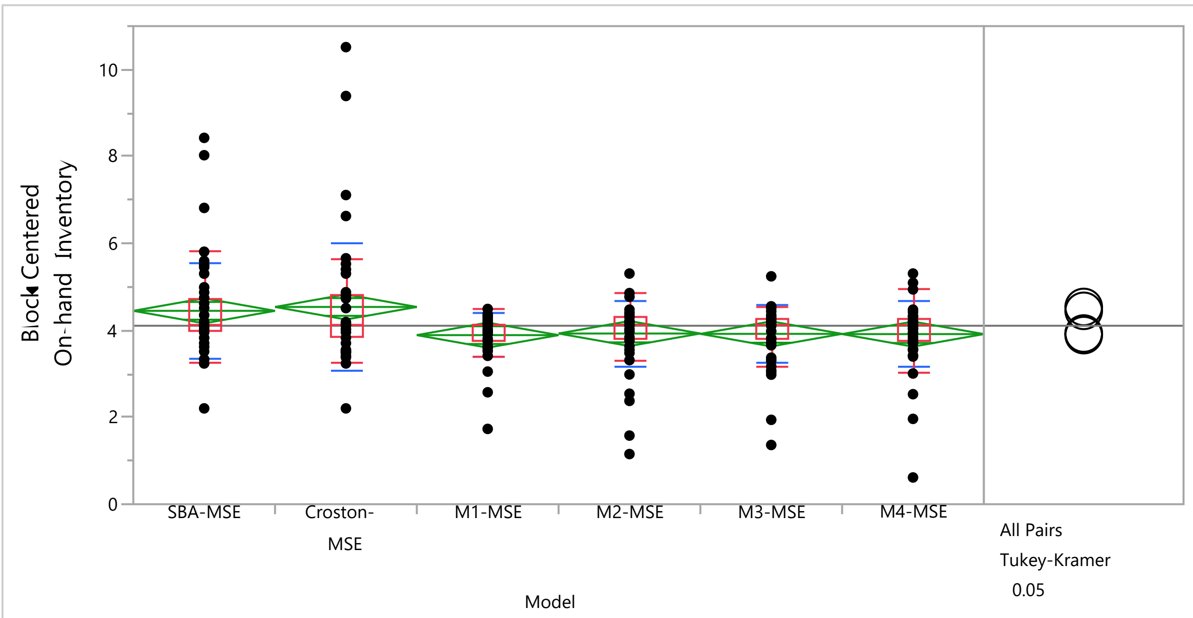

Figure 5-13: Box Plots for the Electronics Data Set (Reg.-Drop)

Since there are only 48 data points, an alpha level of 0.05 will be utilized to ensure that the power of the test is similar to when there was 600 data points. After reviewing both the initial results and the results of the statistical analysis (Table 5.25 and Table 5.26).Holt-MSE tended to over carry on-hand inventory compared to the rest of the models considered. The Holt forecasting technique seemed to struggle the most when there was a sudden shift of demand volume as it transitioned from the reg. to drop phase, resulting in carrying higher inventory levels. See Section 6.2.C.13 of the appendix for the full analysis and the individual comparison of the new methods with Holt, SBA and Croston.

Table 5.26: Tukey-Kramer for the Electronics Data Set (Reg.-Drop) (p-value < 0.05)

Model	Level		Mean
Holt-MSE	A		5.89
Croston-MSE		B	4.54
SBA-MSE		B	4.45
M2-MSE		B	3.93
M3-MSE		B	3.92
M4-MSE		B	3.91
M1-MSE		B	3.89

5.6. Conclusion

Results for the FLC showed that M4-MSE and M2-MSE achieved lower on-hand inventory levels compared to Holt-MSE, Croston-MSE and SBA-MSE across all of the data sets. M4-MSE carried the lowest on-hand inventory level compared to all of the models when demand was moderately or highly intermittent (i.e. Data sets two and three). M3-MSE and M1-MSE outperformed Croston-MSE and SBA-MSE across all of the generated data sets, but only outperformed Holt-MSE when demand was highly intermittent.

The Ramp-Reg phase had an adverse impact on the performance of Holt-MSE, as the model tended to carry significantly higher inventory levels across all data sets. On the contrary, M4-MSE carried significantly lower on-hand inventory levels compared to SBA-MSE and Croston-MSE for the real data set and data set one. M3-MSE, Croston-MSE and M4-MSE achieved the same level of performance when demand was moderately intermittent. When demand was slightly intermittent, M2-MSE carried significantly lower on-hand inventory levels compared to all of the models excluding M4-MSE. Only M4-MSE achieved significantly lower on-hand levels compared to both SBA-MSE and Croston-MSE when the real data was considered.

During the Reg-Drop phases, M4-MSE performed very well by carrying lower on-hand inventory levels across all data sets. When demand was slightly intermittent, Holt-MSE performed similarly to M4-MSE but it outperformed all of the other models. However, for the real data set and when moderately or highly intermittent demand were analyzed, Holt-MSE performed poorly compared to the newly proposed models. M2-MSE performed better than Holt-MSE, SBA-MSE and Croston-MSE when demand was moderately or highly intermittent. For moderately and highly intermittent demand in the Reg-Drop phase, all of the new methods achieved better performance compared to both SBA-MSE and Croston-MSE. Across all of the generated data sets in the Reg-Drop phase, all of the new methods achieved better performance compared to both SBA-MSE and Croston-MSE. Moreover, amongst the new methods themselves, M4-MSE performed better than both M1-MSE and M3-MSE. For the real data set, Holt-MSE carried the highest level of inventory compared to all of the models.

Chapter 6

Conclusions and Future Work

6.1. Conclusions

This study aimed to contribute to the research area of spare parts management. The contributions were made to address the topic of spare parts demand forecasting required for corrective maintenance during the warranty period. Furthermore, analyzing the forecasting approaches with respect to their inventory management performance was also considered within this study. A number of comparative analyses were conducted to address some of the main research needs of this topic.

Research gaps and insights have been identified in Chapter 2. Accordingly, the analyses conducted in Chapter 3 aimed to investigate and compare the performance of Holt's forecasting method with SBA and Croston. SBA and Croston are two of the most widely used forecasting techniques for spare parts demand. Holt was mainly selected to address the fact that the demand of service parts exhibits a trend element that needs to be factored in when forecasting. Despite the numerous studies that have been conducted for forecasting intermittent demand, only a limited number of studies have addressed the trend element in demand (Altay et al. 2008; Lindsey and Pavur 2005; Ghobbar and Friend 2003;Snyder 2002), some of which attributed the trend to the different life cycle (LC) stages of products. The analyses in chapter 3 investigated the accuracy of the forecasting techniques (i.e. SBA, Croston and Holt) in addition to assessing their inventory measures performance. To conduct the analyses, two different industrial data sets were used. The significance of analyzing models using real data rather than solely relying on simulation was emphasized in recent literature review studies (Van der Auweraer et al., 2019; Hu et al., 2018).

The performance of the forecasting techniques was examined using SKU’s with four different demand patterns; intermittent, lumpy, erratic and smooth. The results showed that Holt’s method managed to outperform SBA and Croston for both data sets. This conforms with the claim that the demand of service parts exhibits a trend element. This observation indicated the potential benefit of including a trend element in spare parts forecasting methods.

Research studies have emphasized the importance of integrating different levels of information into the decision making process of spare parts management. The need to incorporate the life cycle process into the demand forecasting and inventory planning decisions was mentioned (Hu et al., 2018). Van der Auweraer et al. (2019) emphasized the need for studies that integrate installed base information with commonly used forecasting techniques. They also suggested identifying the points in the life cycle phases where the installed base information could enhance the performance of forecasting techniques and inventory models. Moreover, it was purposed that future research ought to consider developing new forecasting methods that capture the risk of obsolescence by having frequent and timely updates on demand estimates (Babai, M.Z., et al., 2017).

Consequently, the remainder of this research aimed to develop new forecasting techniques for spare parts demand that addressed the above mentioned research needs. Four new forecasting methods were proposed, each method incorporated different levels of information including demand, probability of demand occurrence, installed base and life cycle phase. The methods were developed to provide an enhanced responsiveness level that generates more accurate demand estimates. The methods were designed with the goal of better handling the complexity of spare parts management, which exists due to the interplay between multiple factors affecting the decision making process (e.g., life cycle stage, product failure rates, installed base information, warranty period, technology and innovation, and component demand patterns).

Comparative analyses were conducted to compare the four new proposed methods with Holt, SBA and Croston. Both generated data sets and a real data set were used to assess the forecasting accuracy and the inventory performance measures. The three generated data sets featured SKUs with different levels of intermittency, ranging from slightly to highly intermittent demand data. The results obtained when all of the SKU's of the real data set were analyzed showed that M4-MSE followed by M2-MSE achieved lower on-hand inventory levels compared to all the models. This indicates the robustness of the models in handling the variability of all the different SKUs undergoing different life cycle phases.

Moreover, to investigate the performance of the forecasting techniques for different life cycle phases, each data set was separated into three subsections: full life cycle phase, Ramp-Reg phase and Reg-Drop phase. The forecasting techniques were assessed for each life cycle phase to help identify the points in the life cycle phases where the use of a certain level of information could enhance the performance of the forecasting techniques with respect to accuracy and inventory measures. In the following section, the observations and conclusions obtained after examining all of the data sets will be reviewed for the LC phases considered with regard to accuracy and inventory measures performance.

Full Life Cycle Phase

Accuracy: M4 and M2 consistently achieved higher levels of accuracy with respect to the MSE metric compared to SBA, Croston and Holt. It was observed that M1 showed superior performance compared to Holt, Croston and SBA during the FLC phase only when the demand data was highly intermittent (i.e. Data Set Three). Both M3 and Holt generated more accurate results compared to Croston and SBA across all demand data sets. Furthermore, the results showed that, on average, SBA and Croston always tended to have negative bias for the FLC phase across all data sets.

Inventory Measures Performance: M4-MSE and M2-MSE achieved lower on-hand inventory levels compared to Holt-MSE, Croston-MSE and SBA-MSE across all the data sets. M3-MSE and M1-MSE outperformed Croston-MSE and SBA-MSE across all of the generated data sets, but only outperformed Holt-MSE when demand was highly intermittent. M4-MSE carried the lowest on-hand inventory level compared to all of the models when demand was moderately or highly intermittent (i.e. Data sets two and three).

Ramp-Reg Phases

Accuracy: it was observed that M2, M3 and M4 achieved a higher level of accuracy compared to Holt, Croston and SBA when demand was moderately intermittent, and they outperformed Croston and SBA when demand was slightly intermittent. On the contrary, when the data set was highly intermittent during this life cycle phase, SBA and Croston achieved the highest levels of accuracy compared to the rest of the models.

Inventory Measures Performance: It was observed that the Ramp-Reg phase had an adverse impact on the performance of Holt-MSE, as the model tended to carry significantly high inventory levels across all data sets. On the contrary, M4-MSE followed by M2-MSE carried the lowest on-hand inventory level compared to all of the models when demand was slightly intermittent (i.e. Data set one). M3-MSE, Croston-MSE and M4-MSE achieved the same level of performance when demand was moderately intermittent. During this phase, SBA-MSE and Croston-MSE achieved lower on-hand levels compared to Holt-MSE and M2-MSE when demand was moderately or highly intermittent. Only M4-MSE achieved significantly lower on-hand levels compared to both SBA-MSE and Croston-MSE when the real data was considered.

Reg-Drop Phases

Accuracy: M1, M2, M3 and M4 consistently achieved higher levels of accuracy compared to both Croston and SBA across all of the generated data sets. M1, M2 and M4 outperformed Holt when demand was moderately or highly intermittent.

Inventory Measures Performance: M4-MSE performed very well by carrying lower on-hand inventory levels across all data sets. When demand was slightly intermittent, Holt-MSE performed similarly to M4-MSE, but it outperformed all of the other models. On the contrary, for the real data set and when moderately or highly intermittent demand were analyzed, Holt-MSE performed poorly. M2-MSE performed better than Holt-MSE, SBA-MSE and Croston-MSE when demand was moderately or highly intermittent. Across all the generated data sets in the Reg-Drop phase, all of the new methods achieved better performance compared to both SBA-MSE and Croston-MSE. Moreover, amongst the new methods themselves, M4-MSE performed better than both M1-MSE and M3-MSE. For the real data set, Holt-MSE carried the highest level of inventory compared to all the models.

Based on the overall results, it can be concluded that acknowledging the LC phase in the forecasting method can yield higher levels of accuracy in most of the scenarios. The most challenging phase to forecast is the ramp phase, which is expected due to the limited number of data points. M1, M2 and M4 performed well during the Reg-Drop phases particularly when demand is moderately or highly intermittent. This highlights the importance of incorporating the probability of demand occurrence and the LC phase to the forecasting approach, as it enables the methods to better handle demand prediction and lower the risks of obsolescence associated with this phase. Generally, it was observed that across the analyses conducted, M4 performed better with respect to both accuracy and inventory measures when compared to all the models. At its worse, M4-MSE performed similar to the best performing models. This implies that if M4 were to be considered for all of the different levels of demand intermittency and across all of the LC cycle phases, it will either outperform SBA, Croston, Holt and the new methods (M1, M2 and M3) or it will provide the same level of performance. The only challenge that might arise from considering the M4 method is that it requires knowledge of different pieces of information which may or may not be available for all companies. The second best performing method was M2-MSE, which requires less information compared to M4-MSE. M1-MSE showed great promise when the demand is highly intermittent and during the Reg-Drop phase.

To the best of our knowledge, this study was the first to address the following multiple research needs in the area of spare parts management. Firstly, the proposal of new forecasting techniques that incorporate different levels of information. Secondly, empirically investigating the new proposed techniques with the two benchmarked techniques in spare parts demand forecasting SBA and Croston. Thirdly, the empirical studies assessed the performance of the models not only with regard to accuracy but also inventory performance. Fourthly, the empirical investigation was extended to assess and evaluate the performance of the models for SKUs with different life cycle phases and intermittency levels. Fifthly, the potential benefits of adding a certain level of information on the accuracy of the forecasting technique and the associated inventory performance was evaluated. Lastly, all of the analyses were performed using real industrial data in addition to theoretical data sets. Testing the performance of methods with real data has been highly recommended in recent literature. The virtue of using actual industrial data is that it encompasses a high level of variability which is not provided by theoretical data, and it is crucially important to ensure that the forecasting techniques will perform well in real business scenarios.

6.2. Future Work and Recommendations

The findings of this research have unfolded a variety of future research avenues that will contribute tremendously to the fields of spare parts management and e-textiles.

One promising research area is to derive the statistical properties for all of the forecasting methods considered in this research. Some work has been done in this area for SBA and Croston. However, different findings have been reported regarding the correct derivations. Moreover, all of the studies only proposed derivations with the assumption that the approaches have a single value for their smoothing constants. Investigating this would yield tremendous benefits to inventory management, as the variability associated with each forecasting technique would be incorporated in the needed safety stock calculations. On a similar note, proposing a more robust inventory model that copes with the transitions in the life cycle phases seems to be a potentially rewarding path for future research. It was observed that incorporating a level of responsiveness into the LC phases in the forecasting techniques generated more accurate demand estimates.

The findings have showed that M1 performed very well compared to the considered models when the demand was highly intermittent and in the Reg-Drop phases. This indicated its potential advantage in handling the EOL phase where the risk of obsolescence is quite high. Consequently, it is important to conduct comparative analyses between M1, TSB, HES and LES to determine which approach is better in handling the risk of obsolescence.

Furthermore, conducting extensive parametric analyses for the newly proposed forecasting techniques could be of great value. For example, it is important to investigate the optimum values with respect to each life cycle phase, the transition between different LC phases and the industry of the serviceable product. One of the main advantages of the newly proposed methods is that they are comprised of parameters that can easily be altered to cater to the specific needs and properties of the product's LC and industry.

Lastly, this research has proposed the notion that E-textiles will be one of the serviceable industry sectors. This emphasized the need for planning for E-textiles serviceability. However, given that this field is still at its infancy, it was not possible to acquire real demand data set for spare parts of e-textiles products. Consequently, the electronics data set was selected, owing to its similarity to the electronic components in the e-textiles products sold in the current market. Both have similar levels of technology, short life cycle of products, prices, warranty periods and risks of obsolescence. To the best of our knowledge, no prior study has discussed this topic from this perspective. This reveals a new research area that addresses the aspects of managing the supply chain of e-textiles products for mass production. Moreover, future studies could explore the possibility of acquiring actual spares demand data sets for e-textiles products and test the performance of our newly proposed methods on these data sets.

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APPENDICES

APPENDIX A

A.1 : MSE COMPARISON FOR ELECTRONICS DATA SET

The MSE was also assessed to evaluate any statistically significant difference between the means. Based on Levene's statistics, we failed to reject the null hypothesis that the variances are equal at p-value of 0.13. Accordingly, a one way ANOVA test was conducted and the null hypothesis was rejected at a p-value of 0.0037. Results from Tukey's test showed that Holt-DES was significantly different than both SBA and Croston at p-values of 0.007 and 0.011, respectively. Box plots of the MSE metric across the four forecasting approaches for the electronics data set are shown in Figure A.1.

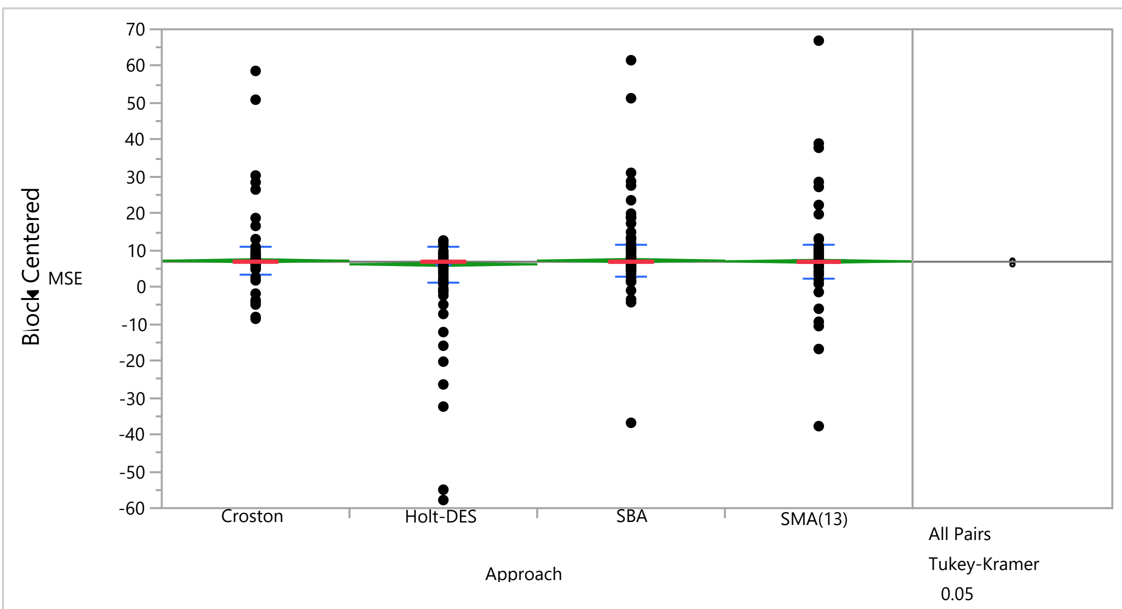

Figure A.1: Box Plots of the "Mean Squared Error (MSE)" Metric - Electronics Data Set

A.2 : ME AND MSE COMPARISONS FOR AUTOMOTIVE DATA SET

To further assess the accuracy of the different forecasting techniques and to evaluate the statistical significance of the forecast error metrics, the hypothesis that there is no statistical difference between the forecasting approaches with respect to the ME was tested. Since the sample size was large (n = 3000), the central limit theorem was invoked and the normality assumption of the data was made. Box plots of the ME metric across the four forecasting approaches for the automotive data set are shown in Figure A.2.

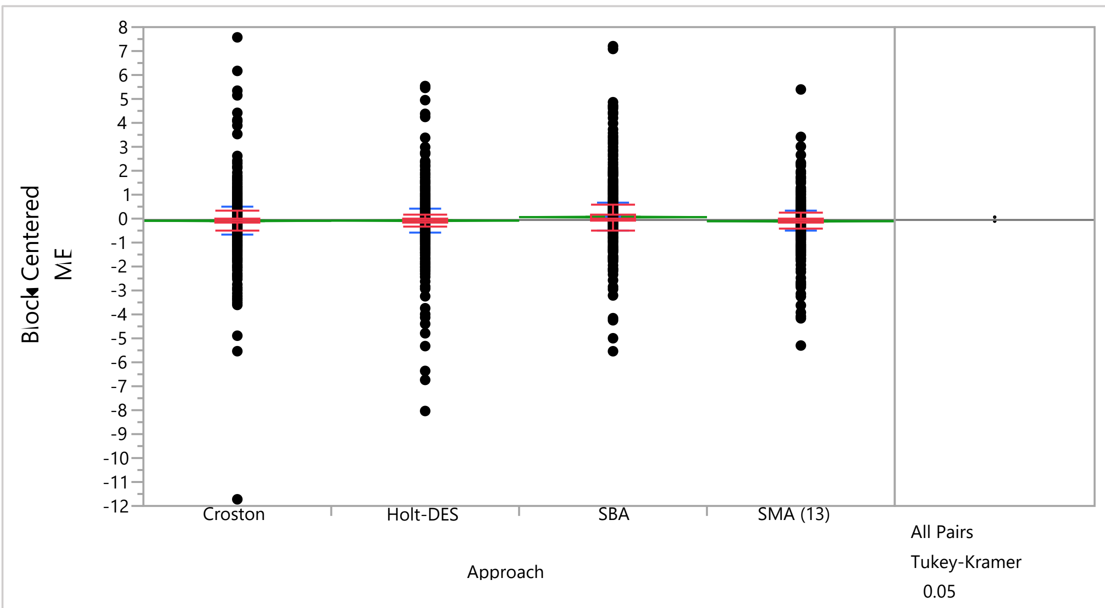

Figure A.2: Box Plots of the "Mean Error (ME)" -Automotive Data Set

Based on Levene's statistics, the null hypothesis that the variances are equal was rejected at p-value of < 0.0001. Accordingly, the Welch's test was conducted and the null hypothesis was again rejected at p-value of <0.0001. Results from Tukey's test showed that SBA was significantly different than SMA (13), Holt-DES and Croston at α = 0.05. Results showed that the highest MSE was achieved by SMA (13) followed by Croston, Holt-DES and SBA. Box Plots of the MSE metric across the four forecasting approaches for the automotive data set are shown in Figure A.3.

To evaluate the statistical significance of the forecast error metrics, the hypothesis that there is no statistical difference between the forecasting approaches with respect to MSE was tested. Based on Levene's statistics, we failed to reject the null hypothesis that the variances are equal p-value of 0.39. According to the one way ANOVA test we failed to reject the null hypothesis at a p-value of 0.78. Thus, it was concluded that there is no statistical difference between any of the approaches with respect to the MSE metric for this data set.

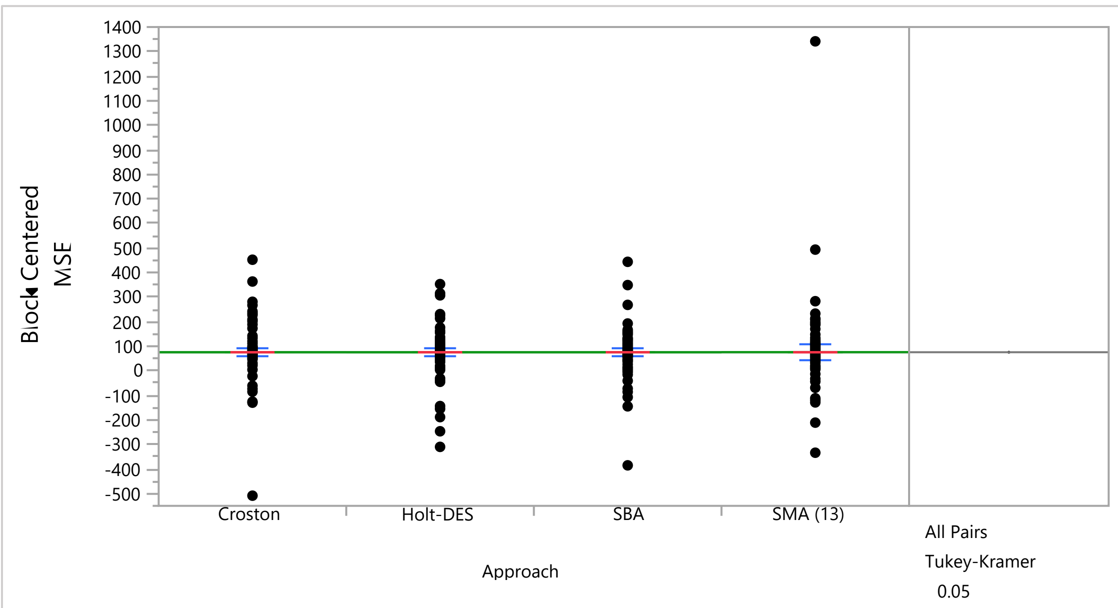

Figure A.3: Box Plots of the "Mean Squared Error (MSE)" Metric- The Automotive Data Set

A.3 : INVENTORY MODEL PERFORMANCE ON ALL SKUS-ELECTRONICS DATA SET

To evaluate the statistical significance of the service level means, the hypothesis that there is no statistical difference between the means was tested. Based on Levene's statistics, the null hypothesis that the variances are equal was rejected at p-value of < 0.0001. Accordingly, the Welch's test was conducted and the null hypothesis was again rejected at a p-value of <0.0001.

Results of the Tukey's test showed that there is statistical evidence that SBA-MSE achieved the lowest service level on average compared to all the other forecasting-inventory models at $\alpha = 0.05$. Similarly, Croston-MSE was significantly lower than Holt-Corr1, Holt-MSE and Holt-Corr2 at $\alpha = 0.05$. As for the variants of Holt-DES inventory models, no statistical difference was detected between Holt-Corr1 and Holt-MSE at $\alpha = 0.05$. Holt-Corr2 achieved significantly higher service levels compared to both Holt-MSE and Holt-Corr1. Box plots of the achieved service levels across all the forecasting-inventory models are shown in Figure A.4.

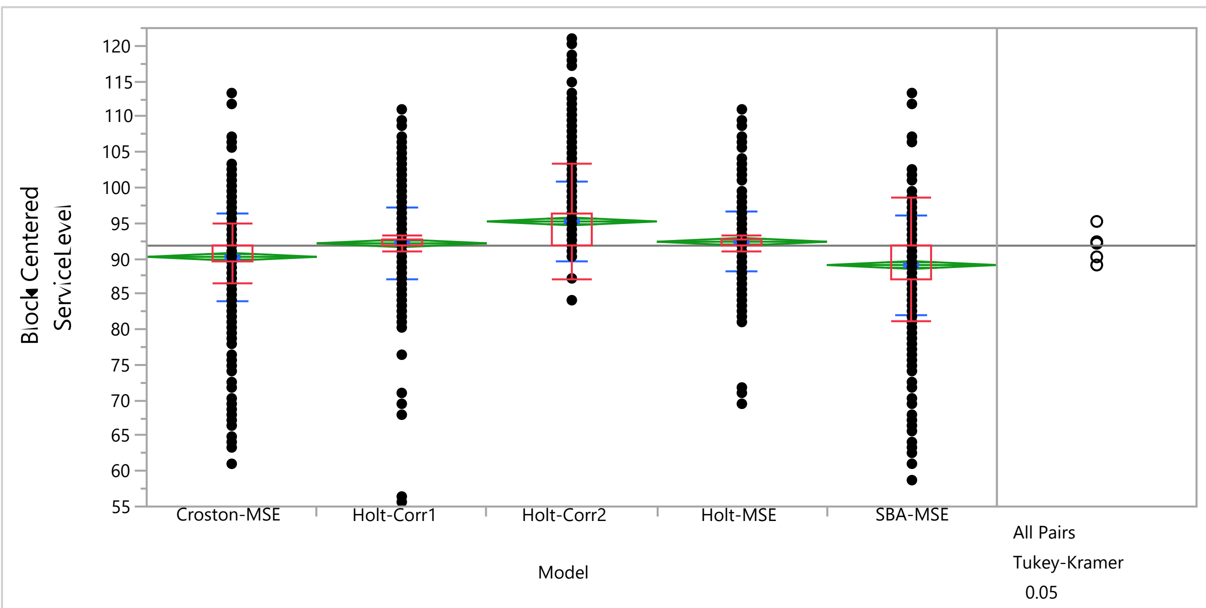

Figure A.4: Box Plots of the "Service Level" Metric of Each Model- Electronics Data Set

Lastly, the fill-rate performance metric was statistically analyzed. Based on Levene's statistics, the null hypothesis that the variances are equal was rejected at p-value of <0.0001. Accordingly, the Welch's test was conducted and the null hypothesis was again rejected at a p-value of <0.0001. Results of the Tukey's test showed that there is statistical evidence that SBA-MSE achieved the lowest fill rate on average compared to Holt-Corr1, Holt-MSE and Holt-Corr2. No significant difference was evident between SBA-MSE and Croston-MSE at $\alpha = 0.05$. Similarly, Croston-MSE was significantly lower than Holt-Corr1, Holt-MSE and Holt-Corr2 at α = 0.05. As for the variants of Holt-DES (Holt-MSE, Holt-Corr1 and Holt-Corr2) inventory models, no statistical difference was detected between Holt-Corr1 and Holt-MSE at α = 0.05. Holt-Corr2 achieved a significantly higher fill rate compared to both Holt-MSE and Holt-Corr1. Box plots of the achieved fill-rates across all the forecasting-inventory models are shown in Figure A.5.

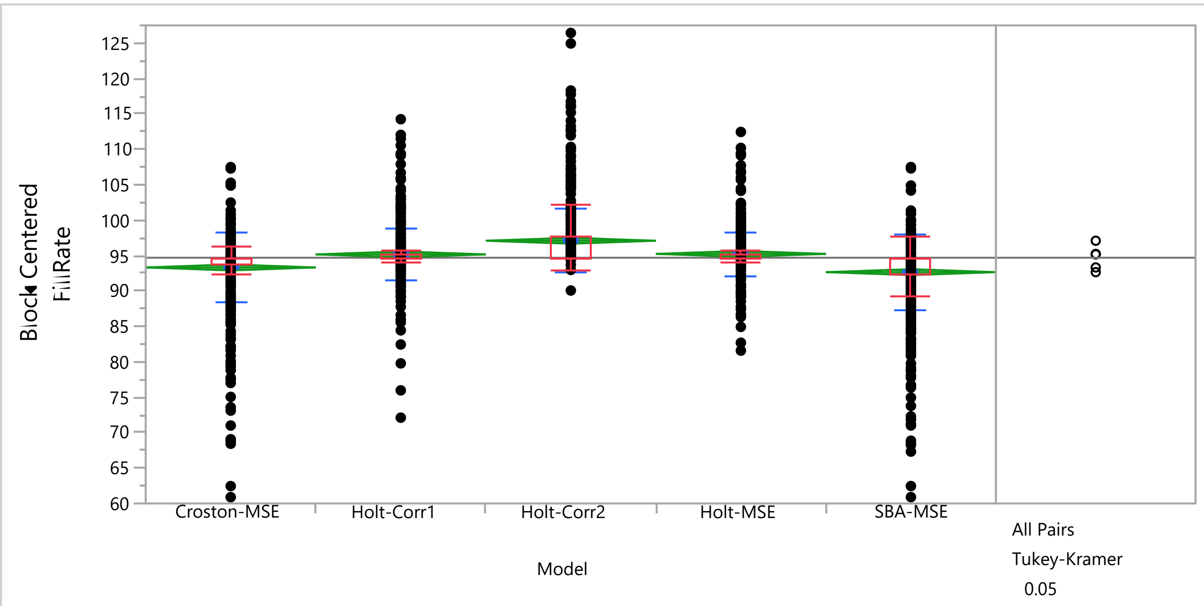

Figure A.5: Box Plots of the "Fill Rate" Metric of Each Model- Electronics Data Set

A.4 : INVENTORY MODEL PERFORMANCE ON ALL SKUS- AUTOMOTIVE DATA SET

To evaluate the statistical significance of the on-hand inventory means, the hypothesis that there is no statistical difference between the means was tested. Based on Levene's statistics, the null hypothesis that the variances are equal was rejected at p-value of <0.0001. Accordingly, the Welch's test was conducted and the null hypothesis was again rejected at a p-value of <0.0001. Results of Tukey's test showed that the SBA-MSE was significantly lower compared to all the other forecasting-inventory models at α = 0.05. On the contrary, Holt-Corr2 was found to be significantly higher than Croston-MSE, Holt-Corr1 and Holt-MSE. Croston-MSE achieved significantly higher levels of inventory compared to Holt-MSE at α = 0.05. Finally, no statistical difference was found between Croston-MSE and Holt-Corr1. Box plots of on-hand inventory quantity across all the forecasting-inventory models are shown in Figure A.6.

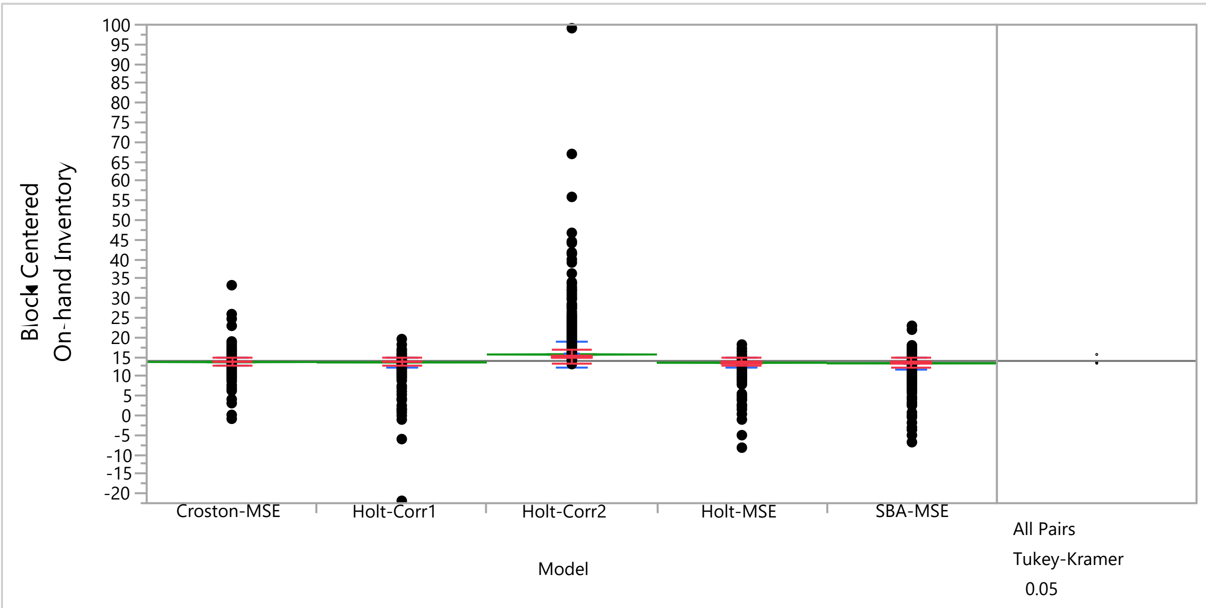

Figure A.6: Box Plots of the "On-hand Inventory" Metric of Each Model- Automotive Data Set

The service level performance metric was statistically analyzed. Based on Levene's statistics, the null hypothesis that the variances are equal was rejected at p-value of <0.0001. Accordingly, the Welch's test was conducted and the null hypothesis was rejected at a p-value of <0.0001. Results of Tukey's test showed that there is statistical evidence that SBA-MSE achieved the lowest service level on average compared all the other forecasting-inventory models at α = 0.05. On the contrary, Holt-Corr2 achieved significantly higher service levels compared to all the models at α = 0.05 and was the only model to achieve approximately 95% service level on average. No statistical difference was detected amongst Holt-MSE, Holt-Corr1 and Croston-MSE. Box plots of service levels across all the forecasting-inventory models are shown in Figure A.7.

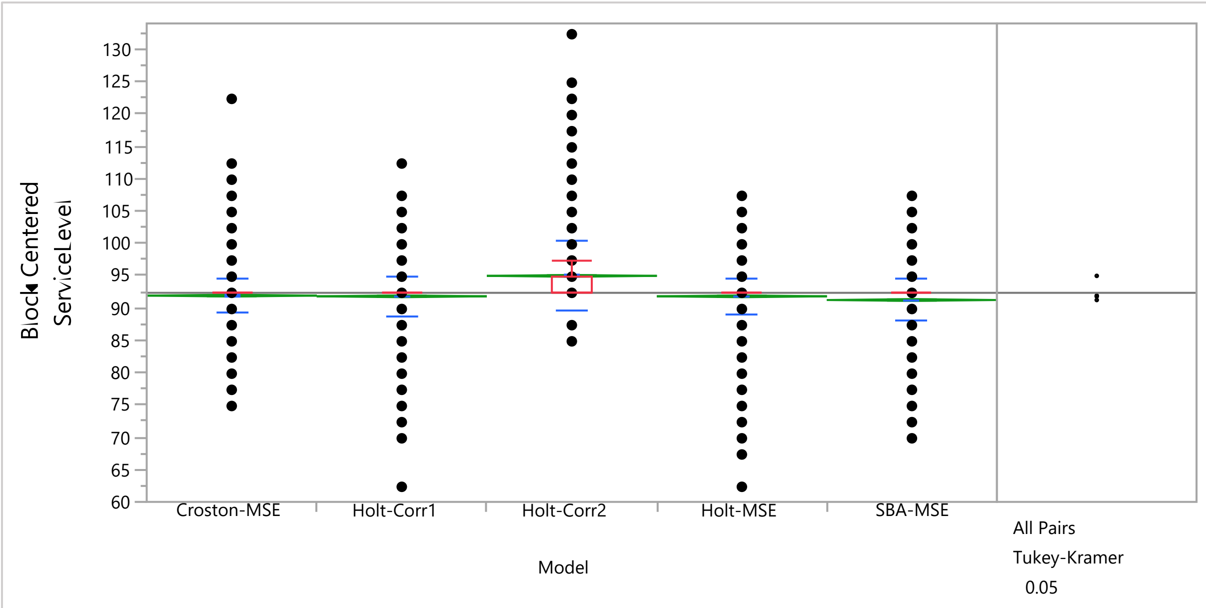

Figure A.7: Box Plots of the "Service Level" Metric of Each Model- Automotive Data Set

The fill-rate performance metric was statistically analyzed. Based on Levene's statistics, the null hypothesis that the variances are equal was rejected at p-value of <0.0001. Accordingly, the Welch's test was conducted and the null hypothesis was again rejected at a p-value of <0.0001. Results of Tukey's test showed that there is statistical evidence that SBA-MSE achieved the lowest fill rate on average compared all the other forecasting-inventory models at $\alpha = 0.05$. On the contrary, Holt-Corr2 achieved a significantly higher fill rate compared to all the models at $\alpha = 0$. No statistical difference was detected amongst Holt-MSE, Holt-Corr1 and Croston-MSE. Box plots of fill rates across all the forecasting-inventory models are shown in Figure A.8.

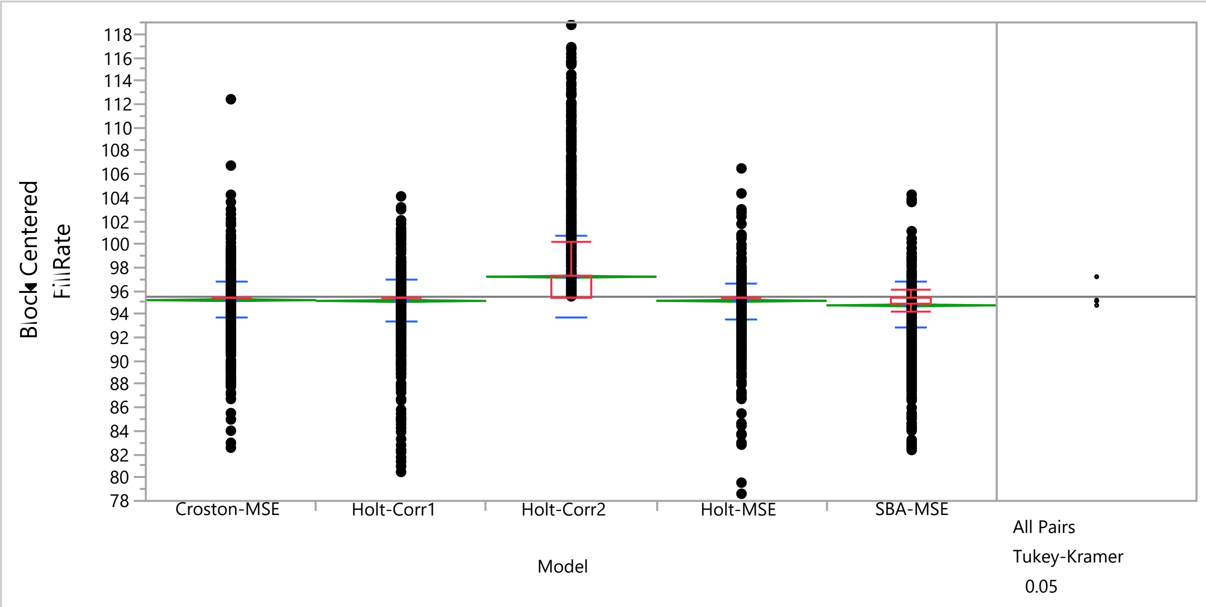

Figure A.8: Box Plots of "Fill Rate" - Automotive Data Set

A.5 : INVENTORY MODEL PERFORMANCE FOR ERRATIC DEMAND PATTERN-ELECTRONICS DATA SET

To evaluate the statistical significance of the on-hand inventory means, the hypothesis that there is no statistical difference between the means was tested. Since the sample size was large enough ($n = 43$), the central limit theorem was invoked and the normality assumption of the data was made. Based on Levene's statistics, the null hypothesis that the variances are equal was rejected at p-value of 0.024. Accordingly, the Welch's test was conducted and the null hypothesis was again rejected at a p-value of <0.0001. Results of the Tukey's test showed that Holt-Corr2 was significantly higher than all the other forecasting-inventory models at $\alpha = 0.05$. Box plots of on-hand inventory quantity across all the forecasting-inventory models are shown in Figure A.9.

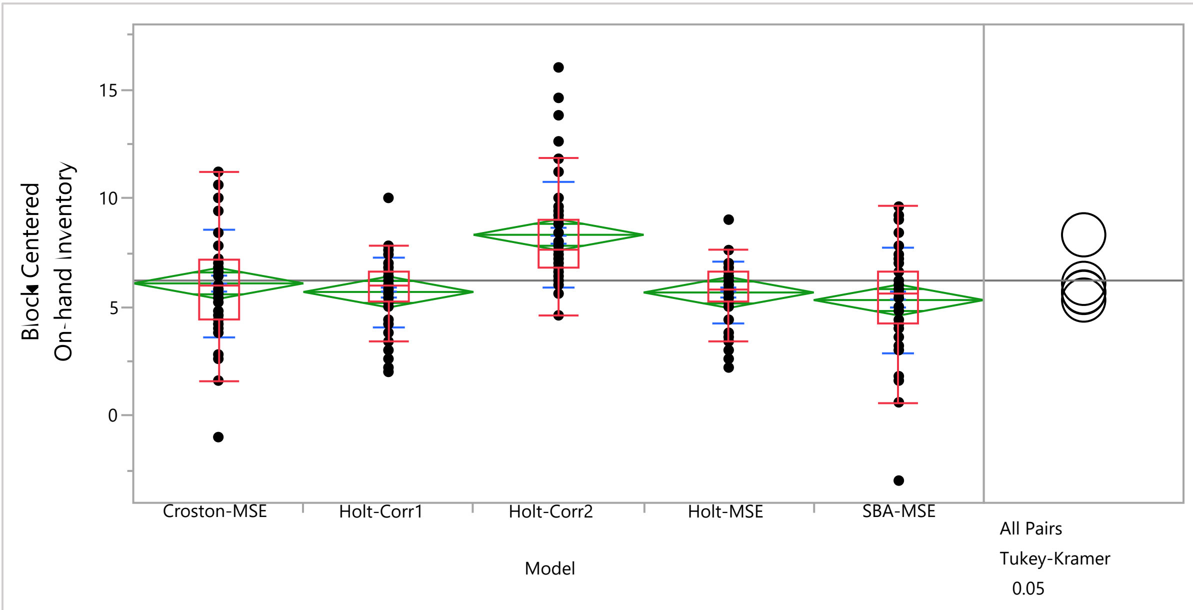

Figure A.9: Box Plots of "On-hand Inventory" for Erratic Demand Pattern- Electronics Data Set

To evaluate the statistical significance of the service level means, the hypothesis that there is no statistical difference between the means was tested. Based on Levene's statistics, we failed to reject the null hypothesis that the variances are equal at p-value of 0.15. According to the one way ANOVA test we failed to reject the null hypothesis at a p-value of <0.0001. Results of the Tukey's test showed that there is statistical evidence that on average Holt-Corr2 achieves significantly higher service levels compared to the other models α = 0.05. Box plots of the service level across all the forecasting-inventory models are shown in Figure A.10.

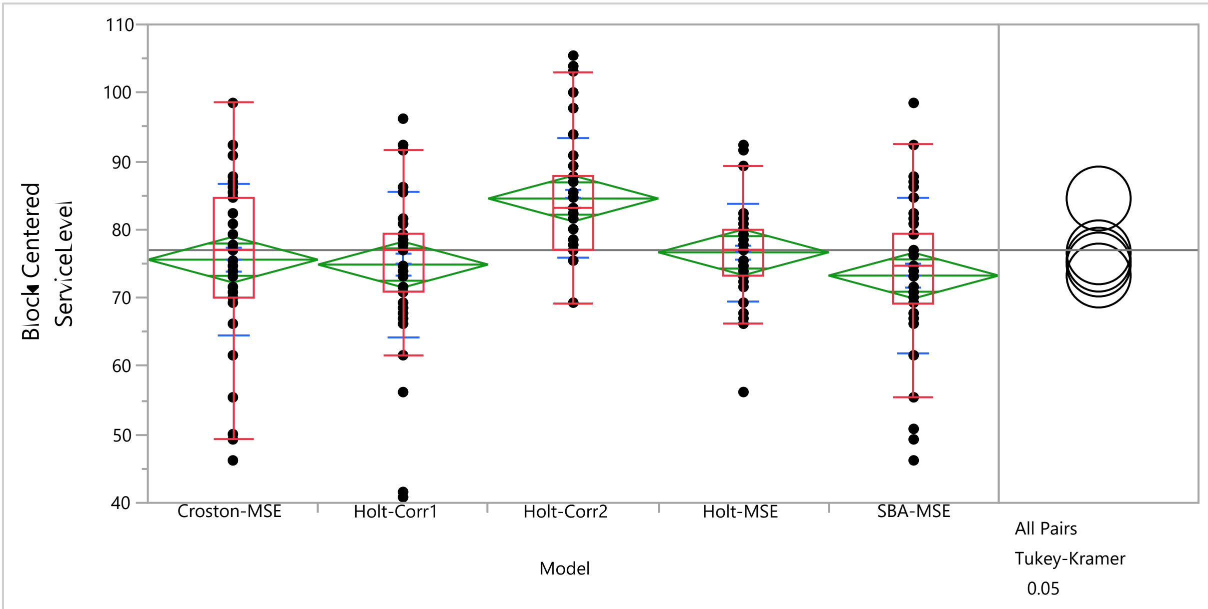

Figure A.10: Box Plots of "Service Level" for Erratic Demand Pattern- Electronics Data Set

To evaluate the statistical significance of the fill rate means, the hypothesis that there is no statistical difference between the means was tested. Based on Levene's statistics, we failed to reject the null hypothesis that the variances are equal at p-value of 0.059. According to the one way ANOVA test we failed to reject the null hypothesis at a p-value of <0.0001. Results of the Tukey's test showed that there is statistical evidence that on average Holt-Corr2 achieves significantly a higher fill rate compared to the other models α = 0.05. Box plots of the fill rate across all the forecasting-inventory models are shown in Figure A.11.

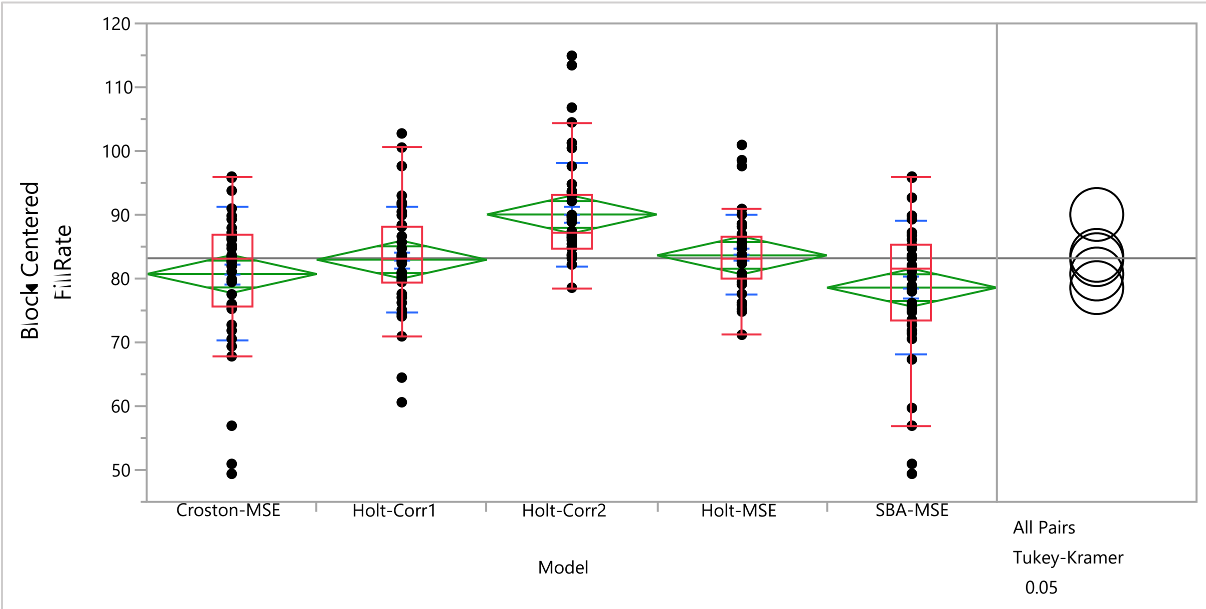

Figure A.11: Box Plots of "Fill Rate" for Erratic Demand Pattern- Electronics Data Set

A.6 INVENTORY MODEL PERFORMANCE FOR INTERMITTENT DEMAND PATTERN – THE ELECTRONICS DATA SET

To evaluate the statistical significance of the on-hand inventory means, the hypothesis that there is no statistical difference between the means was tested. Since the sample size was large (n = 322), the central limit theorem was invoked and the normality assumption of the data was made. Based on Levene's statistics, the null hypothesis that the variances are equal was rejected at p-value of <0.0001. Accordingly, the Welch's test was conducted and the null hypothesis was again rejected at a p-value of <0.0001. Results of the Tukey's test showed that Holt-Corr2 was significantly higher than all the other forecasting-inventory models at $\alpha = 0.05$. Similarly both Holt-MSE and Holt-Corr1 were significantly different than SBA-MSE and Croston-MSE. No statistical difference was captured between SBA-MSE and Croston-MSE. Also, No statistical difference was captured between Holt-MSE and Holt-Corr1. Box plots of the on-hand inventory quantity across all the forecasting-inventory models are shown in Figure A.12.

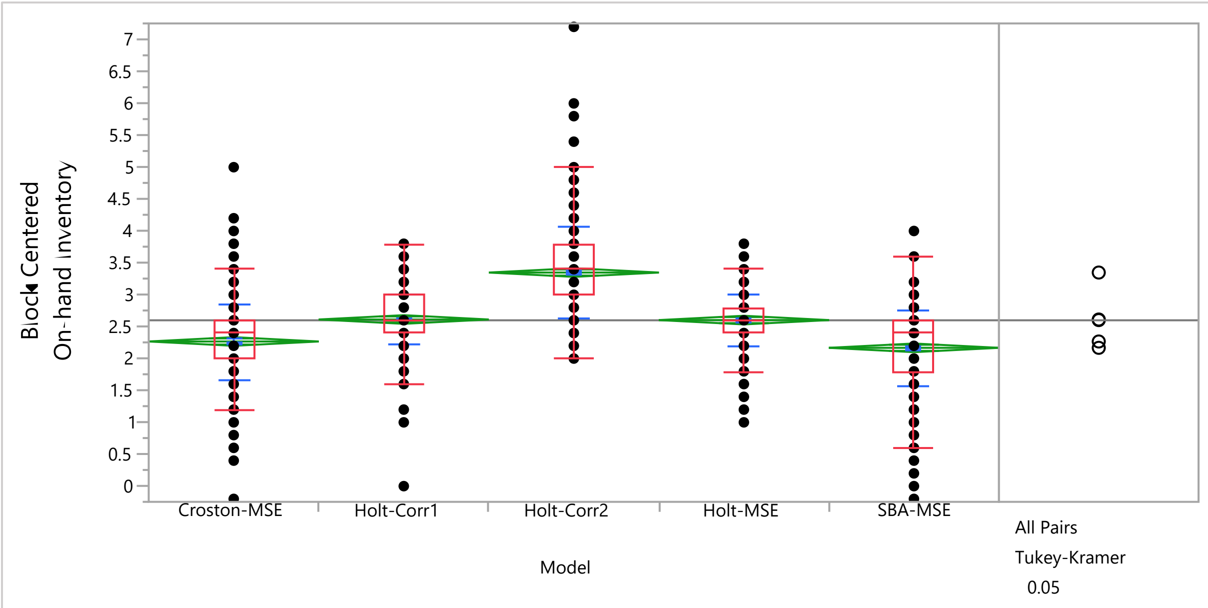

Figure A.12: Box Plots of "Service Level" for Intermittent Demand Pattern- Electronics Data Set

The means of service levels were statistically analyzed. Based on Levene's statistics, the null hypothesis that the variances are equal was rejected at p-value of <0.0001. Accordingly, the Welch's test was conducted and the null hypothesis was again rejected at a p-value of <0.0001. Results of the Tukey's test showed that Holt-Corr2 was significantly higher than all the other forecasting-inventory models at $\alpha = 0.05$. Similarly both Holt-MSE and Holt-Corr1 achieved significantly higher service levels compared to SBA-MSE and Croston-MSE. No statistical difference was captured between SBA-MSE and Croston-MSE. Also, No statistical difference was captured between Holt-MSE and Holt-Corr1. Box plots of service levels across all the forecasting-inventory models are shown in Figure A.13.

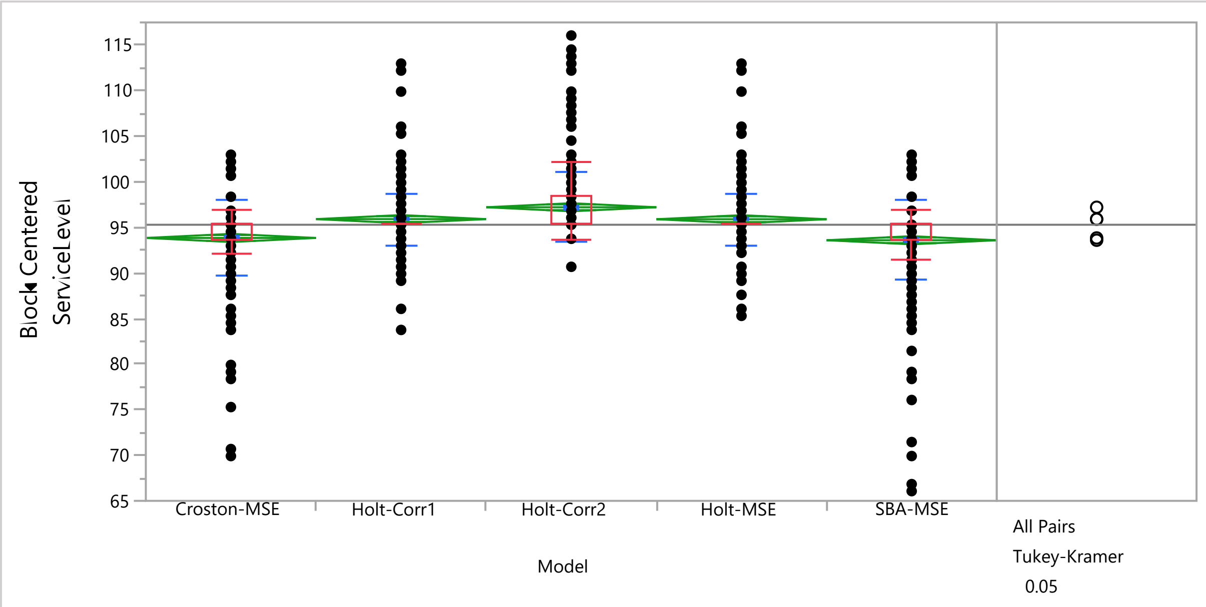

Figure A.13: Box Plots of "Service Level" for Intermittent Demand Pattern- Electronics Data Set

The means of the fill rates were statistically analyzed. Based on Levene's statistics, the null hypothesis that the variances are equal was rejected at p-value of <0.0001. Accordingly, the Welch's test was conducted and the null hypothesis was again rejected at a p-value of <0.0001. Results of the Tukey's test showed that Holt-Corr2 was significantly higher than all the other forecasting-inventory models at α = 0.05. Similarly both Holt-MSE and Holt-Corr1 achieved significantly higher fill rates compared to SBA-MSE and Croston-MSE. No statistical difference was captured between SBA-MSE and Croston-MSE. Also, No statistical difference was captured between Holt-MSE and Holt-Corr1. Box plots of fill rates across all the forecasting-inventory models are shown in Figure A.14.

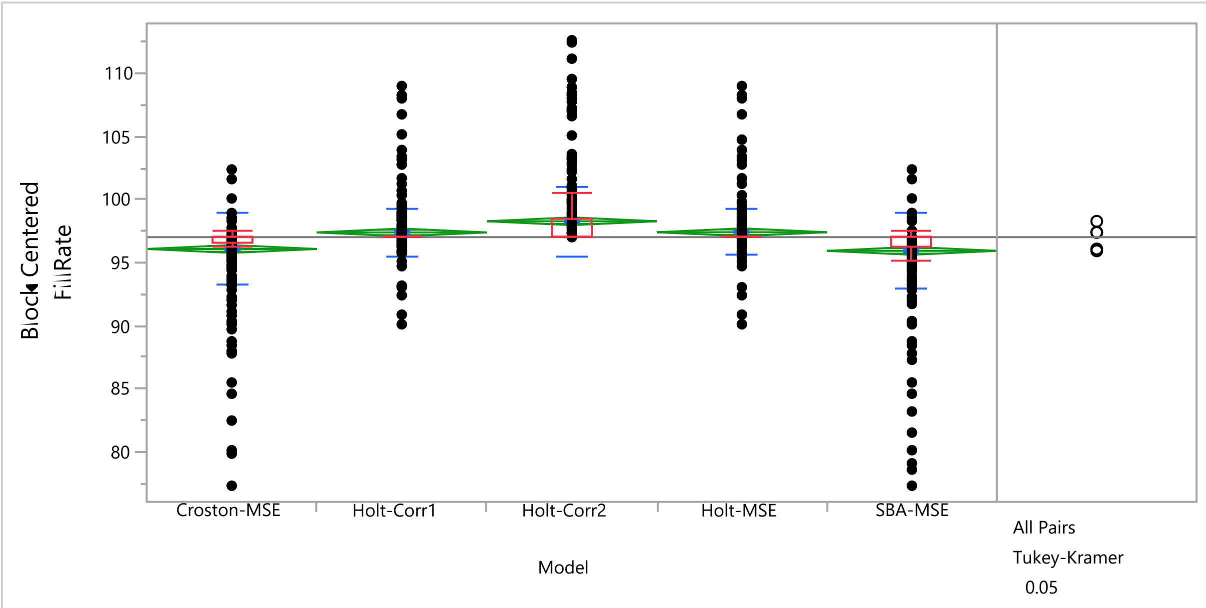

Figure A.14: Box Plots of "Fill Rate" for Intermittent Demand Pattern- Electronics Data Set

A.7 : INVENTORY MODEL PERFORMANCE FOR LUMPY DEMAND PATTERN – THE ELECTRONICS DATA SET

To evaluate the statistical significance of the on-hand inventory means, the hypothesis that there is no statistical difference between the means was tested. Since the sample size was large (n = 80), the central limit theorem was invoked and the normality assumption of the data was made. Based on Levene's statistics, the null hypothesis that the variances are equal was rejected at p-value of <0.0001. Accordingly, the Welch's test was conducted and the null hypothesis was again rejected at a p-value of <0.0001. Results of the Tukey's test showed that Holt-Corr2 was significantly higher than all the other forecasting-inventory models at $\alpha = 0.05$. Similarly both Holt-MSE and Holt-Corr1 were significantly different than SBA-MSE $\alpha = 0.05$. No statistical difference was captured between SBA-MSE and Croston-MSE. Box plots of on-hand inventory quantity across all the forecasting-inventory models are shown in Figure A.15.

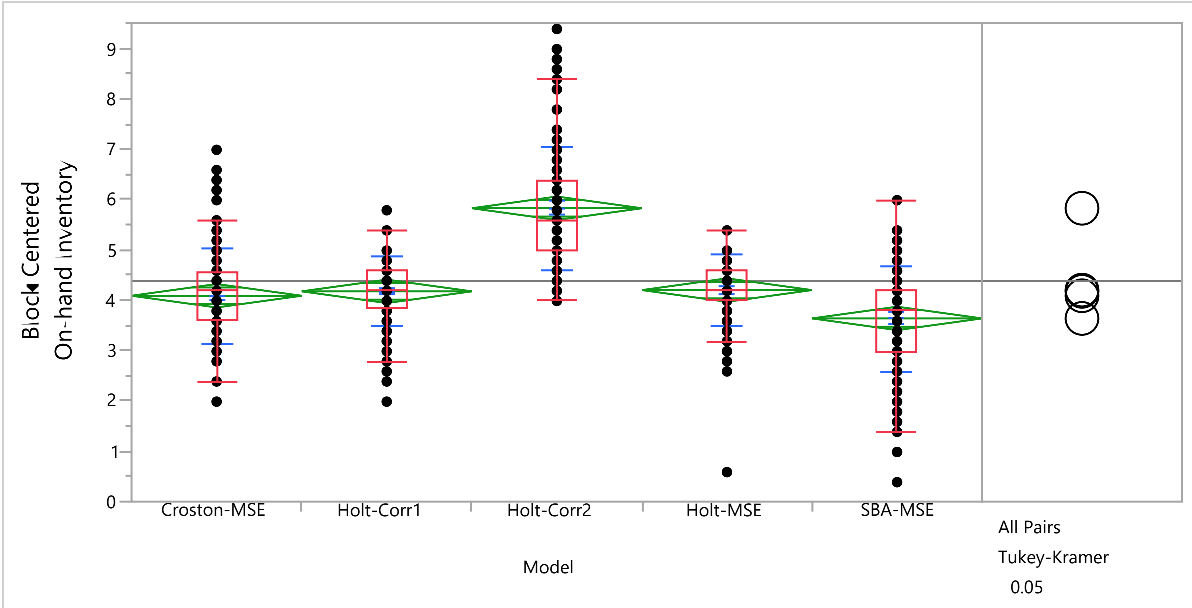

Figure A.15: Box Plots of "On-hand Inventory" for Lumpy Demand Pattern- Electronics Data Set

The means of service levels were statistically analyzed. Based on Levene's statistics, the null hypothesis that the variances are equal was rejected at p-value of <0.0001. Accordingly, the Welch's test was conducted and the null hypothesis was again rejected at a p-value of <0.0001. Results of the Tukey's test showed that Holt-Corr2 was significantly higher than all the other forecasting-inventory models at α = 0.05. Both Holt-MSE and Holt-Corr1 achieved significantly higher service levels compared to SBA-MSE at α = 0.05. Also, Holt-MSE achieved significantly a higher service level compared to Croston-MSE. Box plots of service levels across all the forecasting-inventory models are shown in Figure A.16.

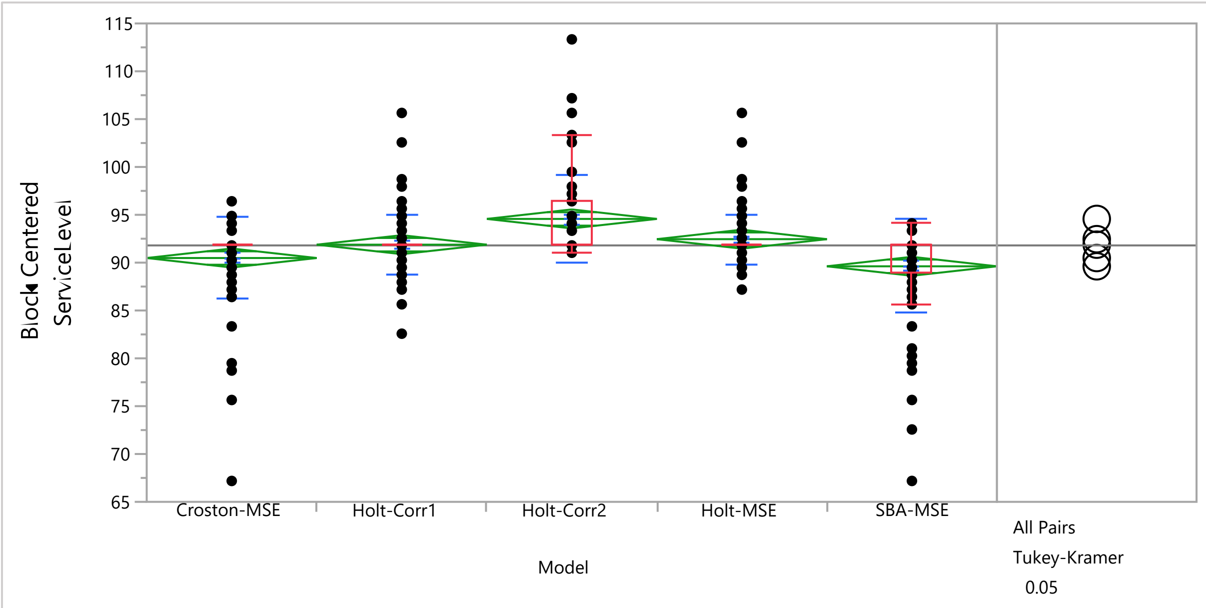

Figure A.16: Box Plots of "Service Level" for Lumpy Demand Pattern - Electronics Data Set

The means of the fill rates were statistically analyzed. Based on Levene's statistics, the null hypothesis that the variances are equal was rejected at p-value of <0.0001. Accordingly, the Welch's test was conducted and the null hypothesis was again rejected at a p-value of 0.0001. Results of the Tukey's test showed that Holt-Corr2 was significantly higher than Holt-Corr1, SBA-MSE and Croston-MSE at $\alpha = 0.05$. Both Holt-MSE and Holt-Corr1 achieved significantly higher fill rates compared to SBA-MSE at $\alpha = 0.05$. Also, Holt-MSE achieved significantly a higher fill rate compared to Croston-MSE. Box plots of fill rates across all the forecasting-inventory models are shown in Figure A.17.

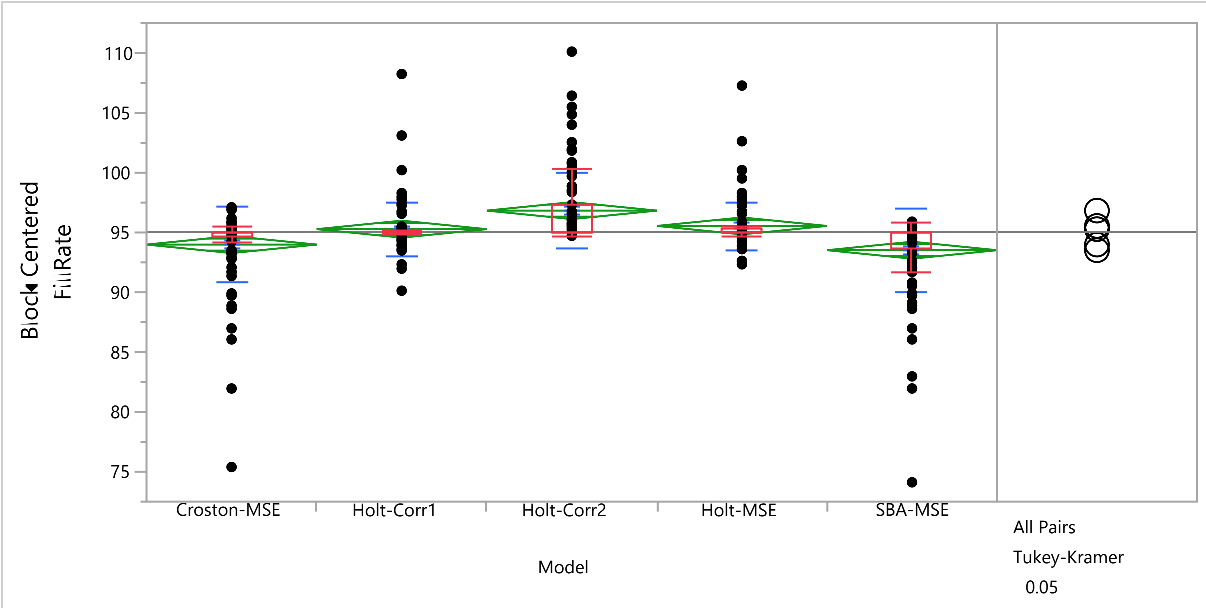

Figure A.17: Box Plots of "Fill Rate" for Lumpy Demand Pattern- Electronics Data Set

A.8 : INVENTORY MODEL PERFORMANCE FOR SMOOTH DEMAND PATTERN – THE ELECTRONICS DATA SET

To evaluate the statistical significance of the on-hand inventory means, the hypothesis that there is no statistical difference between the means was tested. Since the sample size was large (n = 78), the central limit theorem was invoked and the normality assumption of the data was made. Based on Levene's statistics, the null hypothesis that the variances are equal was rejected at p-value of <0.0001. Accordingly, the Welch's test was conducted and the null hypothesis was again rejected at a p-value of <0.0001. Results of the Tukey's test showed that SBA-MSE achieved significantly lower levels of on-hand inventory compared to all the forecasting-inventory models. On the contrary, Holt-Corr2 achieved significantly higher levels of on-hand inventory compared to all the forecasting-inventory models. Box plots of on-hand inventory quantity across all the forecasting-inventory models are shown in Figure A.18

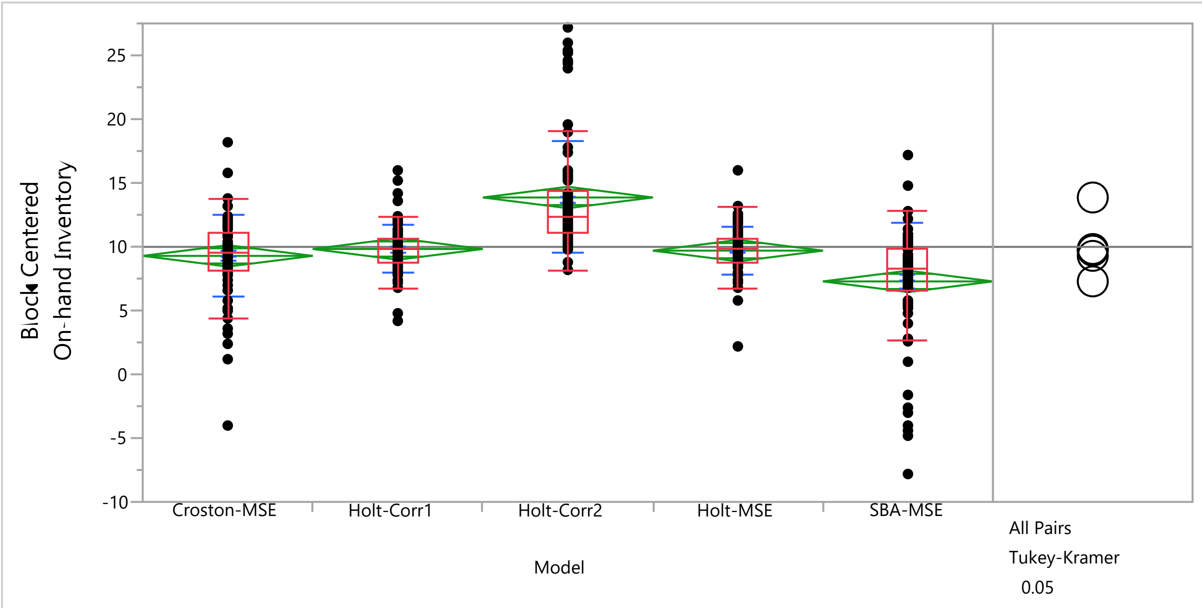

Figure A.18: Box Plots of "On-hand Inventory" for Smooth Demand Pattern-Electronics Data Set

The service level performance metric was statistically. Based on Levene's statistics, the null hypothesis that the variances are equal was rejected at p-value of <0.0001. Accordingly, the Welch's test was conducted and the null hypothesis was again rejected at a p-value of 0.0001. Results of the Tukey's test showed that SBA-MSE achieved significantly lower levels of service compared to all the forecasting-inventory models. On the contrary, Holt-Corr2 achieved significantly higher levels of service compared to all the forecasting-inventory models. Box plots of service levels across all the forecasting-inventory models are shown in Figure A.19.

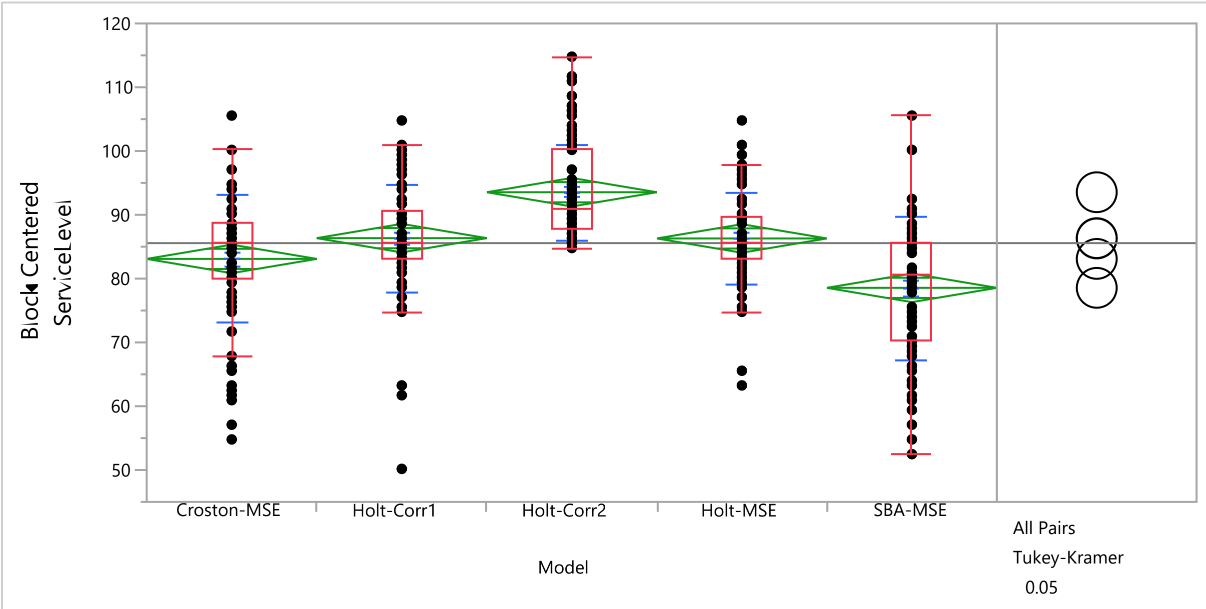

Figure A.19: Box Plots of "Service Level" for Smooth Demand Pattern- Electronics Data Set

The fill rate performance metric was statistically. Based on Levene's statistics, the null hypothesis that the variances are equal was rejected at p-value of 0.0004. Accordingly, the Welch's test was conducted and the null hypothesis was again rejected at a p-value of <0.0001. Results of the Tukey's test showed that SBA-MSE achieved a significantly lower fill rate compared to Holt-Corr1, Holt-MSE and Holt-Corr2. Similarly, Croston-MSE achieved a significantly lower fill rate compared to Holt-Corr1, Holt-MSE and Holt-Corr2. On the contrary, Holt-Corr2 achieved a significantly higher fill rate compared to all the forecasting-inventory models. Box plots of fill rates across all the forecasting-inventory models are shown in Figure A.20.

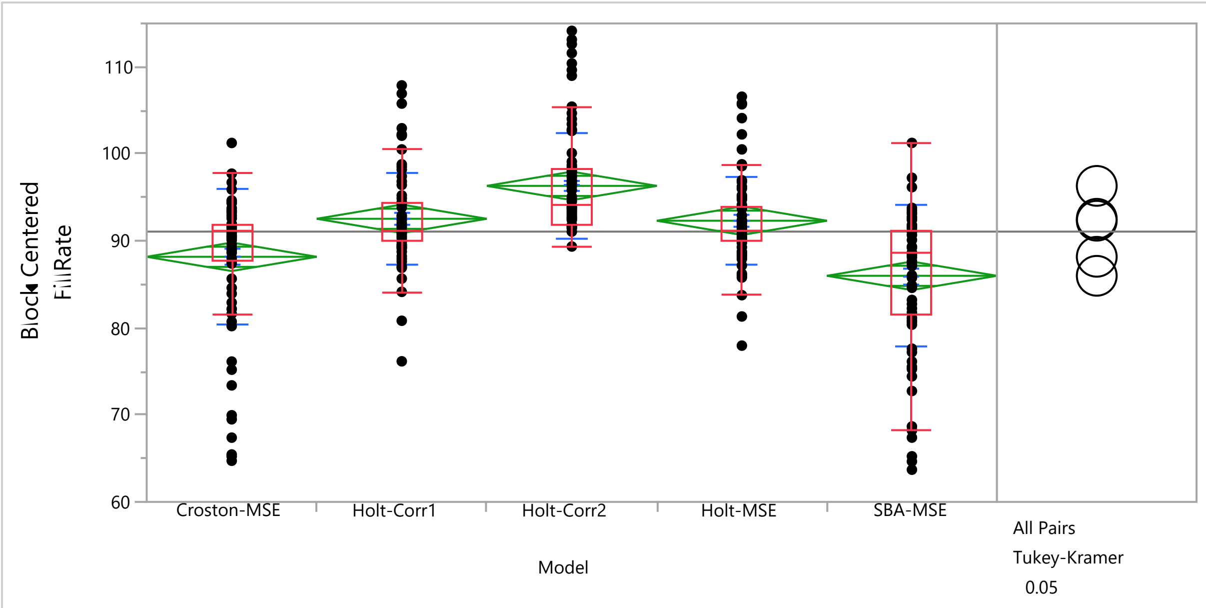

Figure A.20: Box Plots of "Fill Rate" for Smooth Demand Pattern-Electronics Data Set

A.9 : INVENTORY MODEL PERFORMANCE FOR ERRATIC DEMAND PATTERN – THE AUTOMOTIVE DATA SET

To evaluate the statistical significance of the on-hand inventory means, the hypothesis that there is no statistical difference between the means was tested. Since the sample size was large ($n = 468$), the central limit theorem was invoked and the normality assumption of the data was made. Based on Levene's statistics, the null hypothesis that the variances are equal was rejected at p-value of <0.0001. Accordingly, the Welch's test was conducted and the null hypothesis was again rejected at a p-value of <0.0001. Results of the Tukey's test showed that Holt-Corr2 was significantly higher than all the other forecasting-inventory models at $\alpha = 0.05$. Box plots of on-hand inventory quantity across all the forecasting-inventory models are shown in Figure A.21.

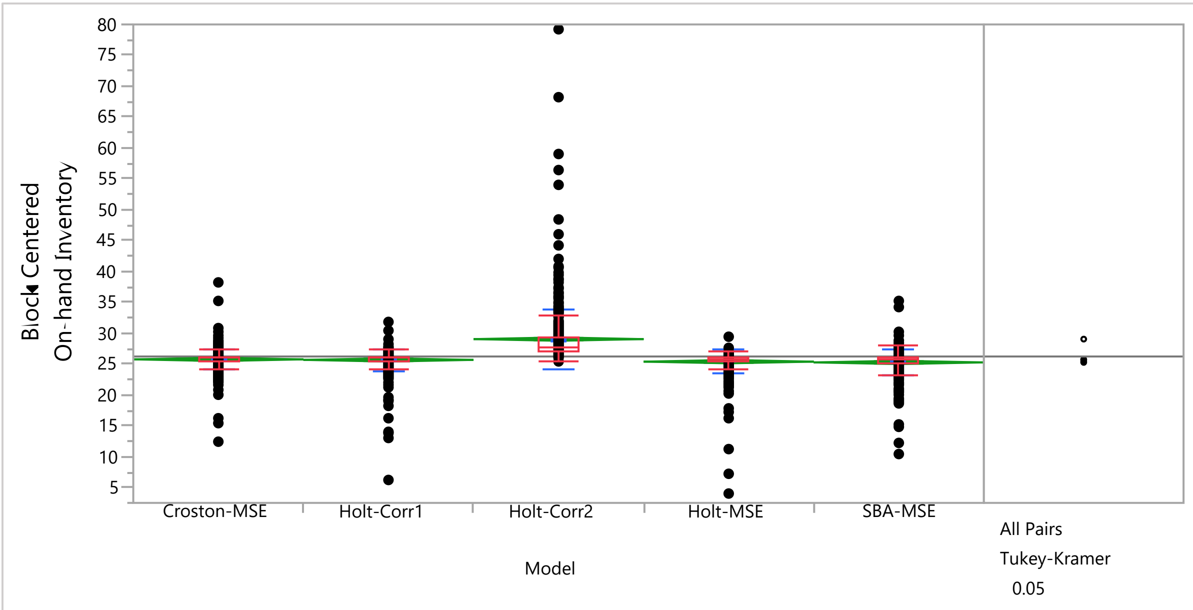

Figure A.21: Box Plots of "On-hand Inventory" for Erratic Demand Pattern-Automotive Data Set

The service level performance metric was statistically analyzed. Based on Levene's statistics, the null hypothesis that the variances are equal was rejected at p-value of <0.0001. Accordingly, the Welch's test was conducted and the null hypothesis was again rejected at a p-value of <0.0001.Results of the Tukey's test showed that Holt-Corr2 achieved a significantly higher service level compared to all the other forecasting-inventory models at $\alpha = 0.05$. Box plots of the service levels across all the forecasting-inventory models are shown in Figure A.22.

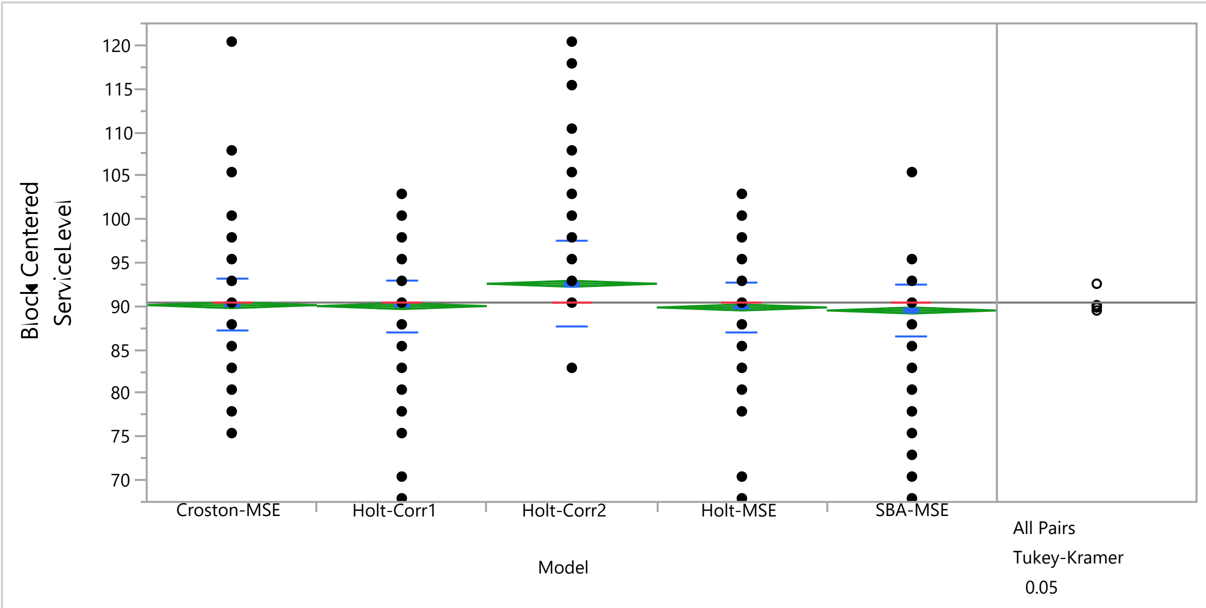

Figure A.22: Box Plots of "Service Level" for Erratic Demand Pattern- Automotive Data Set

The fill rate performance metric was statistically analyzed. Based on Levene's statistics, the null hypothesis that the variances are equal was rejected at p-value of <0.0001. Accordingly, the Welch's test was conducted and the null hypothesis was again rejected at a p-value of <0.0001. Results of the Tukey's test showed that Holt-Corr2 achieved a significantly higher fill rate compared to all the other forecasting-inventory models at $\alpha = 0.05$. Box plots of the fill rates across all the forecasting-inventory models are shown in Figure A.23.

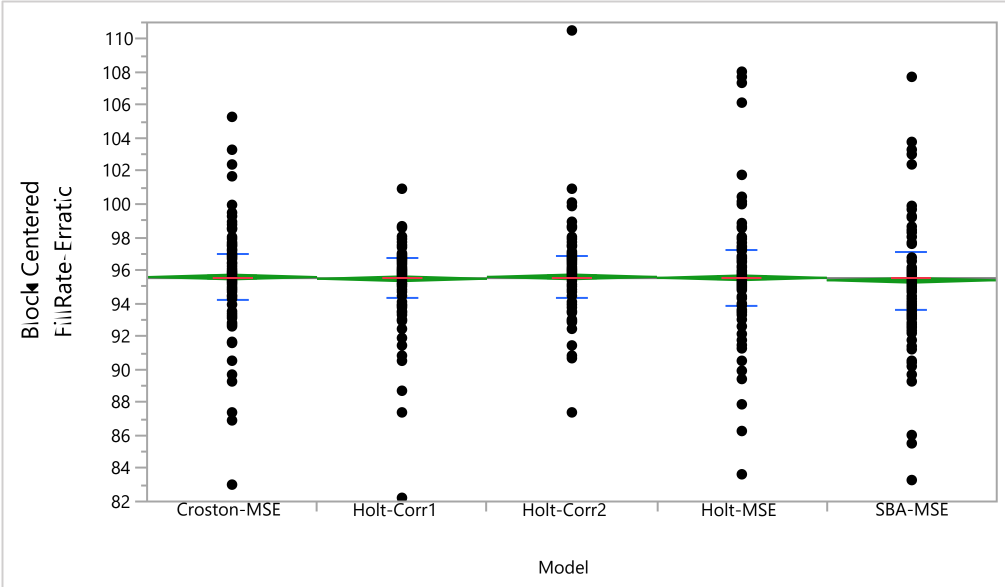

Figure A.23: Box Plots of "Fill Rate" for Erratic Demand Pattern-Automotive Data Set

A.10 : INVENTORY MODEL PERFORMANCE FOR INTERMITTENT DEMAND PATTERN – THE AUTOMOTIVE DATA SET

To evaluate the statistical significance of the on-hand inventory means, the hypothesis that there is no statistical difference between the means was tested. Since the sample size was large (n = 941), the central limit theorem was invoked and the normality assumption of the data was made. Based on Levene's statistics, the null hypothesis that the variances are equal was rejected at p-value of <0.0001. Accordingly, the Welch's test was conducted and the null hypothesis was again rejected at a p-value of <0.0001. Results of the Tukey's test showed that Holt-Corr2 was significantly higher than all the other forecasting-inventory models at $\alpha = 0.05$. No other statistical difference was captured between the means of the other models. Box plots of on-hand inventory quantity across all the forecasting-inventory models are shown in Figure A.24.

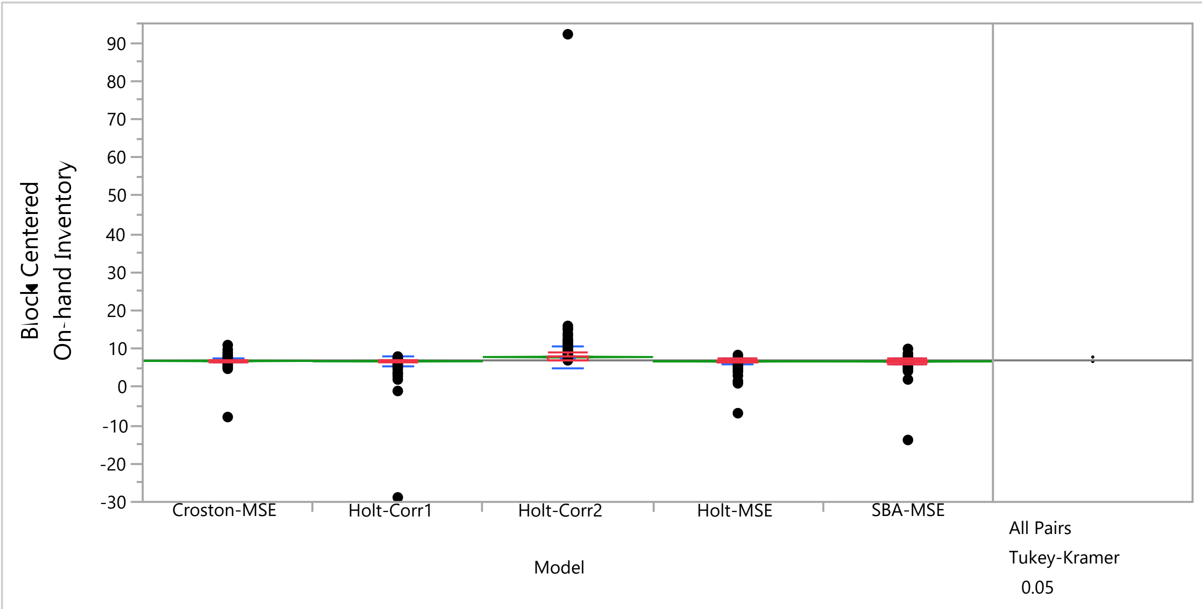

Figure A.24: Box Plots of "On-hand Inventory" for Intermittent Demand Pattern - Automotive Data

The means of service levels were statistically analyzed. Based on Levene's statistics, the null hypothesis that the variances are equal was rejected at p-value of <0.0001. Accordingly, the Welch's test was conducted and the null hypothesis was again rejected at a p-value of <0.0001. Results of the Tukey's test showed that Holt-Corr2 achieved a significantly higher service level compared to all the other forecasting-inventory models at $\alpha = 0.05$. No other statistical difference was captured between the means of the other models. Box plots of service levels across all the forecasting-inventory models are shown in Figure A.25.

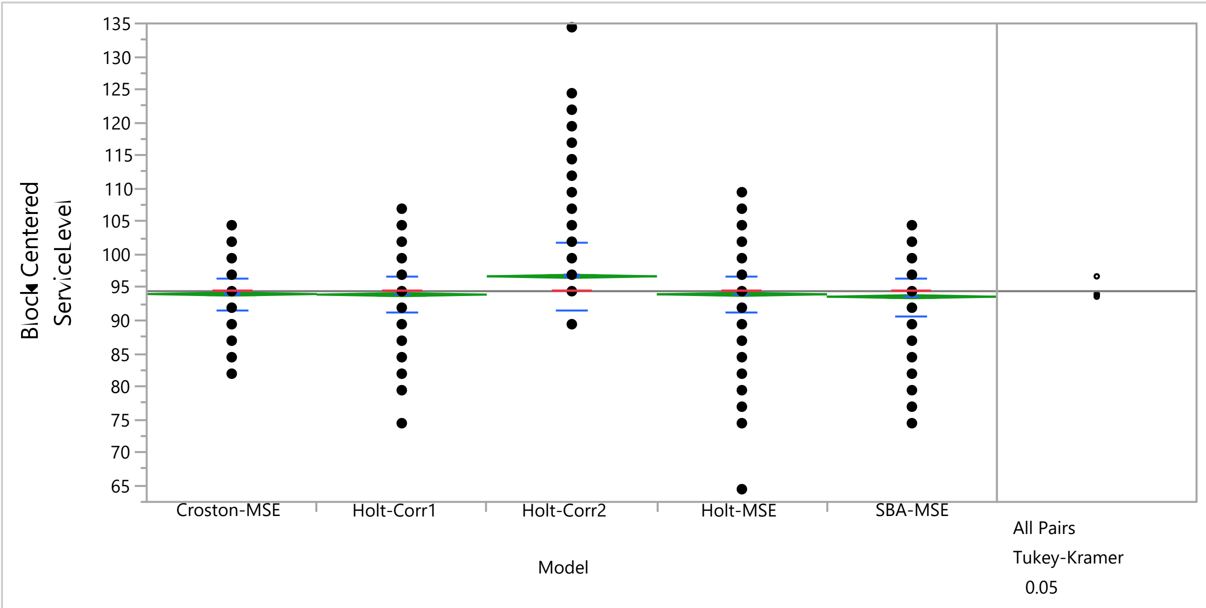

Figure A.25: Box Plots of "Service Level" for Intermittent Demand Pattern- Automotive Data Set

The means of the fill rates were statistically analyzed. Based on Levene's statistics, the null hypothesis that the variances are equal was rejected at p-value of <0.0001. Accordingly, the Welch's test was conducted and the null hypothesis was again rejected at a p-value of <0.0001. Results of the Tukey's test showed that Holt-Corr2 achieved a significantly higher fill rate compared to all the other forecasting-inventory models at $\alpha = 0.05$. No other statistical difference was captured between the means of the other models. Box plots of fill rates across all the forecasting-inventory models are shown in Figure A.26.

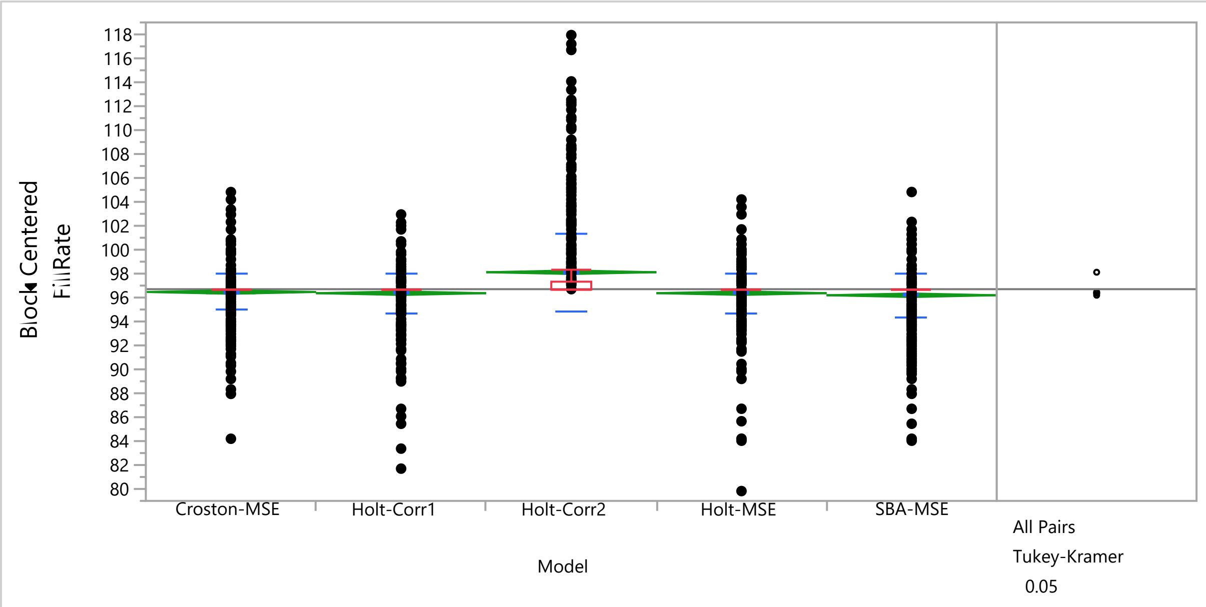

Figure A.26: Box Plots of "Fill Rate" for Intermittent Demand Pattern-Automotive Data Set

A.11 : INVENTORY MODEL PERFORMANCE FOR LUMPY DEMAND PATTERN – THE AUTOMOTIVE DATA SET

To evaluate the statistical significance of the on-hand inventory means, the hypothesis that there is no statistical difference between the means was tested. Since the sample size was large (n = 286), the central limit theorem was invoked and the normality assumption of the data was made. Based on Levene's statistics, the null hypothesis that the variances are equal was rejected at p-value of <0.0001. Accordingly, the Welch's test was conducted and the null hypothesis was again rejected at a p-value of <0.0001. Results of the Tukey's test showed that Holt-Corr2 was significantly higher than all the other forecasting-inventory models at $\alpha = 0.05$. No other statistical difference was captured between the means of the other models. Box plots of on-hand inventory quantity across all the forecasting-inventory models are shown in Figure A.27.

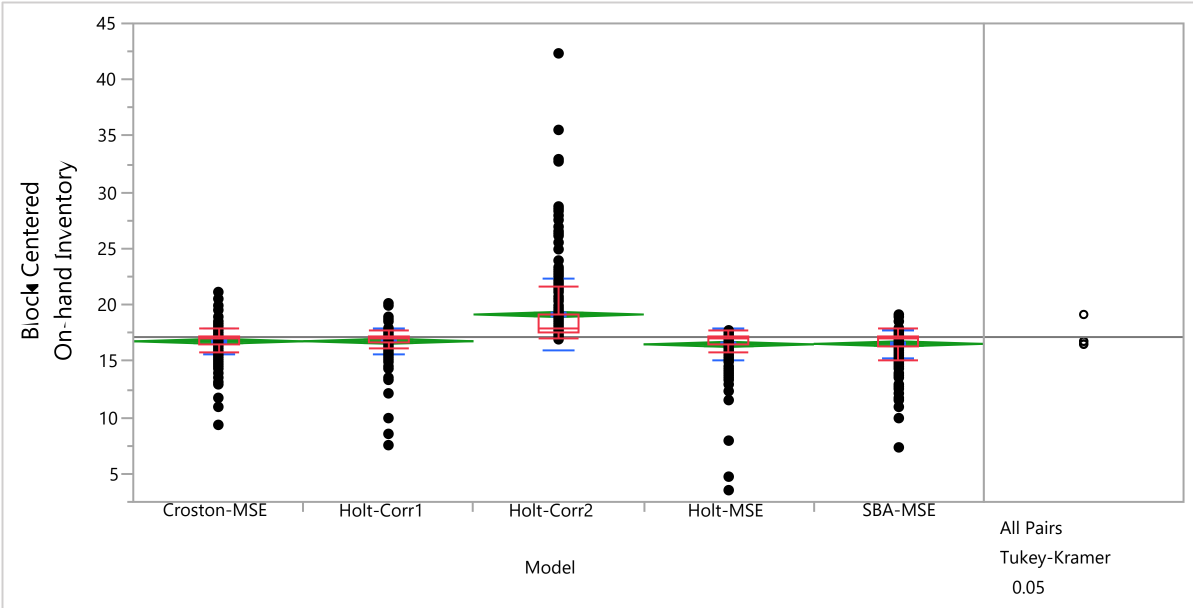

Figure A.27: Box Plots of "On-hand Inventory" for Lumpy Demand Pattern-Automotive Data Set

The means of service levels were statistically analyzed. Based on Levene's statistics, the null hypothesis that the variances are equal was rejected at p-value of <0.0001. Accordingly, the Welch's test was conducted and the null hypothesis was again rejected at a p-value of <0.0001. Results of the Tukey's test showed that Holt-Corr2 achieved a significantly higher service level compared to all the other forecasting-inventory models at $\alpha = 0.05$. No other statistical difference was captured between the means of the other models. Box plots of service levels across all the forecasting-inventory models are shown in Figure A.28.

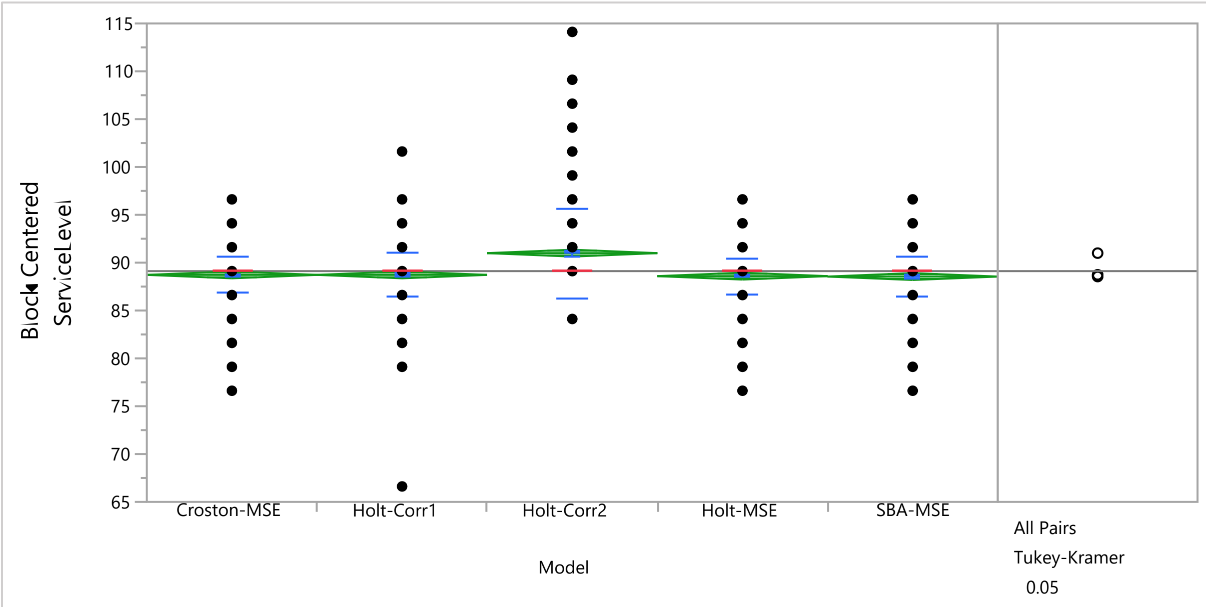

Figure A.28: Box Plots of "Service Level" for Lumpy Demand Pattern-Automotive Data Set

The means of the fill rates were statistically analyzed. Based on Levene's statistics, the null hypothesis that the variances are equal was rejected at p-value of <0.0001. Accordingly, the Welch's test was conducted and the null hypothesis was again rejected at a p-value of <0.0001. Results of the Tukey's test showed that Holt-Corr2 achieved a significantly higher fill rate compared to all the other forecasting-inventory models at $\alpha = 0.05$. No other statistical difference was captured between the means of the other models. Box plots of fill rates across all the forecasting-inventory models are shown in Figure A.29.

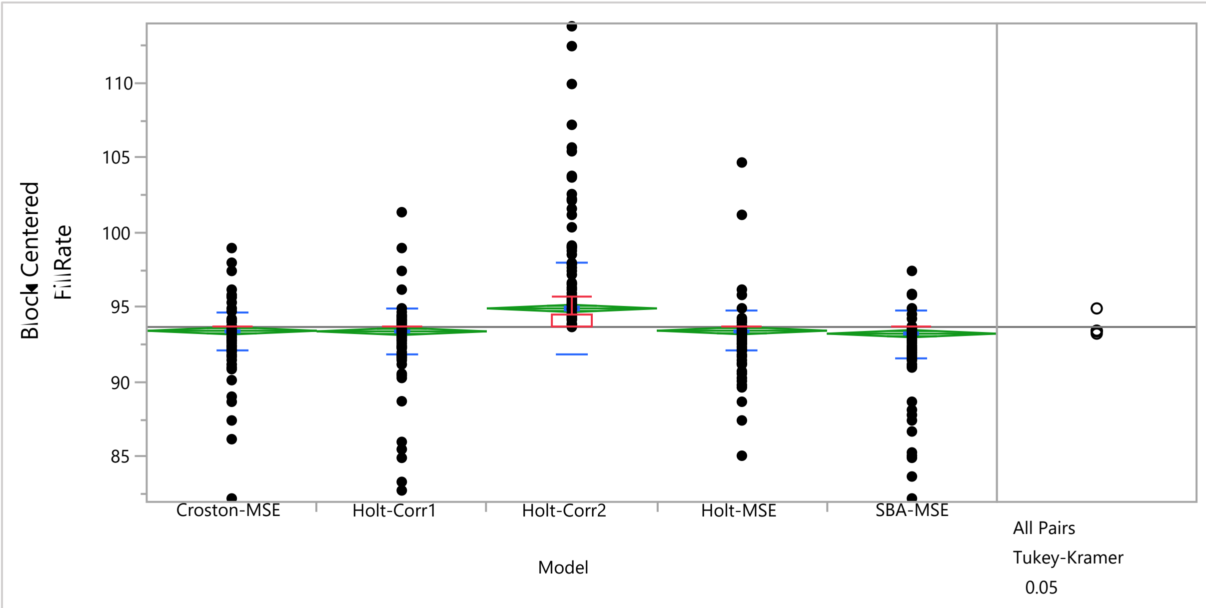

Figure A.29: Box Plots of "Fill Rate" for Lumpy Demand Pattern-Automotive Data Set

A.12 : INVENTORY MODEL PERFORMANCE FOR SMOOTH DEMAND PATTERN – THE AUTOMOTIVE DATA SET

To evaluate the statistical significance of the on-hand inventory means, the hypothesis that there is no statistical difference between the means was tested. Since the sample size was large (n = 1305), the central limit theorem was invoked and the normality assumption of the data was made. Based on Levene's statistics, the null hypothesis that the variances are equal was rejected at p-value of <0.0001. Accordingly, the Welch's test was conducted and the null hypothesis was again rejected at a p-value of <0.0001. Results of the Tukey's test showed that SBA-MSE achieved significantly lower levels of on-hand inventory compared to all the forecasting-inventory models. On the contrary, Holt-Corr2 achieved significantly higher levels of on-hand inventory compared to all the forecasting-inventory models. Box plots of on-hand inventory quantity across all the forecasting-inventory models are shown in Figure A.30.

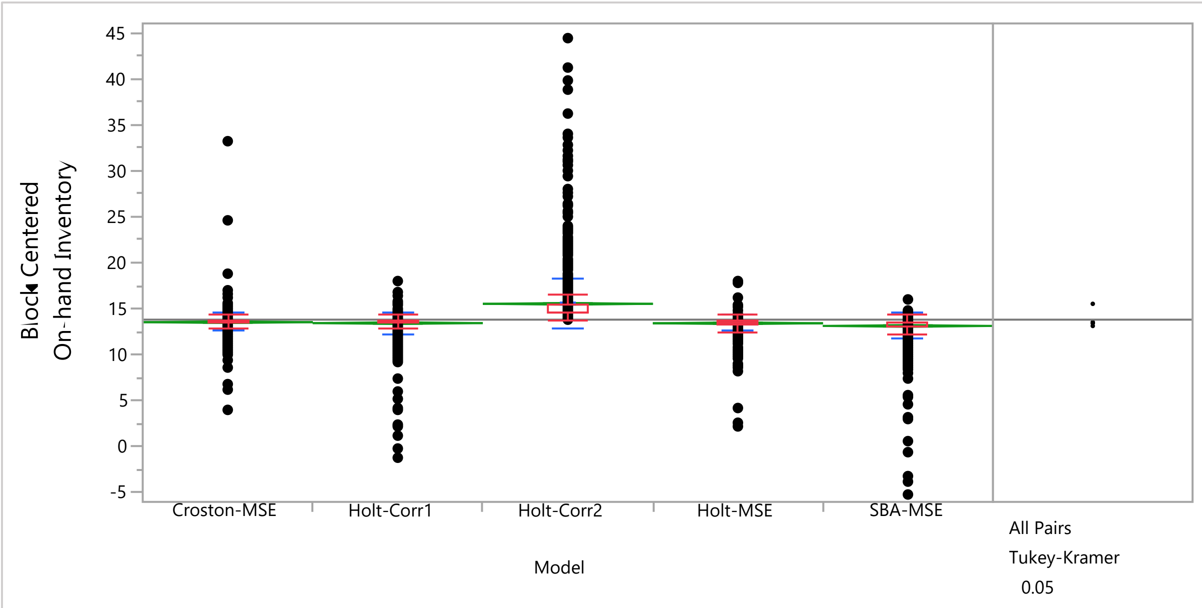

Figure A.30: Box Plots of "On-hand Inventory" for Smooth Demand Pattern-Automotive Data Set

The service level performance metric was statistically analyzed. Based on Levene's statistics, the null hypothesis that the variances are equal was rejected at p-value of <0.0001. Accordingly, the Welch's test was conducted and the null hypothesis was again rejected at a p-value of <0.0001.Results of the Tukey's test showed that SBA-MSE achieved significantly lower levels of service compared to all the forecasting-inventory models. On the contrary, Holt-Corr2 achieved significantly higher levels of service compared to all the forecasting-inventory models. Box plots of service levels across all the forecasting-inventory models are shown in Figure A.31.

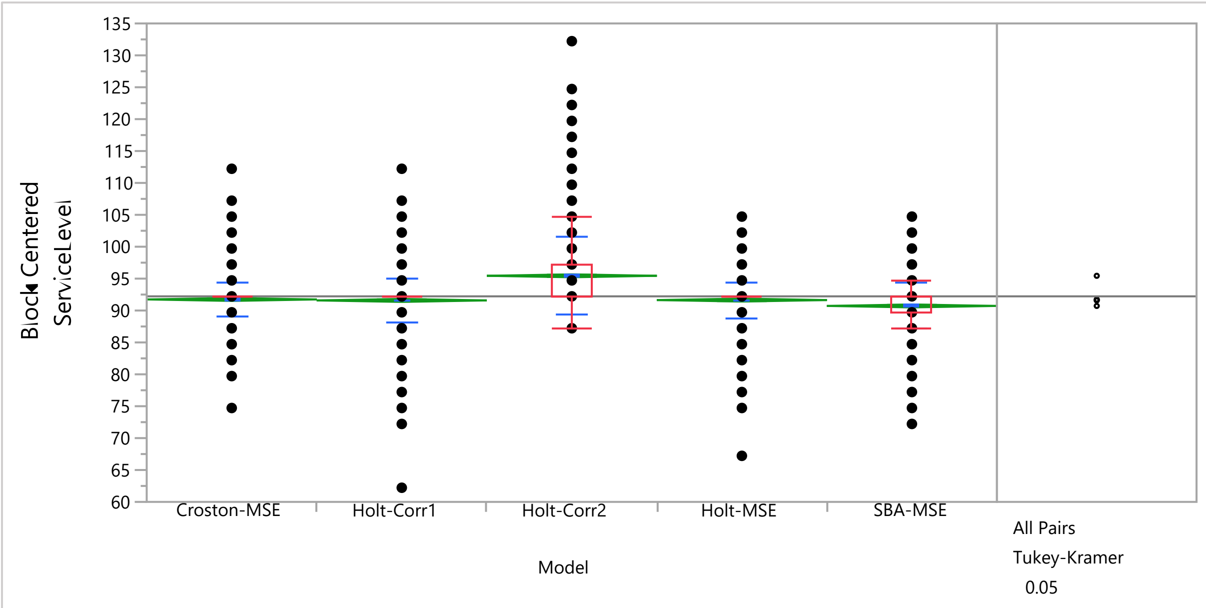

Figure A.31: Box Plots of "Service Level" for Smooth Demand Pattern-Automotive Data Set

The fill rate performance metric was statistically analyzed. Based on Levene's statistics, the null hypothesis that the variances are equal was rejected at p-value of <0.0001. Accordingly, the Welch's test was conducted and the null hypothesis was again rejected at a p-value of <0.0001. Results of the Tukey's test showed that SBA-MSE achieved a significantly lower fill rate compared to all the forecasting-inventory models. On the contrary, Holt-Corr2 achieved a significantly higher fill rate compared to all the forecasting-inventory models. Box plots of fill rates across all the forecasting-inventory models are shown in Figure A.32.

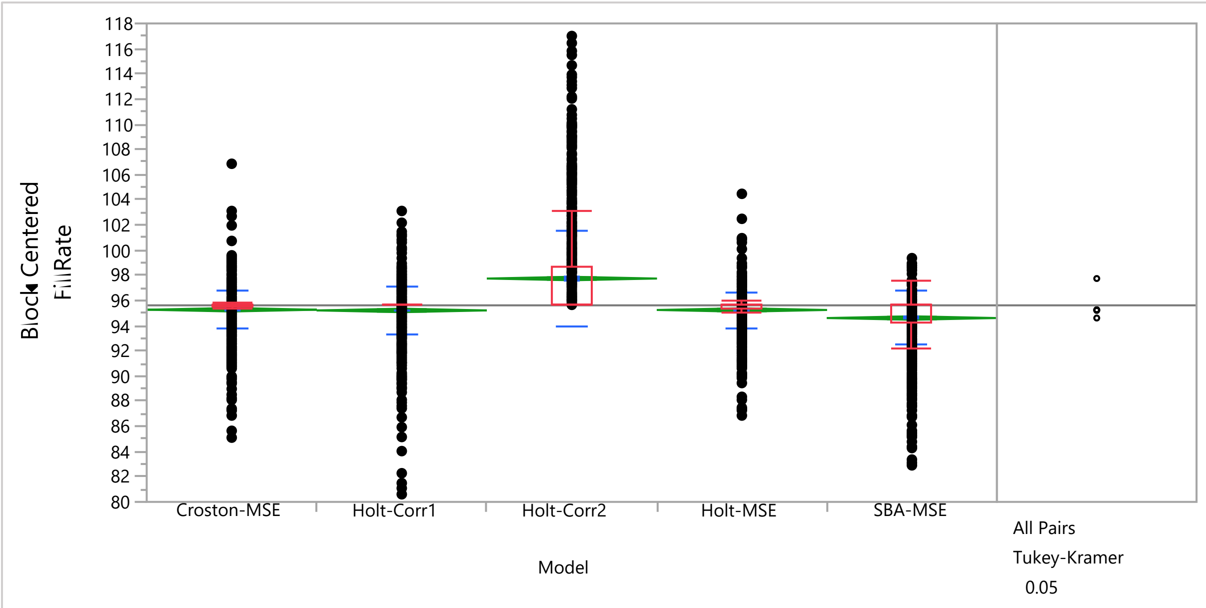

Figure A.32: Box Plots of "Fill Rate" for Smooth Demand Pattern-Automotive Data Set

A.13 : INVENTORY PERFORMANCE-THE ERRATIC DEMAND PATTERN- THE ELECTRONICS DATA SET

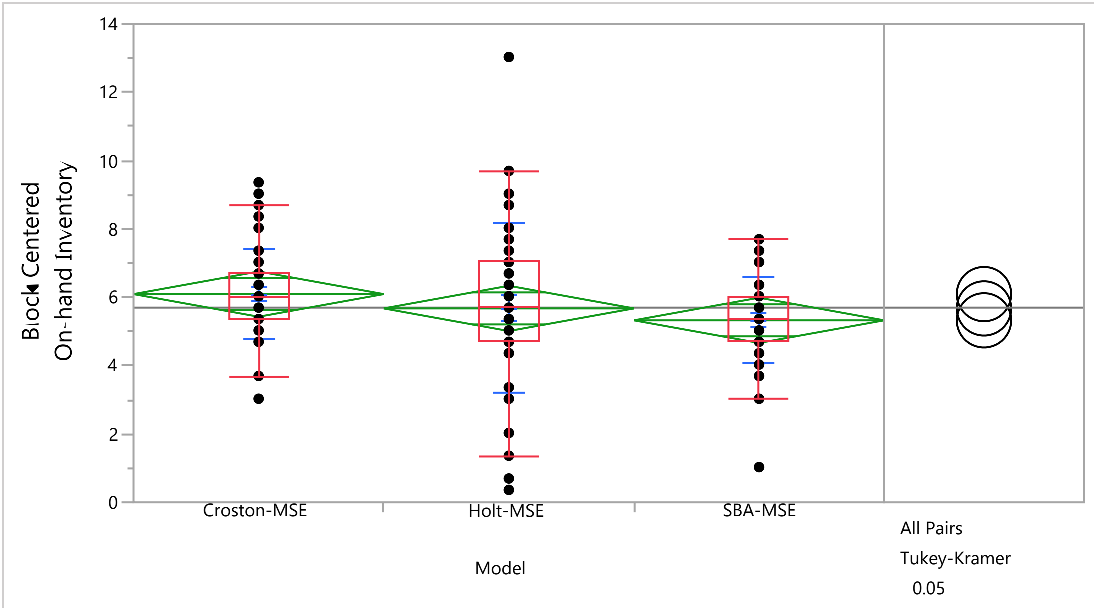

Figure A.33: Box Plots of "On-hand Inventory" for Erratic Demand Pattern-Three Models- Electronics Data

To evaluate the statistical significance of the on-hand inventory means, the hypothesis that there is no statistical difference between the means was tested. Since the sample size was large enough (n = 43), the central limit theorem was invoked and the normality assumption of the data was made. Based on Levene's statistics, the null hypothesis that the variances are equal was rejected at p-value of 0.0008. Accordingly, the Welch's test was conducted and the null hypothesis was again rejected at a p-value of 0.02. Results of the Tukey's test showed that there is no statistical difference across the different means of the on-hand inventory parameter. Box plots of on-hand inventory quantity across all the forecasting-inventory models are shown in Figure A.33.

A similar test was conducted to analyze the on-average service levels across all three models. Based on Levene's statistics, the null hypothesis that the variances are equal was rejected at p-value of 0.0036. Accordingly, the Welch's test was conducted and we failed to reject the null hypothesis at a p-value of 0.13. Box plots of achieved service levels across all the forecasting-inventory models are shown in Figure A.34.

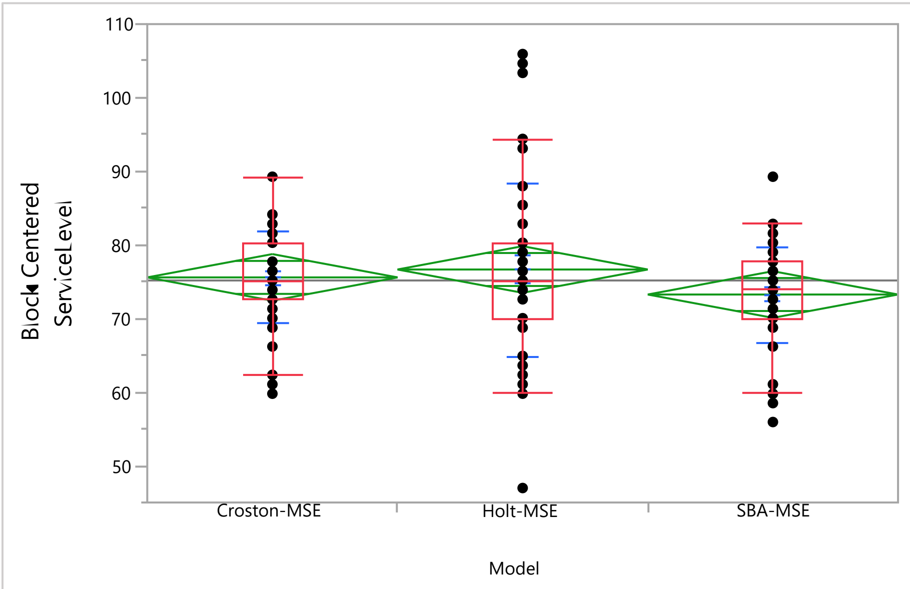

Figure A.34: Box Plots of "Service Level" for Erratic Demand Pattern-Three Models-Electronics Data

Based on Levene's statistics, the null hypothesis that the variances are equal was rejected at p-value of 0.0008. Accordingly, the Welch's test was conducted and the null hypothesis was rejected at a p-value of 0.02. Results of the Tukey's test showed that Holt-MSE achieved a significantly higher fill rate compared to SBA-MSE. Box plots of achieved fill-rates across all the forecasting-inventory models are shown in Figure A.35.

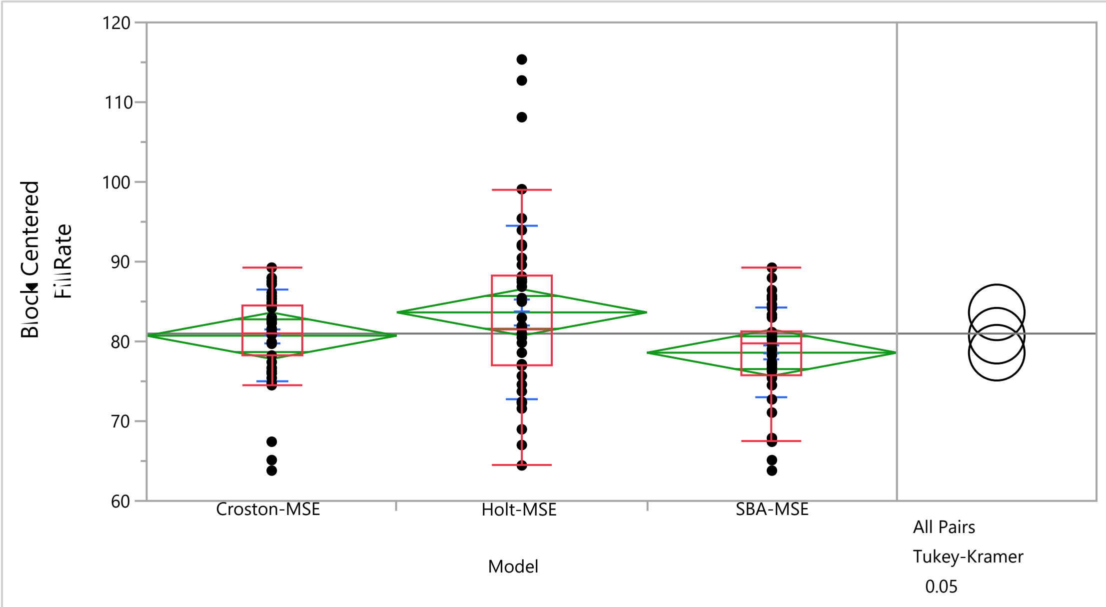

Figure A.35: Box Plots of "Fill Rate" for Erratic Demand Pattern-Three Models-Electronics Data

A.14 : INVENTORY PERFORMANCE-THE INTERMITTENT DEMAND PATTERN-ELECTRONICS DATA SET

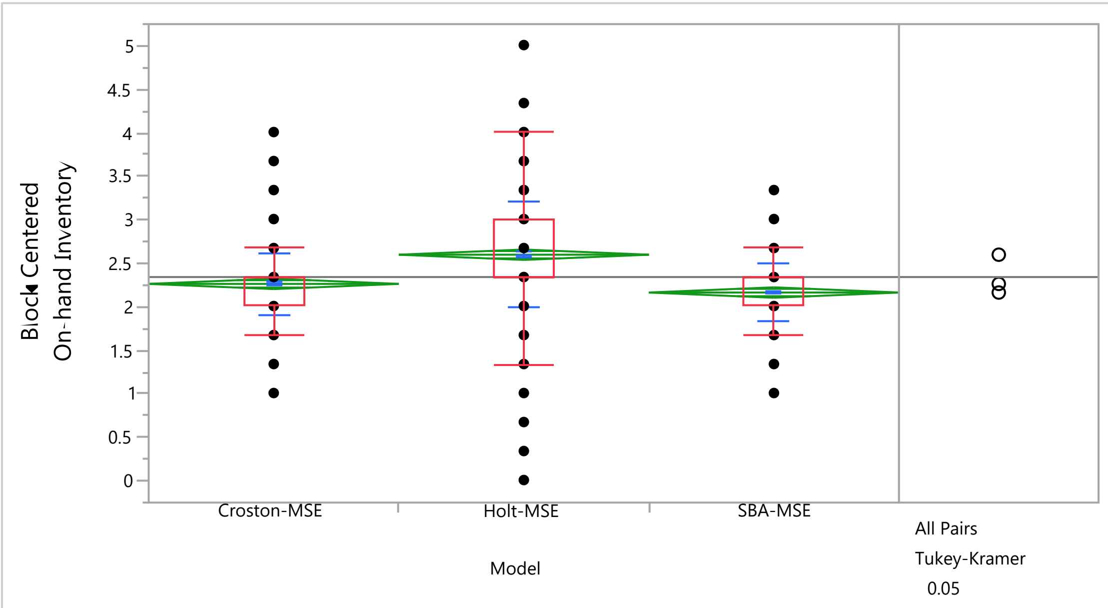

Figure A.36: Box Plots of "On-hand Inventory" for Intermittent Demand Pattern - the Three Models-Electronics Data

To evaluate the statistical significance of the on-hand inventory means, the hypothesis that there is no statistical difference between the means was tested. Since the sample size was large enough (n = 322), the central limit theorem was invoked and the normality assumption of the data was made. Based on Levene's statistics, the null hypothesis that the variances are equal was rejected at p-value of <0.0001. Accordingly, the Welch's test was conducted and the null hypothesis was again rejected at a p-value of <0.0001. Results of the Tukey's test showed that Holt-MSE achieved significantly higher on hand inventory levels compared to both Croston-MSE and SBA-MSE. No statistical difference was found when comparing Croston-MSE and SBA-MSE. Box plots of on-hand inventory quantity across all the forecasting-inventory models are shown in Figure A.36.

A similar test was conducted to analyze the on-average service levels across all three models. Based on Levene's statistics, the null hypothesis that the variances are equal was rejected at p-value of <0.0001. Accordingly, the Welch's test was conducted and the null hypothesis was again rejected at a p-value of <0.0001. Results of the Tukey's test showed that Holt-MSE achieved a significantly higher service level compared to both Croston-MSE and SBA-MSE. No statistical difference was found when comparing Croston-MSE and SBA-MSE. Box plots of achieved service levels across all the forecasting-inventory models are shown in Figure A.37.

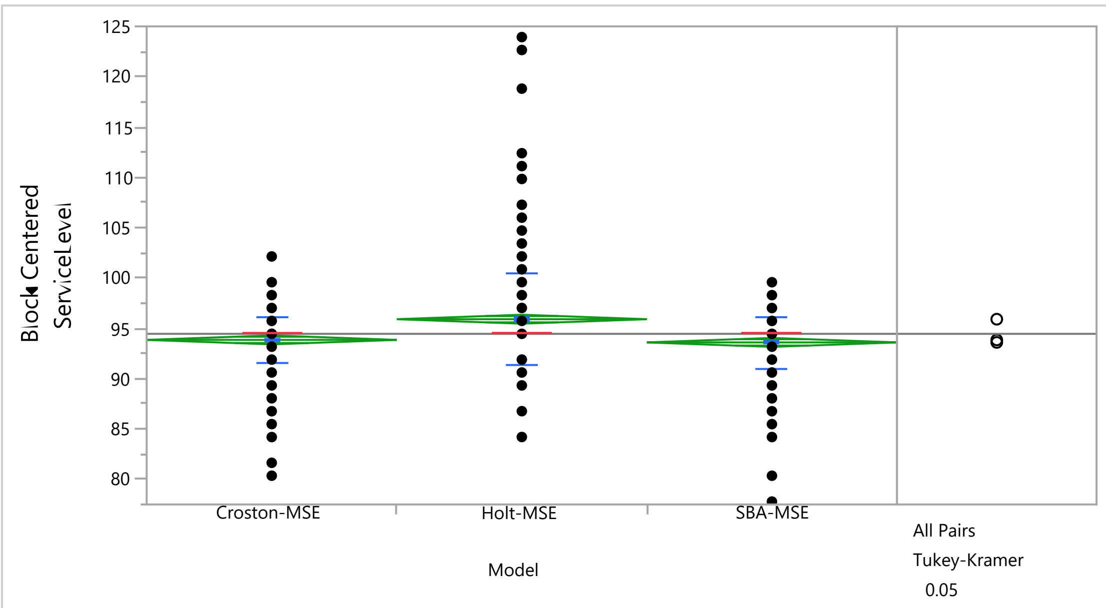

Figure A.37: Box Plots of "Service Level" for Intermittent Demand Pattern-Three Models-Electronics Data

Average fill rates of the models were also statistically compared and analyzed. Based on Levene's statistics, the null hypothesis that the variances are equal was rejected at p-value of <0.0001. Accordingly, the Welch's test was conducted and the null hypothesis was again rejected at a p-value of <0.0001. Results of the Tukey's test showed that Holt-MSE achieved a significantly higher fill-rate compared to both Croston-MSE and SBA-MSE. No statistical difference was found when comparing Croston-MSE and SBA-MSE. Box plots of achieved fill-rates across all the forecasting-inventory models are shown in Figure A.38.

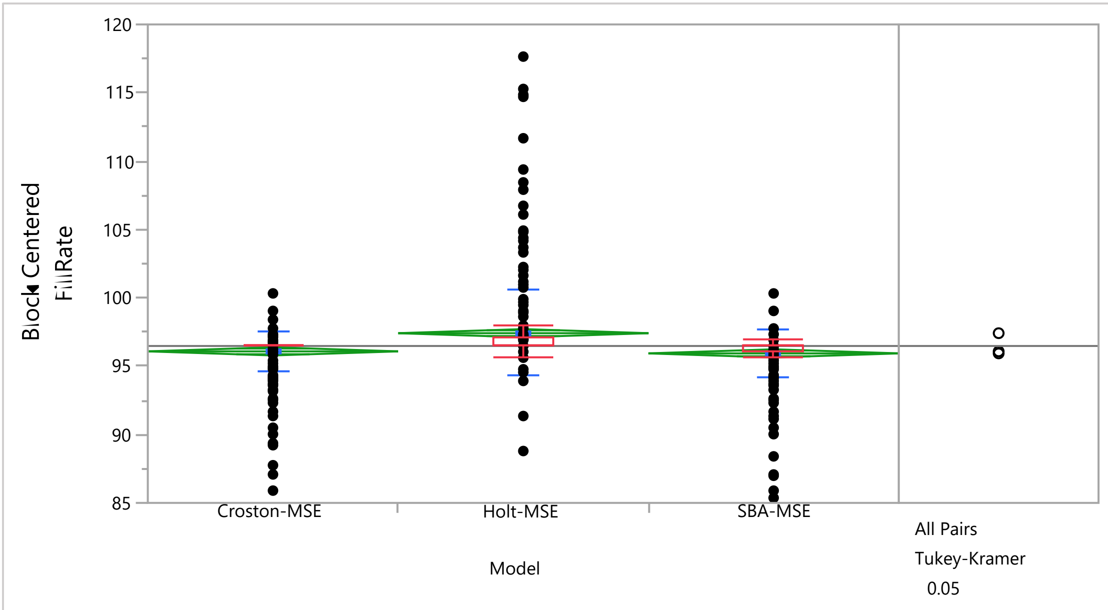

Figure A.38: Box Plots of "Fill Rate" for Intermittent Demand Pattern-Three Models-Electronics Data

A.15 : INVENTORY PERFORMANCE-THE LUMPY DEMAND PATTERN- THE ELECTRONICS DATA SET

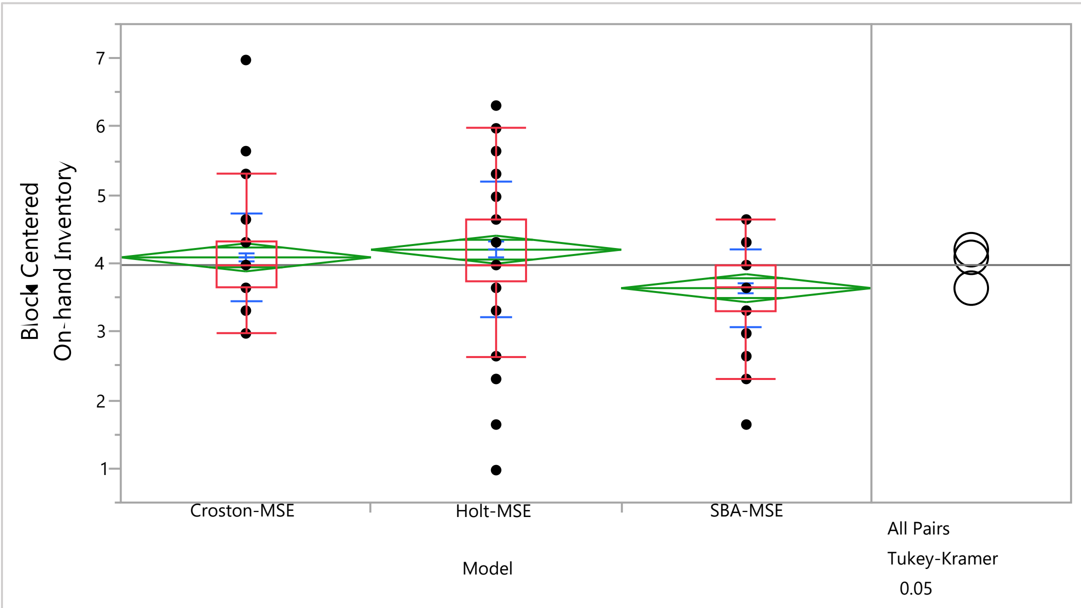

Figure A.39: Box Plots of "On-hand Inventory" for Lumpy Demand Pattern-Three Models- Electronics Data

To evaluate the statistical significance of the on-hand inventory means, the hypothesis that there is no statistical difference between the means was tested. Since the sample size was large enough (n = 80), the central limit theorem was invoked and the normality assumption of the data was made. Based on Levene's statistics, the null hypothesis that the variances are equal was rejected at p-value of 0.0002. Accordingly, the Welch's test was conducted and the null hypothesis was again rejected at a p-value of <0.0001. Results of the Tukey's test showed that SBA-MSE achieved significantly lower on hand inventory levels compared to both Croston-MSE and Holt-MSE. No statistical difference was found when comparing Croston-MSE and Holt-MSE. Box plots of on-hand inventory quantity across all the forecasting-inventory models are shown in Figure A.39.

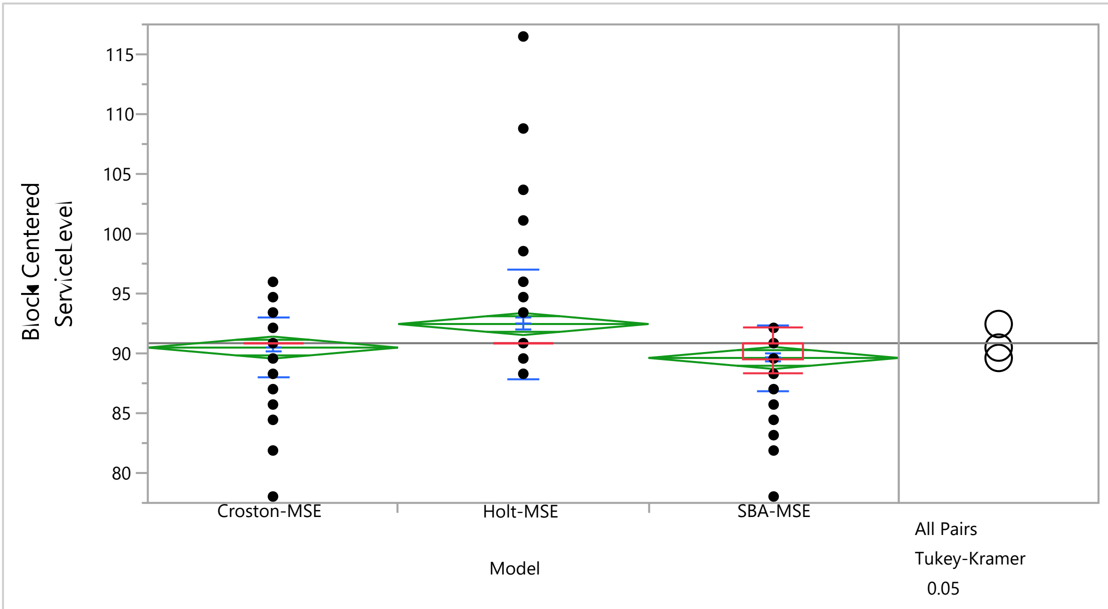

Figure A.40: Box Plots of "Service Level" for Lumpy Demand Pattern-Three Models-Electronics Data

A similar test was conducted to analyze the on-average service levels across all three models. Based on Levene's statistics, the null hypothesis that the variances are equal was rejected at p-value of 0.0008. Accordingly, the Welch's test was conducted and the null hypothesis was again rejected at a p-value of <0.0001. Results of the Tukey's test showed that Holt-MSE achieved a significantly higher service level compared to both Croston-MSE and SBA-MSE. No statistical difference was found when comparing Croston-MSE and SBA-MSE. Box plots of achieved service levels across all the forecasting-inventory models are shown in Figure A.40.

Average fill rates of the models were also statistically compared and analyzed. Based on Levene's statistics, the null hypothesis that the variances are equal was rejected at p-value of 0.0021. Accordingly, the Welch's test was conducted and the null hypothesis was again rejected at a p-value of <0.0001. Results of the Tukey's test showed that Holt-MSE achieved a significantly higher fill rate compared to both Croston-MSE and SBA-MSE. No statistical difference was found when comparing Croston-MSE and SBA-MSE. Box plots of achieved fill-rates across all the forecasting-inventory models are shown in Figure A.41.

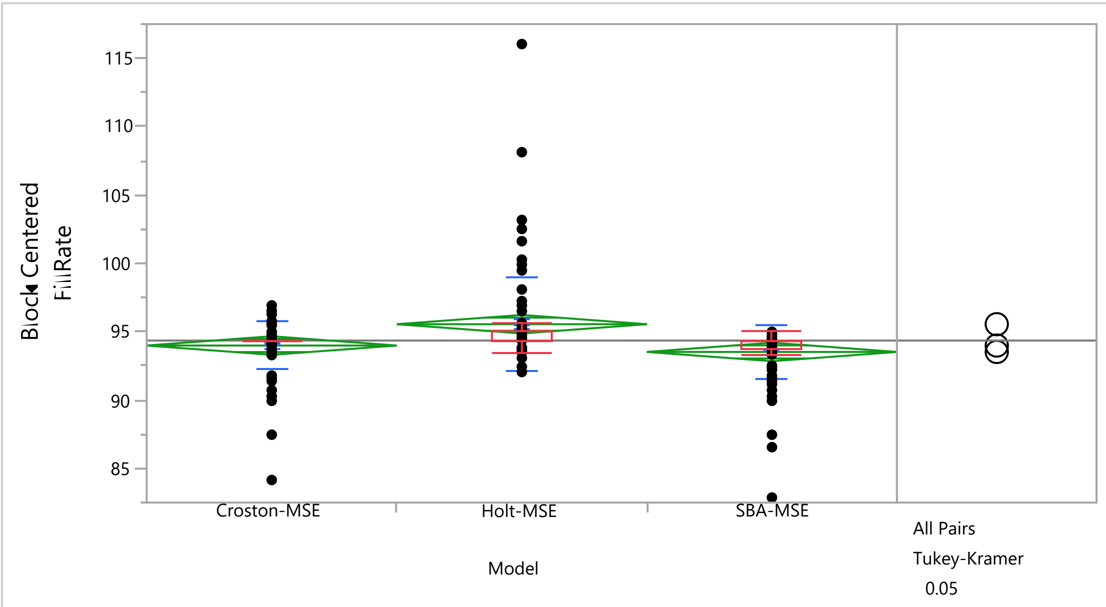

Figure A.41: Box Plots of "Fill Rate" for Lumpy Demand Pattern-Three Models-Electronics Data

A.16 : INVENTORY PERFORMANCE-SMOOTH DEMAND PATTERN ELECTRONICS DATA SET-THREE MODELS

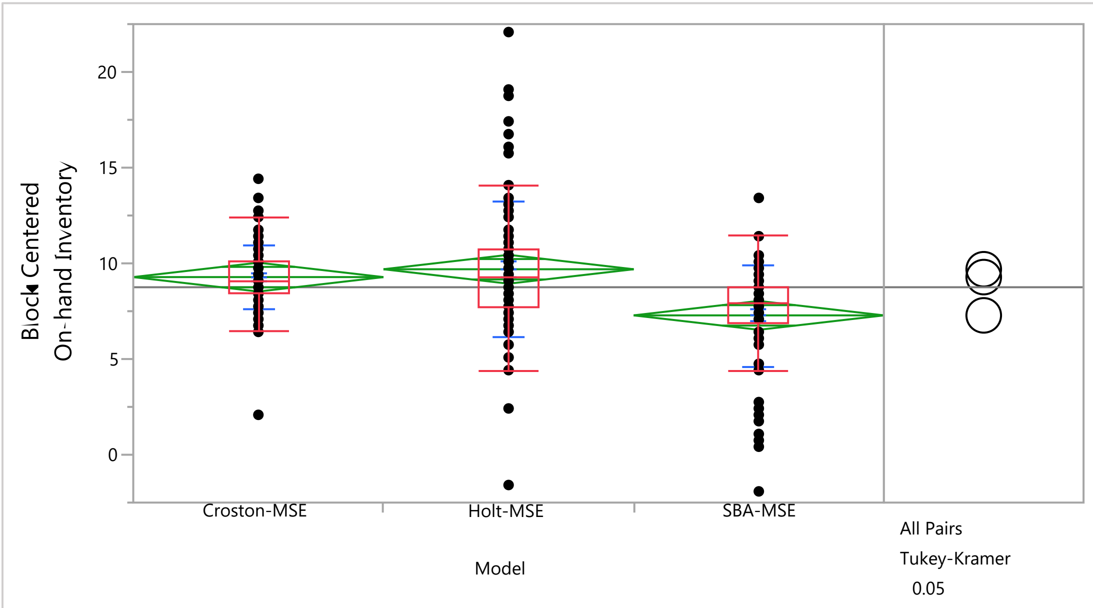

Figure A.42: Box Plots of "On-hand Inventory" for Smooth Demand Pattern-Three Models-Electronics Data

To evaluate the statistical significance of the on-hand inventory means, the hypothesis that there is no statistical difference between the means was tested. Since the sample size was large enough (n = 78), the central limit theorem was invoked and the normality assumption of the data was made. Based on Levene's statistics, the null hypothesis that the variances are equal was rejected at p-value of 0.0006. Accordingly, the Welch's test was conducted and the null hypothesis was again rejected at a p-value of <0.0001. Results of the Tukey's test showed that SBA-MSE achieved significantly lower on hand inventory levels compared to both Croston-MSE and Holt-MSE. No statistical difference was found when comparing Croston-MSE and Holt-MSE. Box plots of on-hand inventory quantity across all the forecasting-inventory models are shown in Figure A.42.

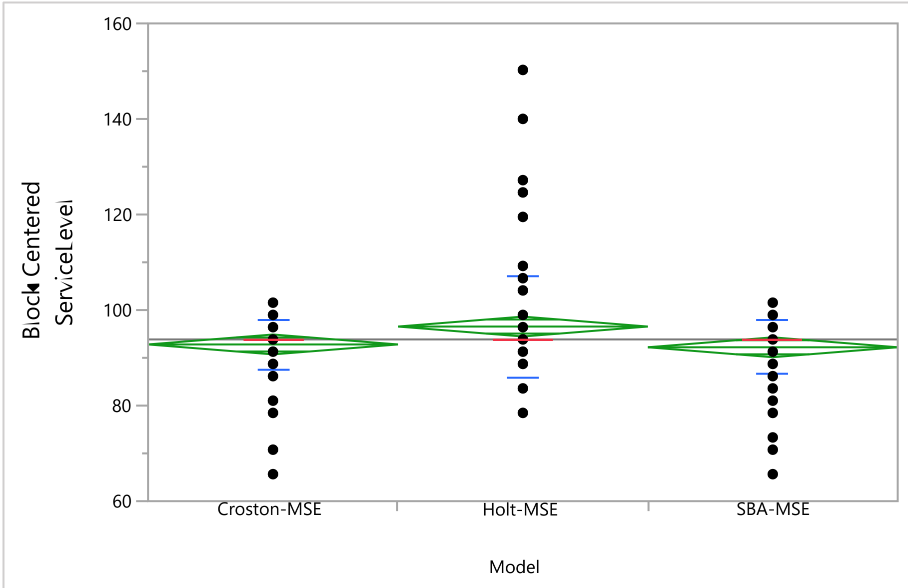

Figure A.43: Box Plots of "Service Level" for Smooth Demand Pattern-Three Models-Electronics Data

A similar test was conducted to analyze the on-average service levels across all three models. Based on Levene's statistics, the null hypothesis that the variances are equal was rejected at p-value of <0.0001. Accordingly, the Welch's test was conducted and the null hypothesis was again rejected at a p-value of <0.0001. Results of the Tukey's test showed that SBA-MSE achieved a significantly lower service level compared to both Croston-MSE and Holt-MSE. No statistical difference was found when comparing Croston-MSE and Holt-MSE. Box plots of achieved service levels across all the forecasting-inventory models are shown in Figure A.43.

Average fill rates of the models were also statistically compared and analyzed. Based on Levene's statistics, the null hypothesis that the variances are equal was rejected at p-value of <0.0001. Accordingly, the Welch's test was conducted and the null hypothesis was again rejected at a p-value of <0.0001. Results of the Tukey's test showed that Holt-MSE achieved a statistically higher fill rate compared to both SBA-MSE and Croston-MSE. No statistically significant difference was detected between SBA-MSE and Croston-MSE for this metric. Also, Holt-MSE was the only model that yielded fill rates above 90% on average. Box plots of the achieved fill-rates across all the forecasting-inventory models are shown in Figure A.44.

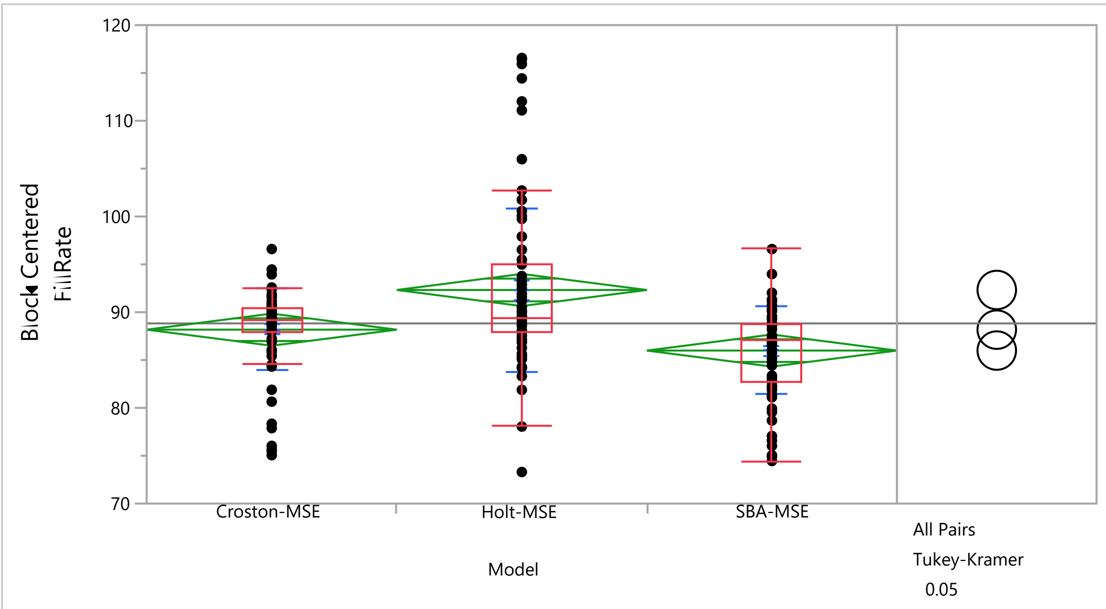

Figure A.44: Box Plots of "Fill Rate" for Smooth Demand Pattern-Three Models-Electronics Data

A.17 : INVENTORY PERFORMANCE- ERRATIC DEMAND PATTERN-AUTOMOTIVE DATA SET-THREE MODELS

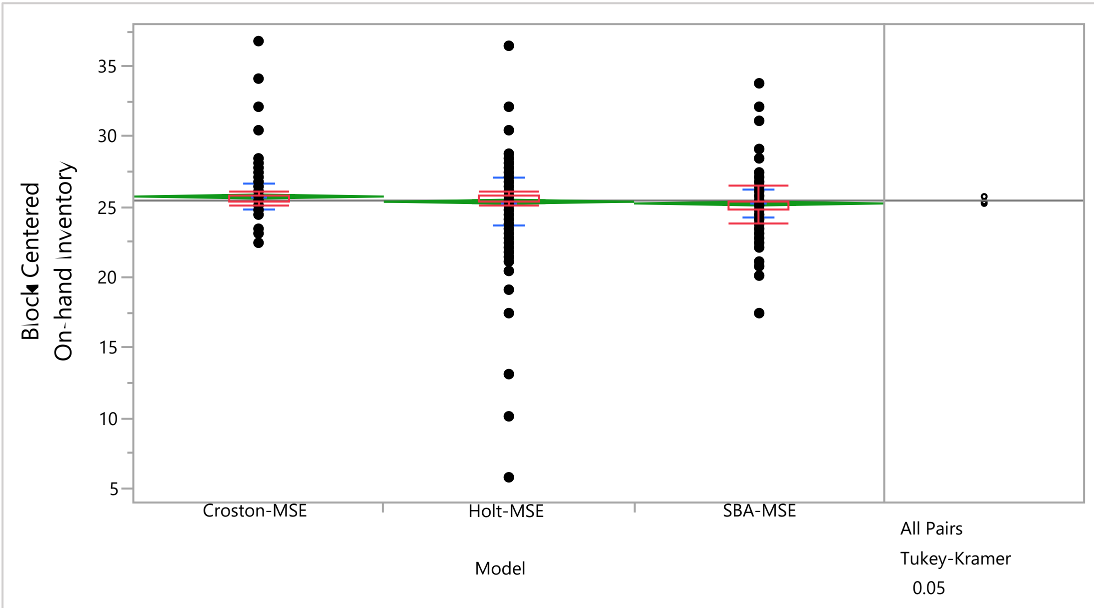

Figure A.45: Box Plots of "On-hand Inventory" for Erratic Demand Pattern-Three Models-Automotive Data

To evaluate the statistical significance of the on-hand inventory means, the hypothesis that there is no statistical difference between the means was tested. Since the sample size was large enough (n = 468), the central limit theorem was invoked and the normality assumption of the data was made. Based on Levene's statistics, the null hypothesis that the variances are equal was rejected at p-value of 0.0167. Accordingly, the Welch's test was conducted and the null hypothesis was again rejected at a p-value of <0.0001. Results of the Tukey's test showed that Croston-MSE carried significantly higher on hand inventory levels compared to both Holt-MSE and SBA-MSE. Box plots of on-hand inventory quantity across all the forecasting-inventory models are shown in Figure A.45.

A similar test was conducted to analyze the on-average service levels across all three models. Based on Levene's statistics, we failed to reject the null hypothesis that the variances are equal at p-value of 0.9. Accordingly, a one way ANOVA test was conducted and the null hypothesis was rejected at a p-value of 0.007. Results of the Tukey's test showed that Croston-MSE achieved a significantly higher service level compared to SBA-MSE. No statistical difference was found between Holt-MSE and Croston-MSE. Box plots of achieved service levels across all the forecasting-inventory models are shown in Figure A.46.

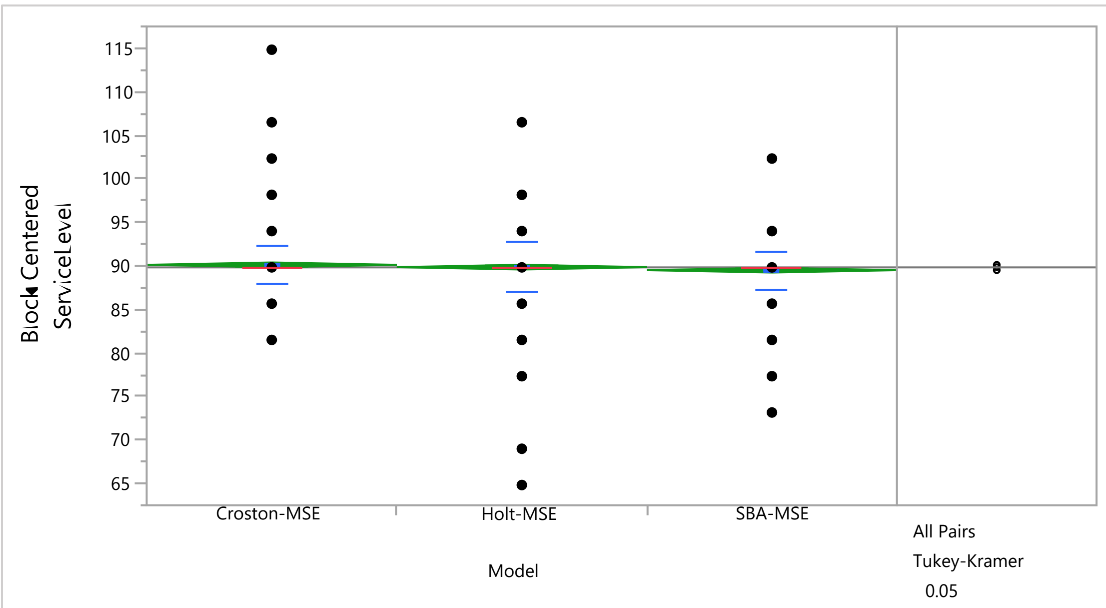

Figure A.46: Box Plots of "Service Level" for Erratic Demand Pattern-Three Models-Automotive Data

Average fill rates of the models were also statistically compared and analyzed. Based on Levene's statistics, we failed to reject the null hypothesis that the variances are equal at p-value of 0.3. Accordingly, a one way ANOVA test was conducted and the null hypothesis was rejected at a p-value of 0.005. Results of the Tukey's test showed that Croston-MSE achieved a significantly higher fill rate compared to SBA-MSE. No statistical difference was found between Holt-MSE and Croston-MSE. Box plots of achieved fill-rates across all the forecasting-inventory models are shown in Figure A.47.

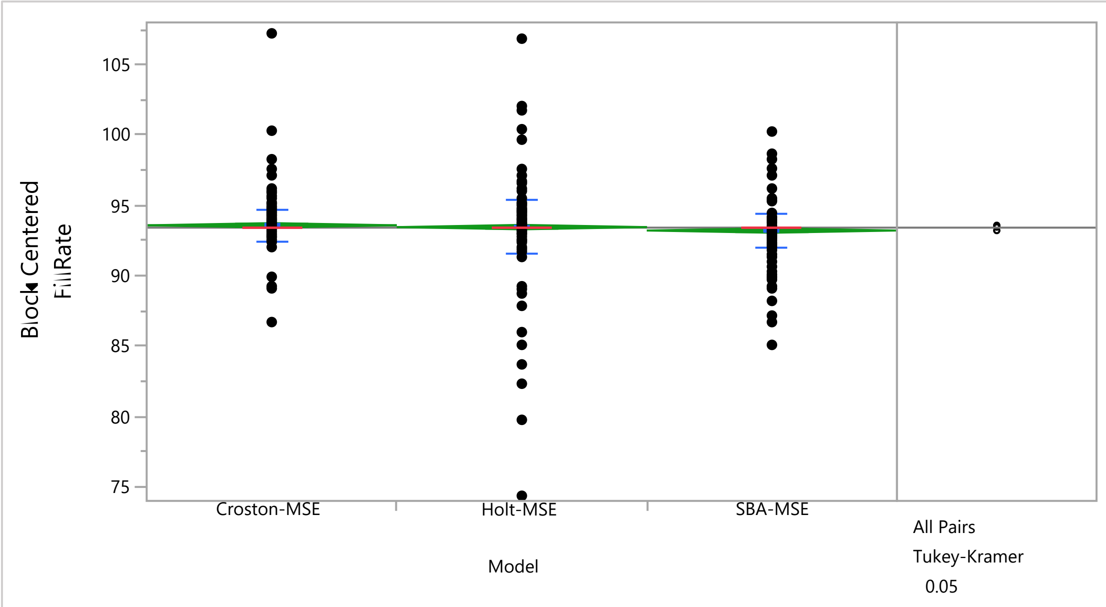

Figure A.47: Box Plots of "Fill Rate" for Erratic Demand Pattern-Three Models-Automotive Data

A.18 : INVENTORY PERFORMANCE- INTERMITTENT DEMAND PATTERN-AUTOMOTIVE DATA SET-THREE MODELS

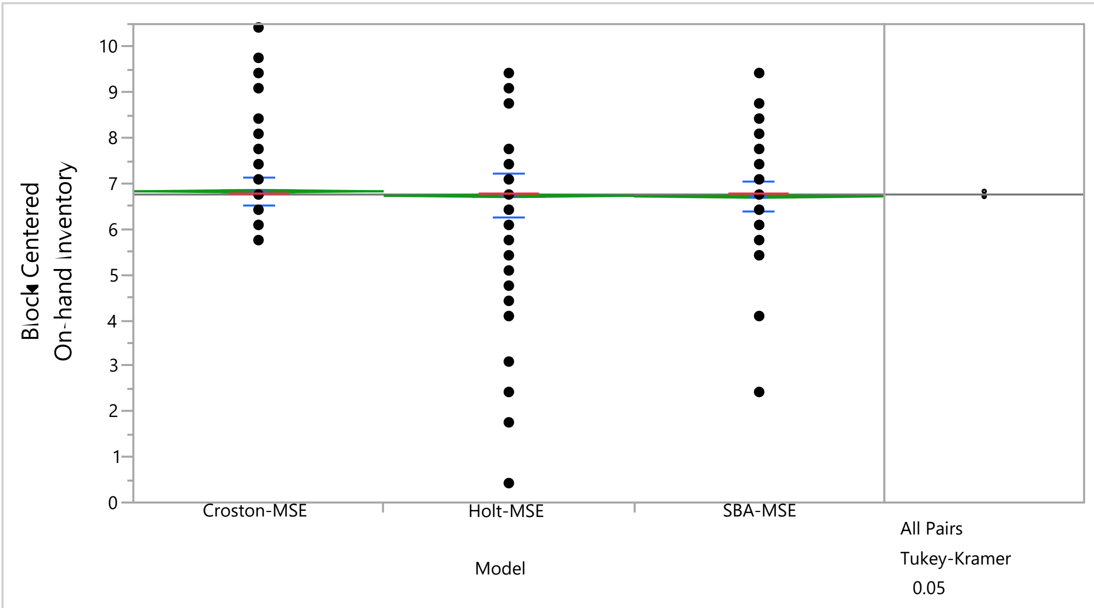

Figure A.48: Box Plots of "On-hand Inventory" for Intermittent Demand Pattern- the Three Models – the Automotive Data

To evaluate the statistical significance of the on-hand inventory means, the hypothesis that there is no statistical difference between the means was tested. Since the sample size was large enough ($n = 941$), the central limit theorem was invoked and the normality assumption of the data was made. Based on Levene's statistics, the null hypothesis that the variances are equal was rejected at p-value of 0.0051. Accordingly, the Welch's test was conducted and the null hypothesis was rejected at a p-value of <0.0001. Results of the Tukey's test showed that Croston-MSE achieved a significantly higher level of inventory compared to both Holt-MSE and SBA-MSE. No statistical difference was found between Holt-MSE and SBA-MSE. Box plots of on-hand inventory quantity across all the forecasting-inventory models are shown in Figure A.48.

Based on Levene's statistics, the null hypothesis that the variances are equal was rejected at p-value of 0.017. Accordingly, the Welch's test was conducted and the null hypothesis was rejected at a p-value of <0.0001. Results of the Tukey's test showed that SBA-MSE achieved a significantly lower level of service compared to both Croston-MSE and Holt-MSE. No statistical difference was found between Holt-MSE and Croston-MSE. Box plots of achieved service levels across all the forecasting-inventory models are shown in Figure A.49.

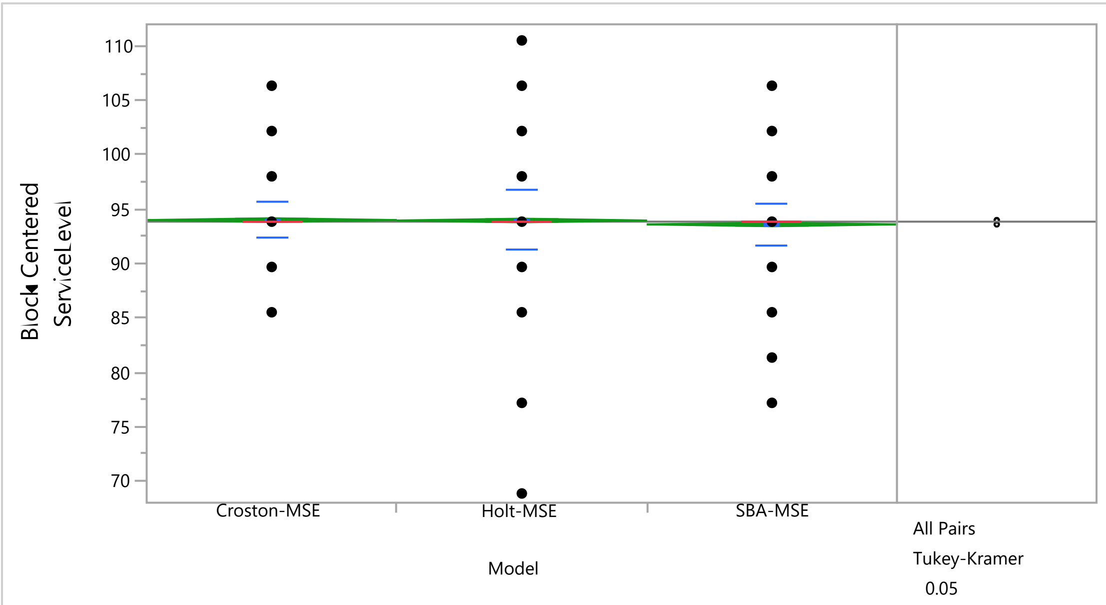

Figure A.49: Box Plots of "Service Level" for Intermittent Demand Pattern-Three Models-Automotive Data

Average fill rates of the models were also statistically compared and analyzed. Based on Levene's statistics, we failed to reject the null hypothesis that the variances are equal at p-value of 0.14. According to the one way ANOVA test we rejected the null hypothesis at a p-value of 0.001. Results of the Tukey's test showed that SBA-MSE achieved a significantly lower fill rate compared to Croston-MSE. No statistical difference was found between Holt-MSE and Croston-MSE. Box plots of achieved fill-rates across all the forecasting-inventory models are shown in Figure A.50.

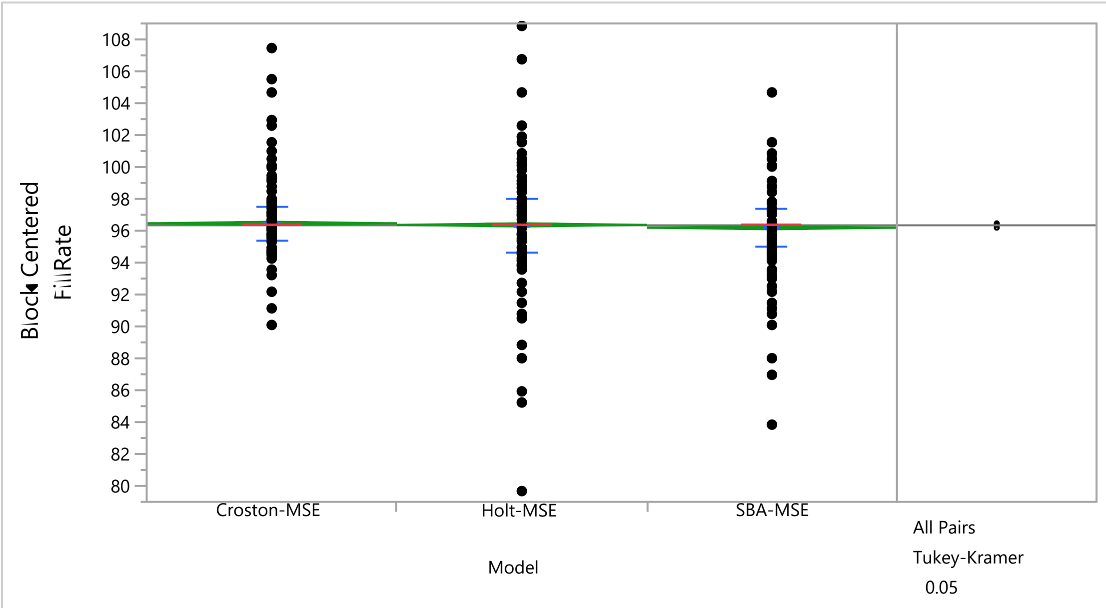

Figure A.50: Box Plots of "Fill Rate" for Intermittent Demand Pattern-Three Models-Automotive Data

A.19 : INVENTORY PERFORMANCE- LUMPY DEMAND PATTERN-AUTOMOTIVE DATA SET-THREE MODELS

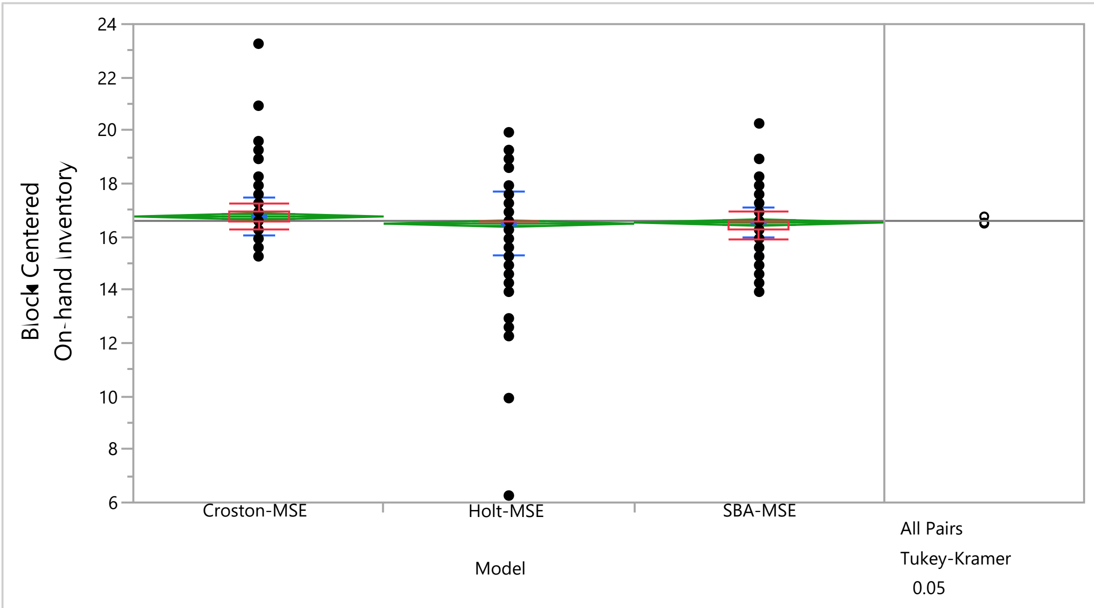

Figure A.51: Box Plots of "On-hand Inventory" for Lumpy Demand Pattern-Three Models-Automotive Data

To evaluate the statistical significance of the on-hand inventory means, the hypothesis that there is no statistical difference between the means was tested. Since the sample size was large enough (n = 286), the central limit theorem was invoked and the normality assumption of the data was made. Based on Levene's statistics, the null hypothesis that the variances are equal was rejected at p-value of <0.0001. Accordingly, the Welch's test was conducted and the null hypothesis was rejected at a p-value of <0.0001. Results of the Tukey's test showed that Croston-MSE achieved significantly higher levels of inventory compared to both Holt-MSE and SBA-MSE. Box plots of on-hand inventory quantity across all the forecasting-inventory models are shown in Figure A.51.

A similar test was conducted to analyze the on-average service levels across all three models. Based on Levene's statistics, we failed to reject the null hypothesis that the variances are equal at p-value of 0.9. According to the one way ANOVA test we failed to reject the null hypothesis at a p-value of 0.3. Thus, no statistical difference was found between the means for the service level metric.

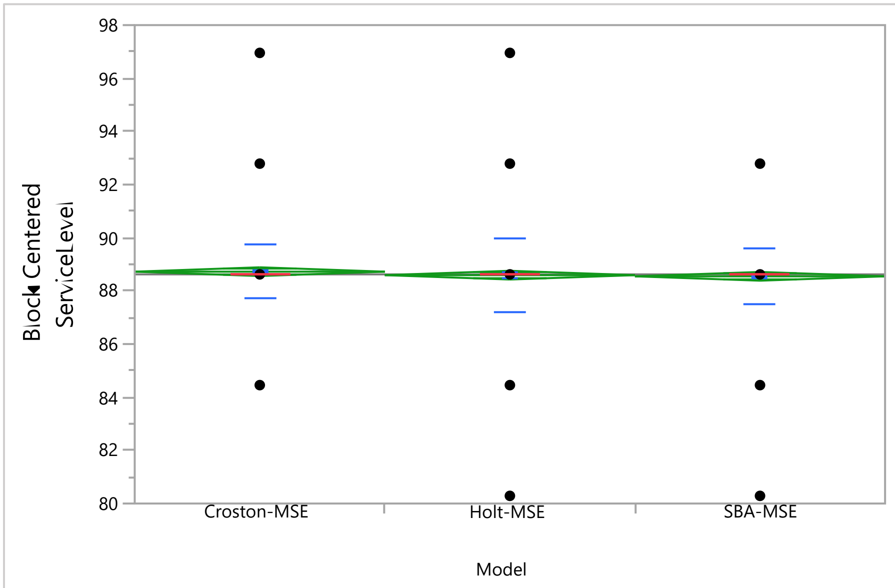

Figure A.52: Box Plots of "Service Level" for Lumpy Demand Pattern-Three Models-Automotive Data

Box plots of achieved service levels across all the forecasting-inventory models are shown in Figure A.52. Average fill rates of the models were also statistically compared and analyzed. Based on Levene's statistics, we failed to reject the null hypothesis that the variances are equal at p-value of 0.35. According to the one way ANOVA test we failed to reject the null hypothesis at a p-value of 0.1. Thus, no statistical difference was found between the means for the fill rate metric. Box plots of achieved fill-rates across all the forecasting-inventory models are shown in Figure A.53.

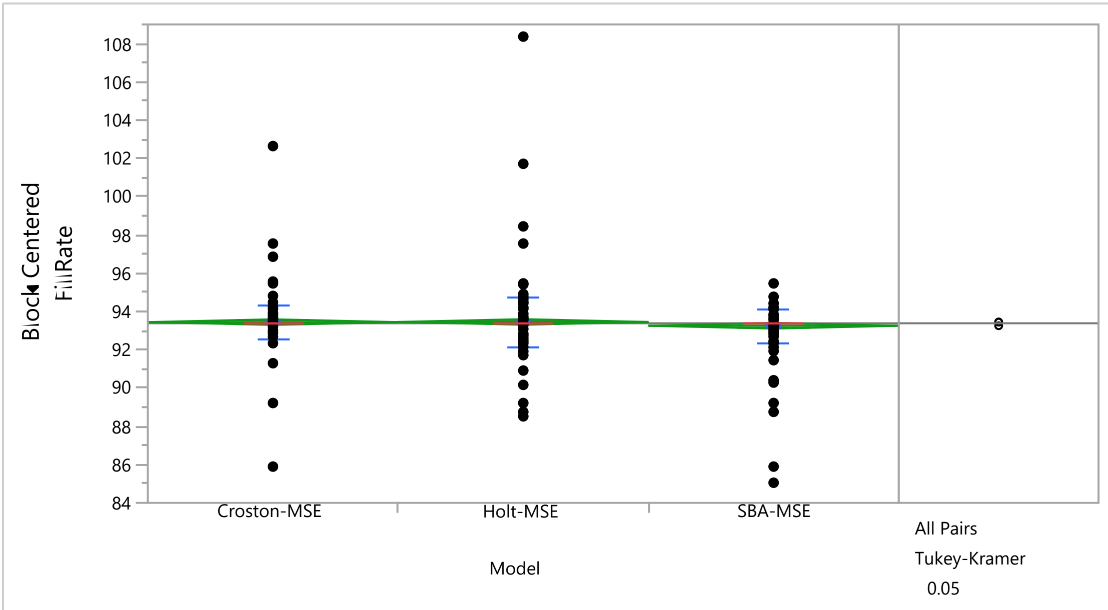

Figure A.53: Box Plots of "Fill Rate" for Lumpy Demand Pattern-Three Models-Automotive Data

A.20 : INVENTORY PERFORMANCE- SMOOTH DEMAND PATTERN-AUTOMOTIVE DATA SET-THREE MODELS

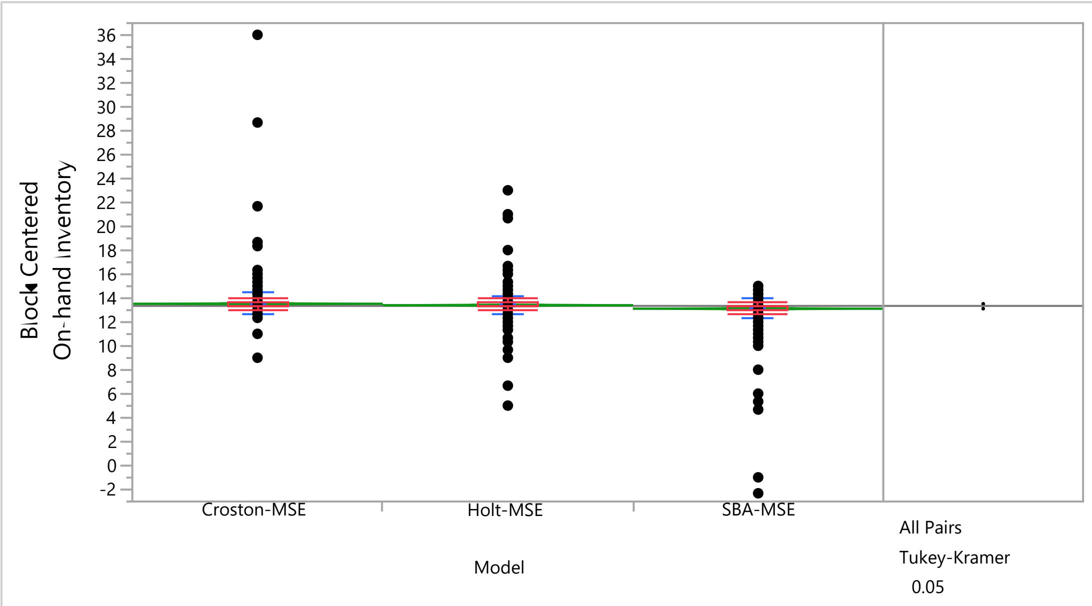

Figure A.54: Box Plots of "On-hand Inventory" for Smooth Demand Pattern-Three Models-Automotive Data

Statistical analysis of the means of the on-hand inventory levels was conducted. . Based on Levene's statistics, we failed to reject the null hypothesis that the variances are equal at p-value of 0.06. Accordingly, the Welch's test was conducted and the null hypothesis was rejected at a p-value of <0.0001. Results of Tukey's test showed that SBA-MSE achieved significantly lower on hand inventory level compared to both Holt-MSE and Croston-MSE. Holt-MSE was also significantly lower than Croston-MSE. Box plots of on-hand inventory quantity across all the forecasting-inventory models are shown in Figure A.54.

A similar test was conducted to analyze the on-average service levels across all three models. Based on Levene's statistics, the null hypothesis that the variances are equal was rejected at p-value of <0.0001. Accordingly, the Welch's test was conducted and the null hypothesis was rejected at a p-value of <0.0001. Results of the Tukey's test showed that SBA-MSE achieved a significantly lower service level compared to both Holt-MSE and Croston-MSE. No statistical difference was detected between Holt-MSE and Croston-MSE. Box plots of achieved service levels across all the forecasting-inventory models are shown in Figure A.55.

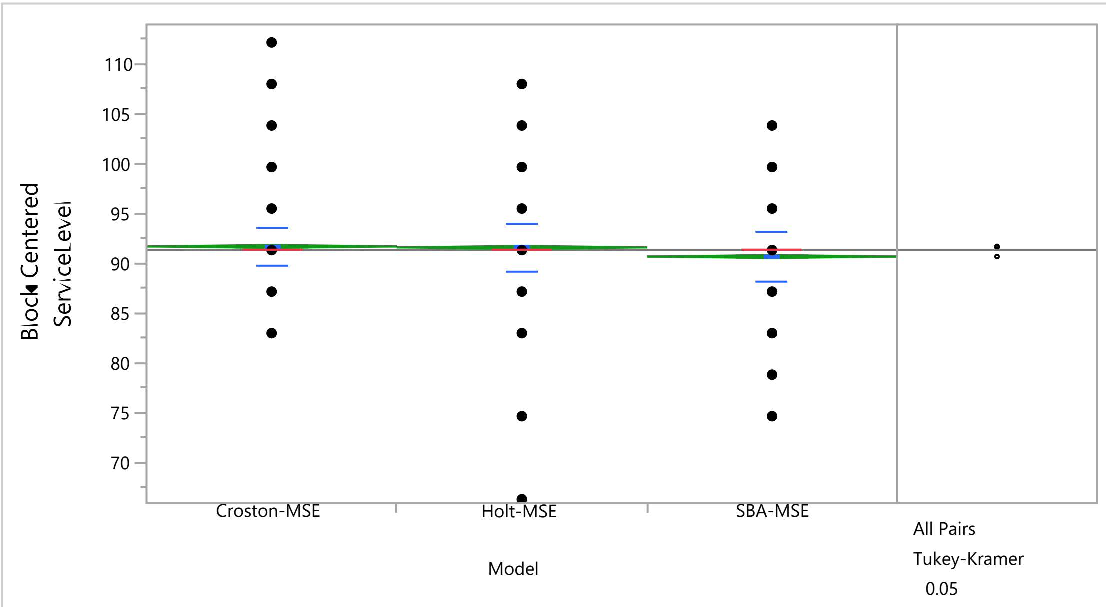

Figure A.55: Box Plots of "Service Level" for Smooth Demand Pattern-Three Models-Automotive Data

Average fill rates of the models were also statistically compared and analyzed. Based on Levene's statistics, the null hypothesis that the variances are equal was rejected at p-value of <0.0001. Accordingly, the Welch's test was conducted and the null hypothesis was rejected at a p-value of <0.0001. Results of the Tukey's test showed that SBA-MSE achieved a significantly lower fill rate compared to both Holt-MSE and Croston-MSE. No statistical difference was detected between Holt-MSE and Croston-MSE. Box plots of achieved fill-rates across all the forecasting-inventory models are shown in Figure A.56

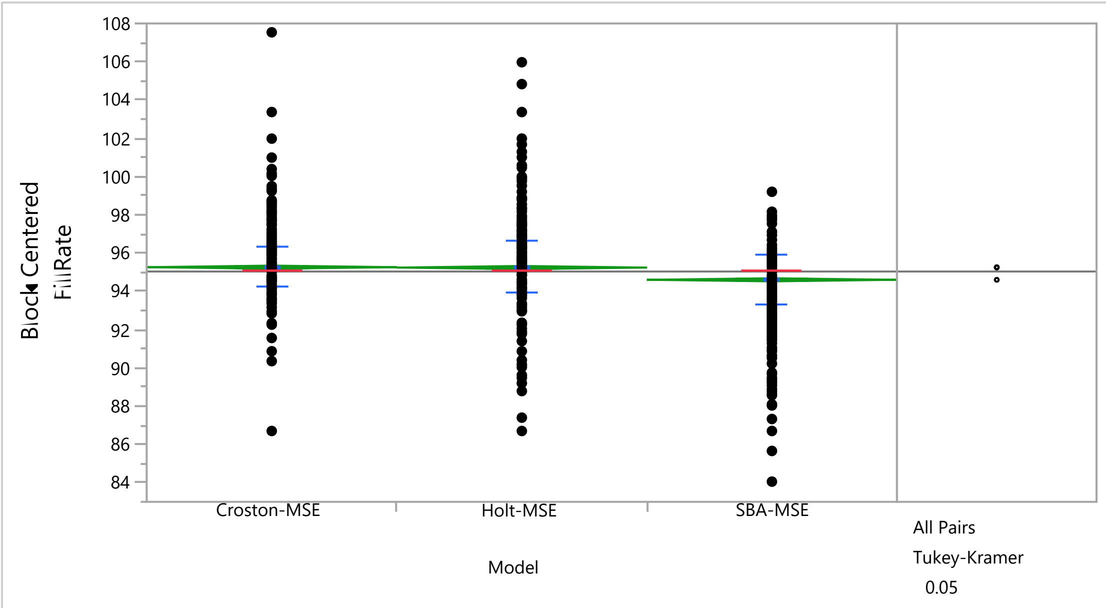

Figure A.56: Box Plots of "Fill Rate" for Smooth Demand Pattern-Three Models-Automotive Data

A.21 : CASE-STUDY DRIVEN ANALYSIS- INVENTORY MODEL PERFORMANCE

The results showed that the lowest on-hand inventory levels on average were achieved by SBA-MSE followed by Croston-MSE. However, carrying lower levels of inventory came at the expense of the service based performance metrics, as they achieved lower SL and FR. Nevertheless, a more detailed assessment of the results is deemed necessary to provide statistical evidence on the significance of the observed performance. To this purpose, a statistical comparison of means was conducted for each inventory performance measure. Since the sample size was large ($n = 523$), the central limit theorem was invoked and the normality assumption of the data was made.

To evaluate the statistical significance of the on-hand inventory means, the hypothesis that there is no statistical difference between the means was tested. Based on Levene's statistics, the null hypothesis that the variances are equal was rejected at p-value of < 0.0001. Accordingly, the

Welch's test was conducted and the null hypothesis was rejected at a p-value of <0.0001. Results of the Tukey's test showed that all of the proposed forecasting-inventory models achieved significantly lower levels of on hand inventory on average compared to the Current method. Moreover, Holt-Corr2 achieved significantly higher levels of on hand inventory compared to SBA-MSE, Croston-MSE, Holt-MSE and Holt-Corr1. Box plots of on-hand inventory quantity across all the forecasting-inventory models are shown in Figure A.57.

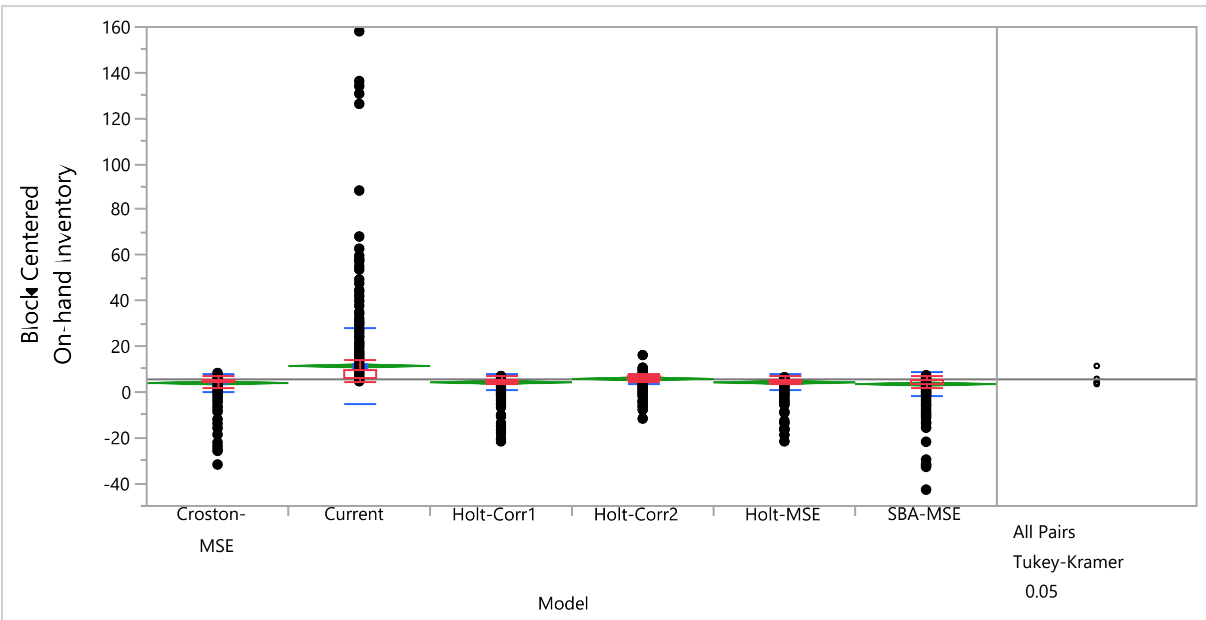

Figure A.57: Box Plots of "On-hand Inventory"- Case Study

The service level performance metric was statistically analyzed. Based on Levene's statistics, the null hypothesis that the variances are equal was rejected at p-value of < 0.0001. Accordingly, the Welch's test was conducted and the null hypothesis was rejected at a p-value of <0.0001. Results of the Tukey's test showed that there is statistical evidence that SBA-MSE achieved the lowest service level on average compared to Croston-MSE, Holt-Corr1, Holt-MSE, Holt-Corr2 and Current. Similarly, Croston-MSE was significantly lower than Holt-Corr1, Holt-MSE, Holt-Corr2 and Current at $\alpha = 0.05$. As for the variants of Holt-DES inventory models, no statistical difference was detected between Holt-Corr1 and Holt-MSE $\alpha = 0.05$. Both Holt-MSE and Holt-Corr1 achieved statistically lower levels of service compared with Current model. On the contrary, no statistical difference was found between Holt-Corr2 and Current. Box plots of achieved service levels across all the forecasting-inventory models are shown in Figure A.58.

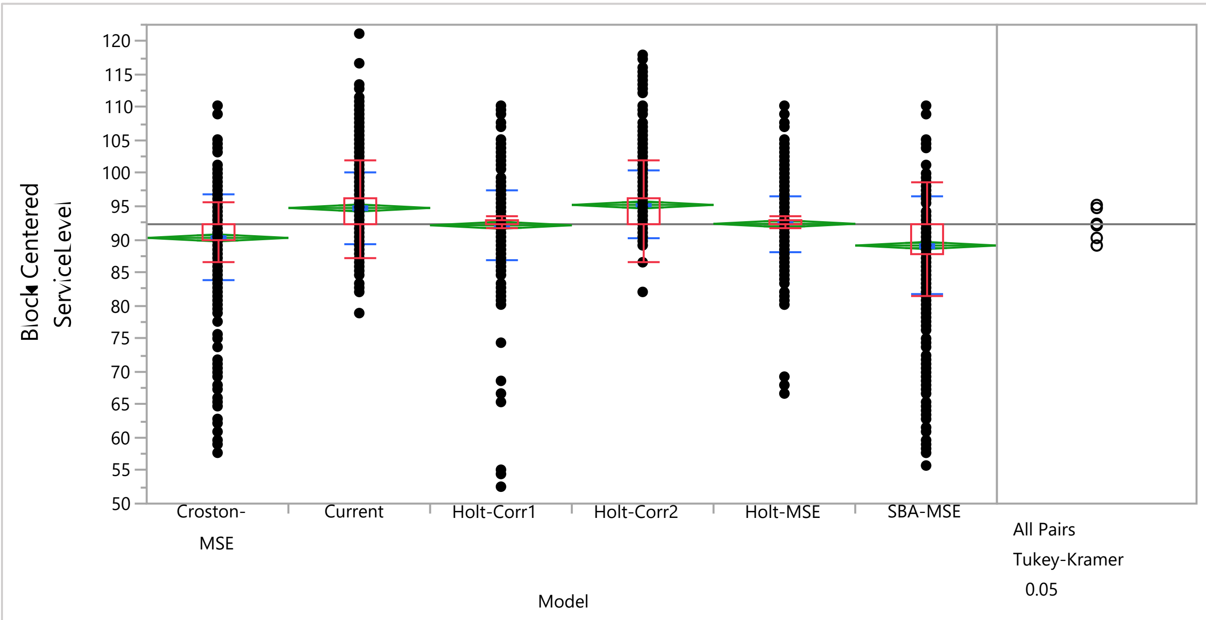

Figure A.58: Box Plots of the "Service Level" - Case Study

Lastly, the fill-rate performance metric was statistically analyzed. Based on Levene's statistics, the null hypothesis that the variances are equal was rejected at p-value of < 0.0001. Accordingly, the Welch's test was conducted and the null hypothesis was rejected at a p-value of <0.0001. Results of Tukey's test showed that there is statistical evidence that SBA-MSE achieved the lowest fill rate on average compared to Holt-Corr1, Holt-MSE, Holt-Corr2 and Current. No significant difference was evident between SBA-MSE and Croston-MSE at $\alpha = 0.05$. Similarly, Croston-MSE was significantly lower than Holt-Corr1, Holt-MSE, Holt-Corr2 and Current at $\alpha = 0.05$. As for the variants of Holt-DES inventory models, no statistical difference was detected between Holt-Corr1 and Holt-MSE $\alpha = 0.05$. Both Holt-MSE and Holt-Corr1 achieved statistically lower fill rates compared with Current model. On the contrary, no statistical difference was found between Holt-Corr2 and Current. Box plots of achieved fill-rates across all the forecasting-inventory models are shown in Figure A.59.

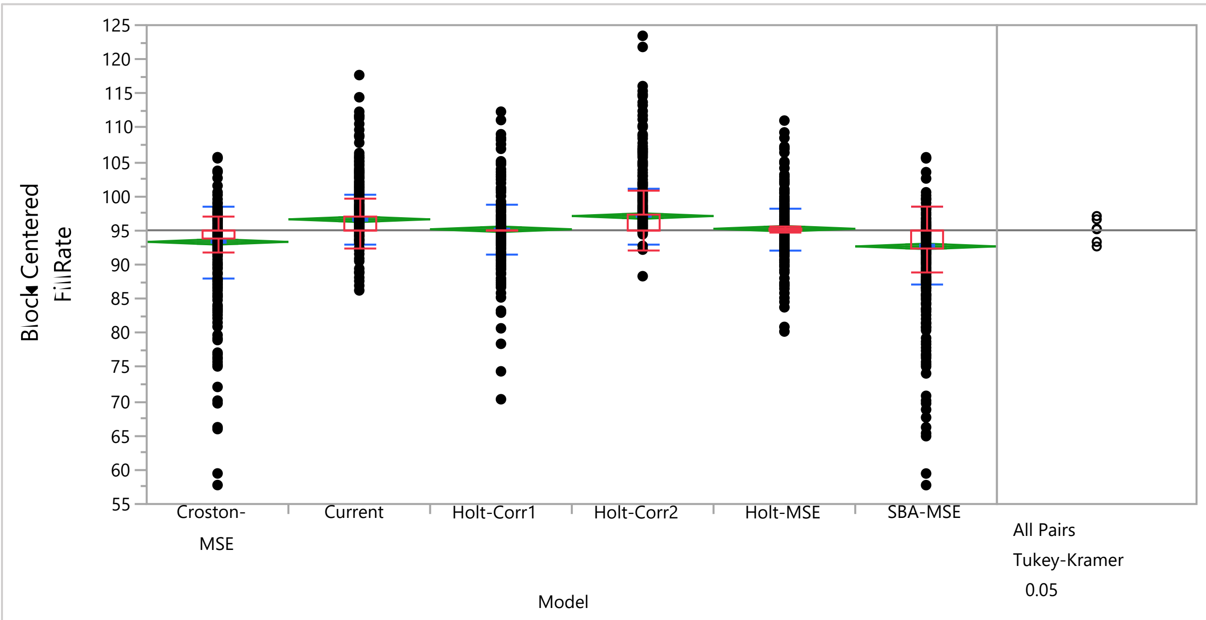

Figure A.59: Box Plots of the "Fill Rate" - Case Study

A.22 : CASE-STUDY DRIVEN ANALYSIS- INVENTORY MODEL PERFORMANCE-ERRATIC DEMAND PATTERN

Statistical analysis of the means of the on-hand inventory levels was conducted. Based on Levene's statistics, the null hypothesis that the variances are equal was rejected at p-value of <0.0001. Accordingly, the Welch's test was conducted and the null hypothesis was rejected at a p-value of <0.0001. Results of the Tukey's test showed that all the proposed models achieved significantly lower levels of inventory compared to the Current approach. Box plots of on-hand inventory quantity across all the forecasting-inventory models are shown in Figure A.60.

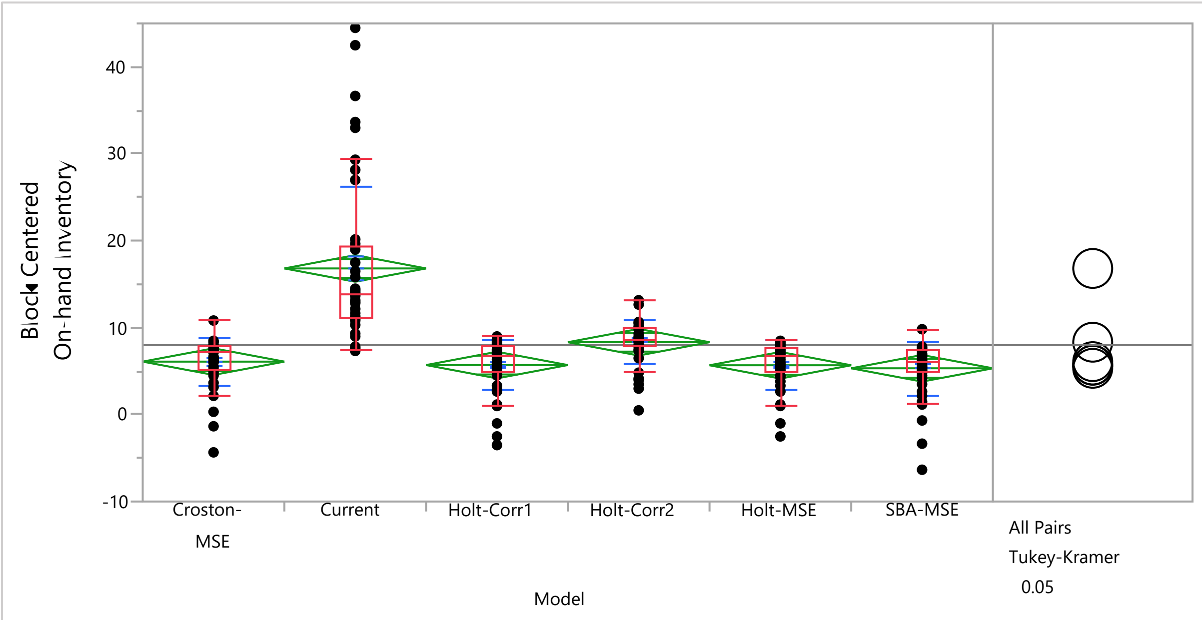

Figure A.60: Box Plots of "On-hand Inventory" for "Erratic Demand Pattern" - Case Study

The service level performance metric was statistically analyzed. Based on Levene's statistics, we failed to reject the null hypothesis that the variances are equal at p-value of 0.07. According to the one way ANOVA test we rejected the null hypothesis at a p-value of <0.0001. Results of the Tukey's test showed that SBA-MSE, Holt-Corr1, Croston-MSE, Holt-MSE achieved significantly lower service levels compared to the Current model. No statistical difference was found between Holt-Corr2 and Current. Moreover, Holt-Corr2 achieved a significantly higher service level compared to SBA-MSE, Holt-Corr1, Croston-MSE, and Holt-MSE. Box plots of the service levels across all the forecasting-inventory models are shown in Figure A.61.

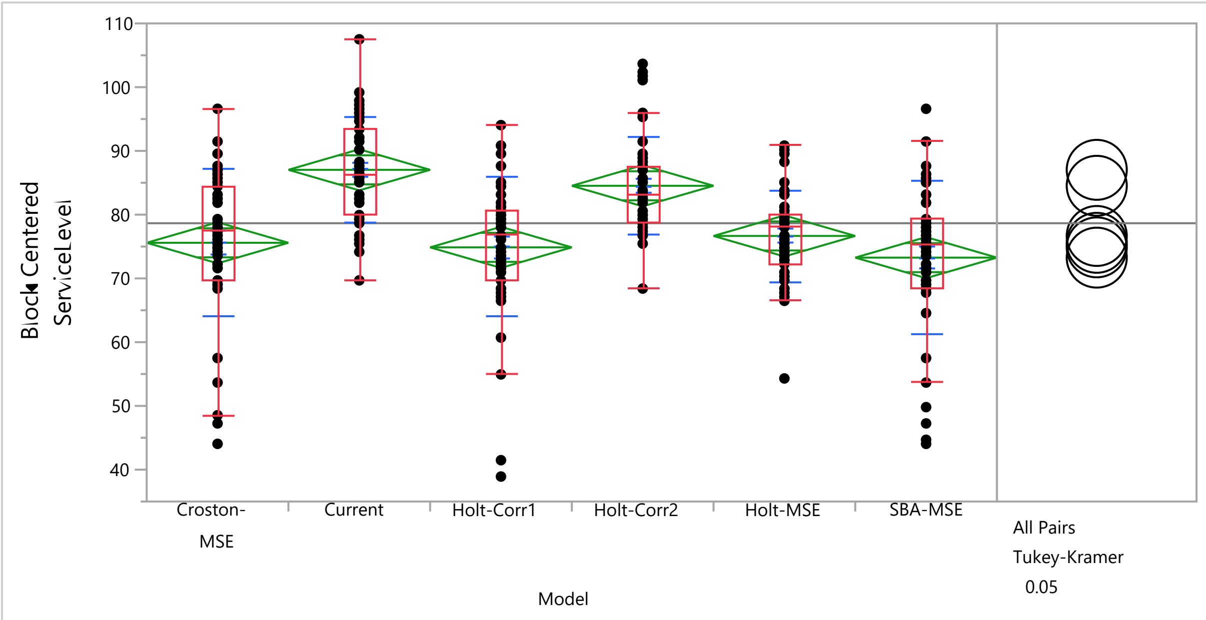

Figure A.61: Box Plots of "Service Level" for “Erratic Demand Pattern” - Case Study

Average fill rates of the models were also statistically compared and analyzed. Based on Levene’s statistics, the null hypothesis that the variances are equal was rejected at p-value of 0.04. Accordingly, the Welch’s test was conducted and the null hypothesis was rejected at a p-value of <0.0001. Results of the Tukey’s test showed that SBA-MSE, Holt-Corr1, Croston-MSE, Holt-MSE achieved significantly lower fill rates compared to the Current model. No statistical difference was found between Holt-Corr2 and Current. Moreover, Holt-Corr2 achieved a significantly higher fill rate compared to SBA-MSE, Holt-Corr1, Croston-MSE, and Holt-MSE. Box plots of achieved fill-rates across all the forecasting-inventory models are shown in Figure A.62.

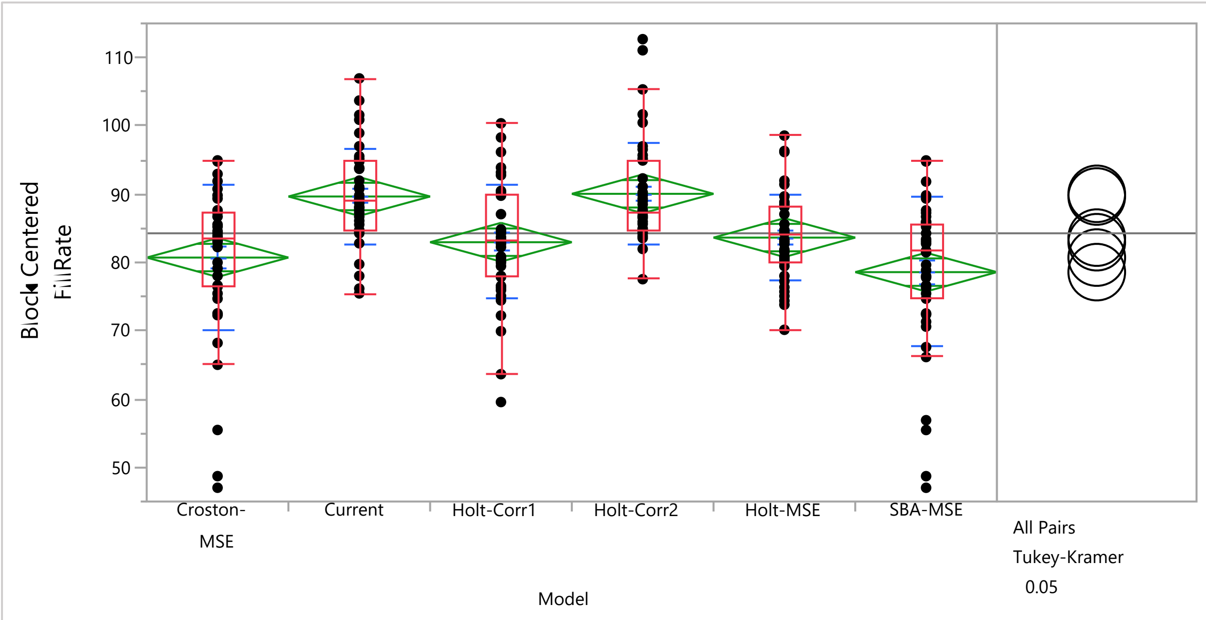

Figure A.62: Box Plots of "Fill Rate" for "Erratic Demand Pattern" - Case Study

A.23 : CASE-STUDY DRIVEN ANALYSIS- INVENTORY MODEL PERFORMANCE - INTERMITTENT DEMAND PATTERN

Statistical analysis of the means of the on-hand inventory levels was conducted. Based on Levene's statistics, the null hypothesis that the variances are equal was rejected at p-value of <0.0001. Accordingly, the Welch's test was conducted and the null hypothesis was rejected at a p-value of <0.0001. Results of the Tukey's test showed that all the proposed models achieved significantly lower levels of inventory compared to the Current approach. Holt-Corr2 achieved a significantly higher level of inventory compared to Holt-Corr1, Holt-MSE, Croston-MSE and SBA-MSE. Lastly, Both Holt-Corr1 and Holt-MSE achieved significantly higher levels of inventory compared to each of SBA-MSE and Croston-MSE. No statistical difference was found between SBA-MSE and Croston-MSE. Moreover, No statistical difference was found between Holt-Corr1 and Holt-MSE. Box plots of on-hand inventory quantity across all the forecasting-inventory models are shown in Figure A.63.

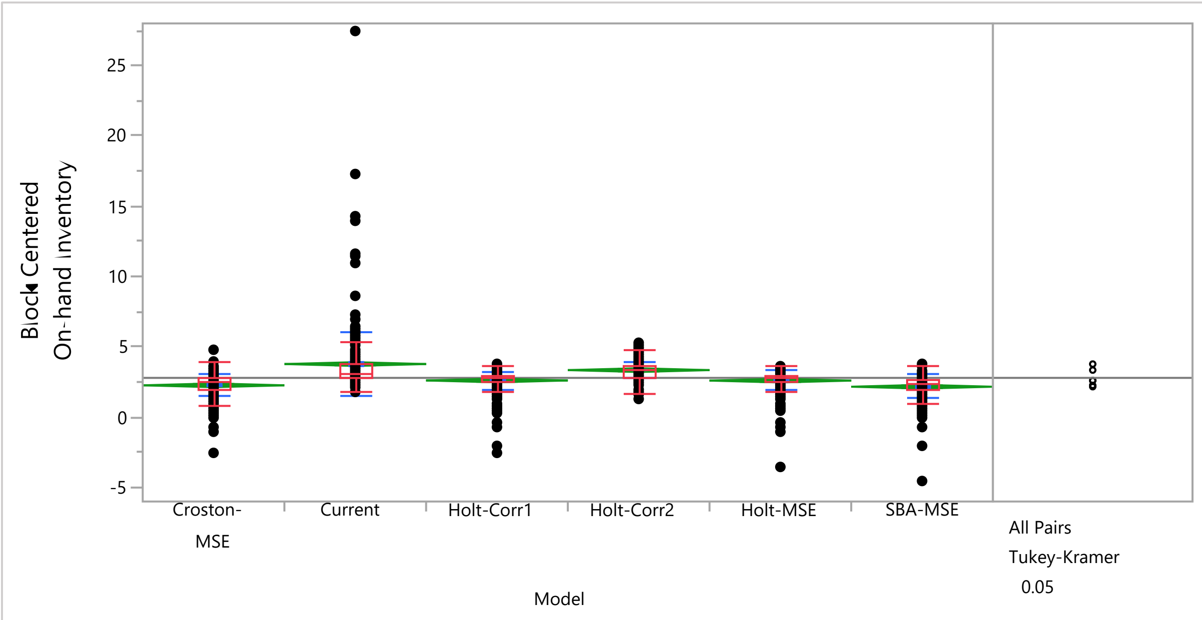

Figure A.63: Box Plots of "On-hand Inventory" for “Intermittent Demand Pattern”-Case Study

The service level performance metric was statistically analyzed. Based on Levene’s statistics, the null hypothesis that the variances are equal was rejected at p-value of <0.0001. Accordingly, the Welch’s test was conducted and the null hypothesis was rejected at a p-value of <0.0001. Results of the Tukey’s test showed that there is statistical evidence that SBA-MSE achieved the lowest service level on average compared to Holt-Corr1, Holt-MSE, Holt-Corr2 and Current. No significant difference was evident between SBA-MSE and Croston-MSE at $\alpha = 0.05$. Similarly, Croston-MSE was significantly lower than Holt-Corr1, Holt-MSE, Holt-Corr2 and Current at $\alpha = 0.05$. As for the variants of Holt-DES inventory models, no statistical difference was detected when comparing each of Holt-Corr1, Holt-MSE with the Current model. Holt-Corr2 achieved a significantly higher service level compared to all the models. Box plots of achieved service levels across all the forecasting-inventory models are shown in Figure A.64.

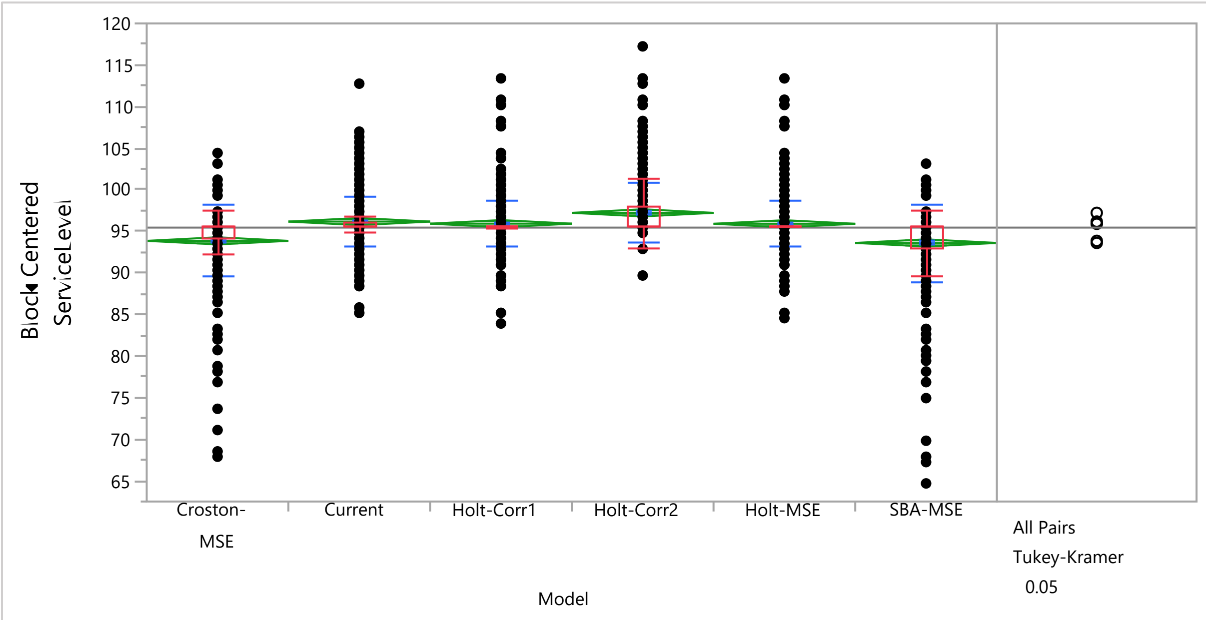

Figure A.64: Box Plots of "Service Level" for “Intermittent Demand Pattern”-Case Study

Average fill rates of the models were also statistically compared and analyzed. Based on Levene’s statistics, the null hypothesis that the variances are equal was rejected at p-value of 0.04. Accordingly, the Welch’s test was conducted and the null hypothesis was rejected at a p-value of <0.0001. Results of the Tukey’s test showed that there is statistical evidence that SBA-MSE achieved the lowest fill rate on average compared to Holt-Corr1, Holt-MSE, Holt-Corr2 and Current. No significant difference was evident between SBA-MSE and Croston-MSE at $\alpha = 0.05$. Similarly, Croston-MSE was significantly lower than Holt-Corr1, Holt-MSE, Holt-Corr2 and Current at $\alpha = 0.05$. As for the variants of Holt-DES inventory models, no statistical difference was detected when comparing each of Holt-Corr1, Holt-MSE with the Current model. Holt-Corr2 achieved a significantly higher fill rate compared to SBA-MSE, Holt-Corr1, Holt-MSE, and Holt-Corr2. Box plots of achieved fill rates across all the forecasting-inventory models are shown in Figure A.65.

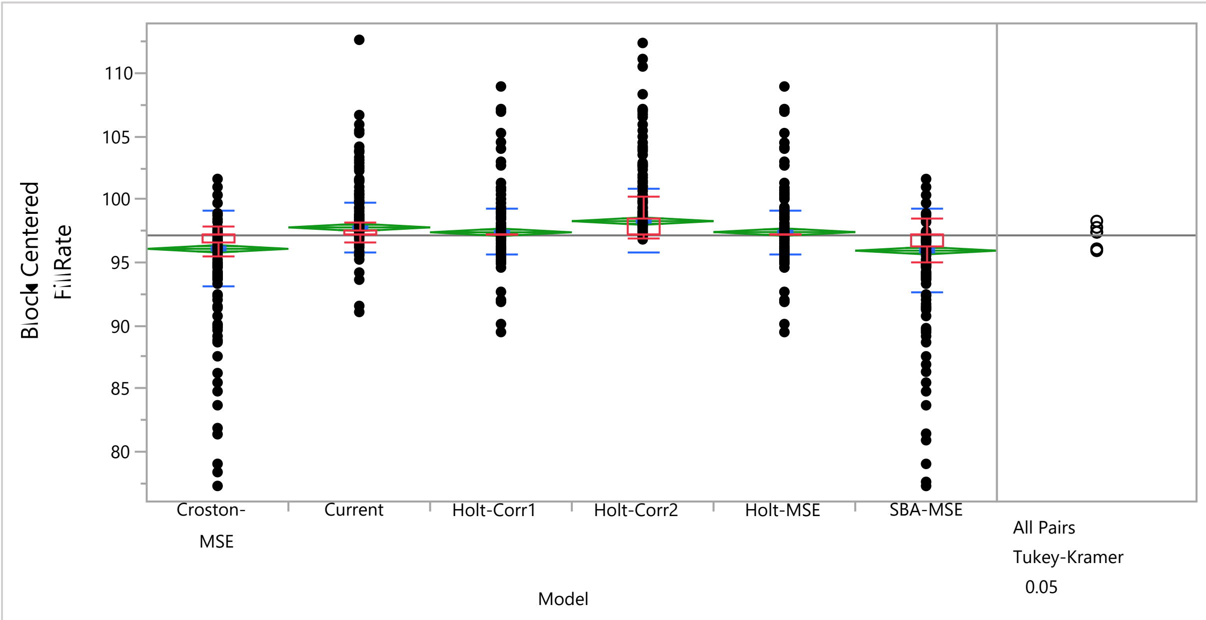

Figure A.65: Box Plots of "Fill Rate" for "Intermittent Demand Pattern"-Case Study

A.24 : CASE-STUDY DRIVEN ANALYSIS- INVENTORY MODEL PERFORMANCE - LUMPY DEMAND PATTERN

Statistical analysis of the means of the on-hand inventory levels was conducted. Based on Levene's statistics, the null hypothesis that the variances are equal was rejected at p-value of <0.0001. Accordingly, the Welch's test was conducted and the null hypothesis was rejected at a p-value of <0.0001. Results of the Tukey's test showed that all the proposed models achieved significantly lower levels of inventory compared to the Current approach. Moreover, Holt-Corr2 achieved a significantly higher level of inventory compared to SBA-MSE. Box plots of the on-hand inventory quantity across all the forecasting-inventory models are shown in Figure A.66.

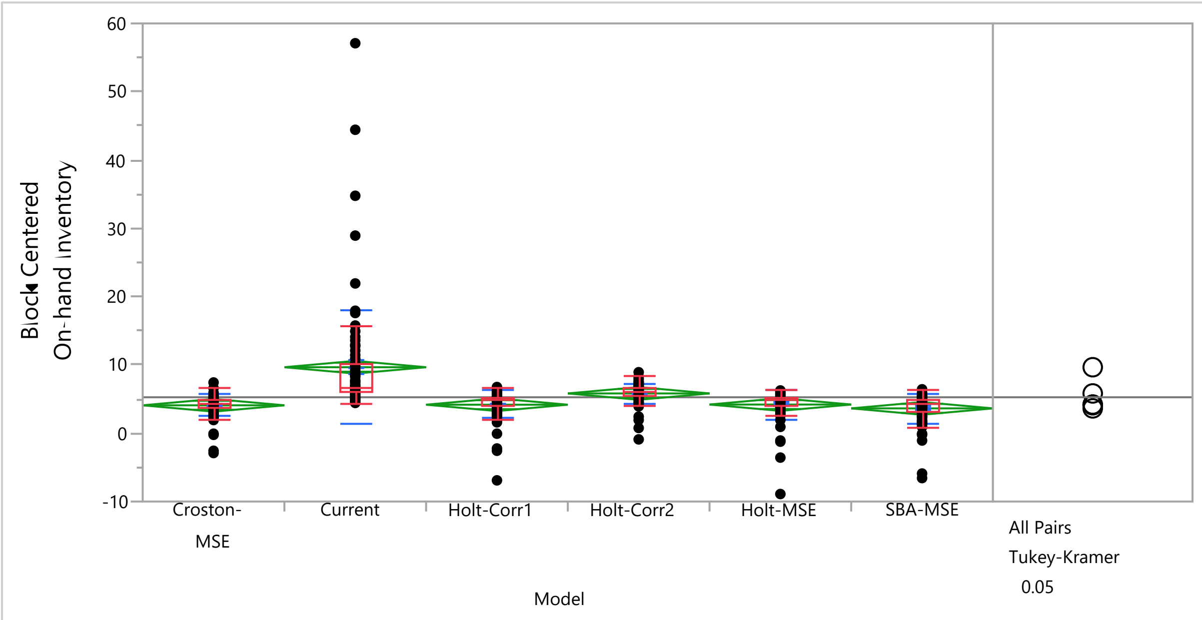

Figure A.66: Box Plots of "On-hand Inventory" for “Lumpy Demand Pattern”-Case Study

The service level performance metric was statistically analyzed. Based on Levene’s statistics, the null hypothesis that the variances are equal was rejected at p-value of <0.0001. Accordingly, the Welch’s test was conducted and the null hypothesis was rejected at a p-value of <0.0001. Results of the Tukey’s test showed that that there is statistical evidence that SBA-MSE achieved lower service levels compared to Holt-Corr1, Holt-Corr2, Current and Holt-MSE. Moreover, Croston-MSE achieved a significantly lower level of inventory compared to Current, Holt-Corr1, Holt-Corr2, Current and Holt-MSE. Box plots of the achieved service levels across all the forecasting-inventory models are shown in Figure A.67..

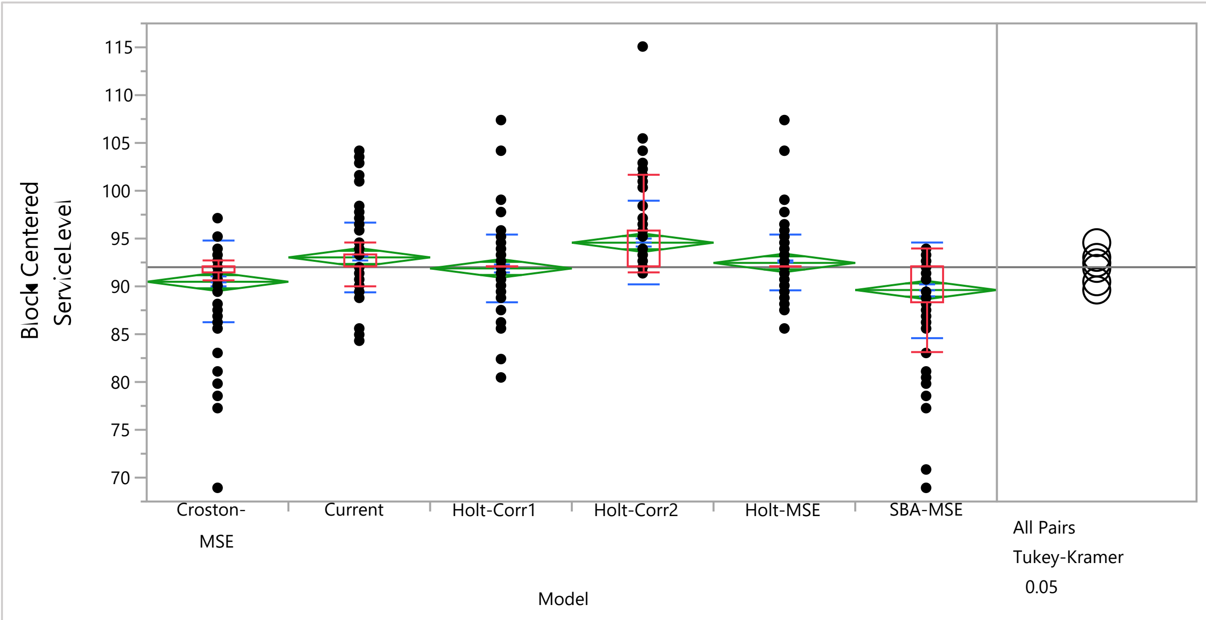

Figure A.67: Box Plots of "Service Level" for “Lumpy Demand Pattern”- Case Study

Average fill rates of the models were also statistically compared and analyzed. Based on Levene’s statistics, the null hypothesis that the variances are equal was rejected at p-value of 0.0002. Accordingly, the Welch’s test was conducted and the null hypothesis was rejected at a p-value of <0.0001. Results of Tukey’s test showed that Holt-Corr2 Achieved significantly higher fill rate compared to Holt-MSE, Holt-Corr1, SBA-MSE and Croston-MSE. Croston-MSE achieved a significantly lower fill rate compared to Holt-Corr2, Holt-MSE, Current and Holt-Corr1. Similarly, SBA-MSE achieved a significantly lower fill rate compared to Holt-Corr2, Holt-MSE, Current and Holt-Corr1. Box plots of achieved fill-rates across all the forecasting-inventory models were plotted in Figure A.68.

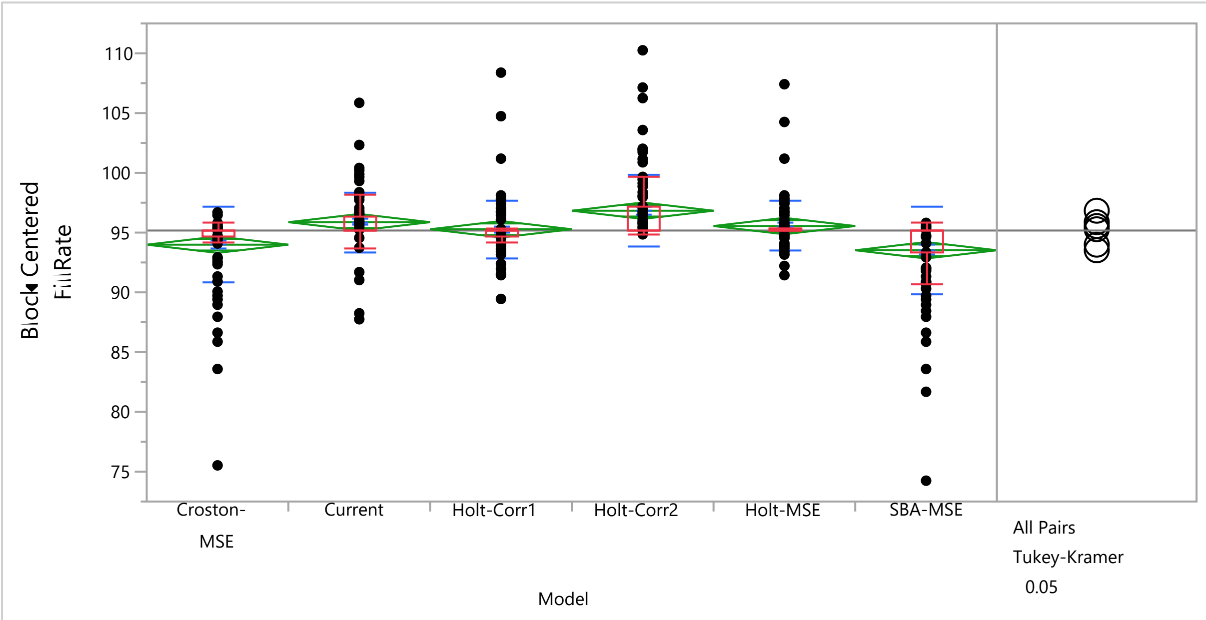

Figure A.68: Box Plots of "Fill Rate" for "Lumpy Demand Pattern"-Case Study

A.25 : CASE-STUDY DRIVEN ANALYSIS- INVENTORY MODEL PERFORMANCE-SMOOTH DEMAND PATTERN

Statistical analysis of the means of the on-hand inventory levels was conducted. Based on Levene's statistics, the null hypothesis that the variances are equal was rejected at p-value of <0.0001. Accordingly, the Welch's test was conducted and the null hypothesis was rejected at a p-value of <0.0001. Results of the Tukey's test showed that all the proposed models achieved significantly lower levels of inventory compared to the Current approach**.** Box plots of on-hand inventory quantity across all the forecasting-inventory models are shown in Figure A.69.

The service level performance metric was statistically analyzed. Based on Levene's statistics, the null hypothesis that the variances are equal was rejected at p-value of <0.0001. Accordingly, the Welch's test was conducted and the null hypothesis was rejected at a p-value of <0.0001. Results of the Tukey's test showed that there is statistical evidence that SBA-MSE achieved a significantly lower service level compared to all the proposed models. Moreover, Croston-MSE achieved a significantly lower service level compared to Holt-Corr2 and Current.

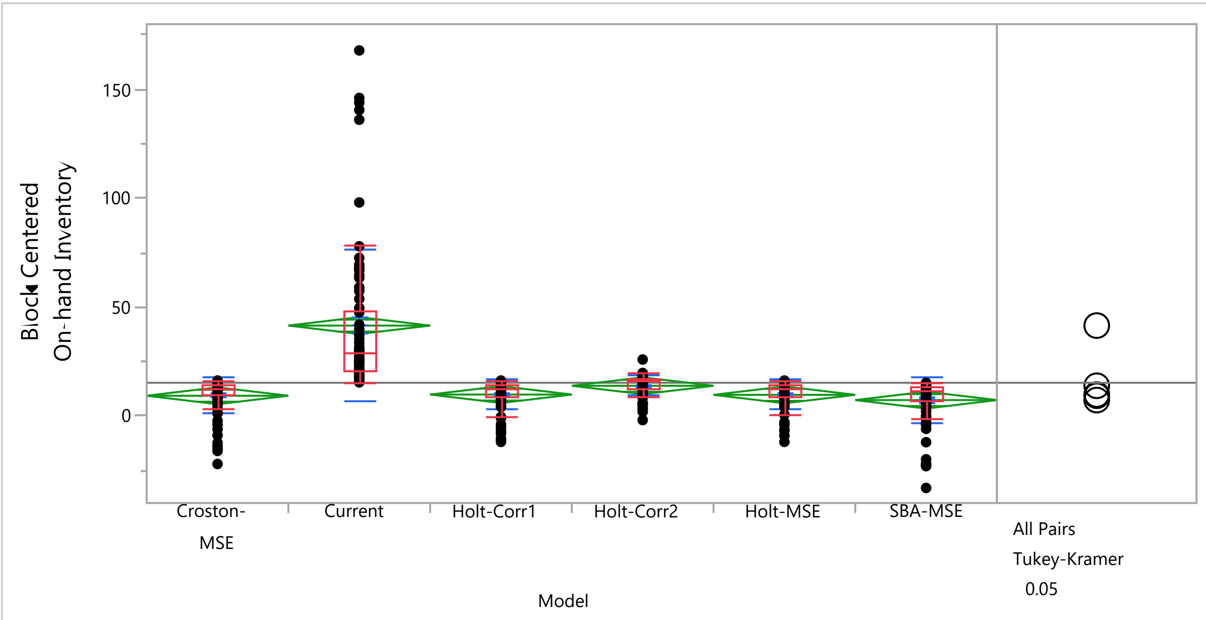

Figure A.69: Box Plots of "On-hand Inventory" for "Smooth Demand Pattern"-Case Study

Results also showed that Holt-Corr2 achieved a significantly higher service level compared to Holt-MSE, Holt-Corr1, Croston-MSE and SBA-MSE. No statistical difference was found between Holt-Corr2 and Current. All the proposed forecasting-inventory models except for Holt-Corr2 achieved statistically lower service levels compared to Current. Box plots of achieved service levels across all the forecasting-inventory models are shown in Figure A.70.

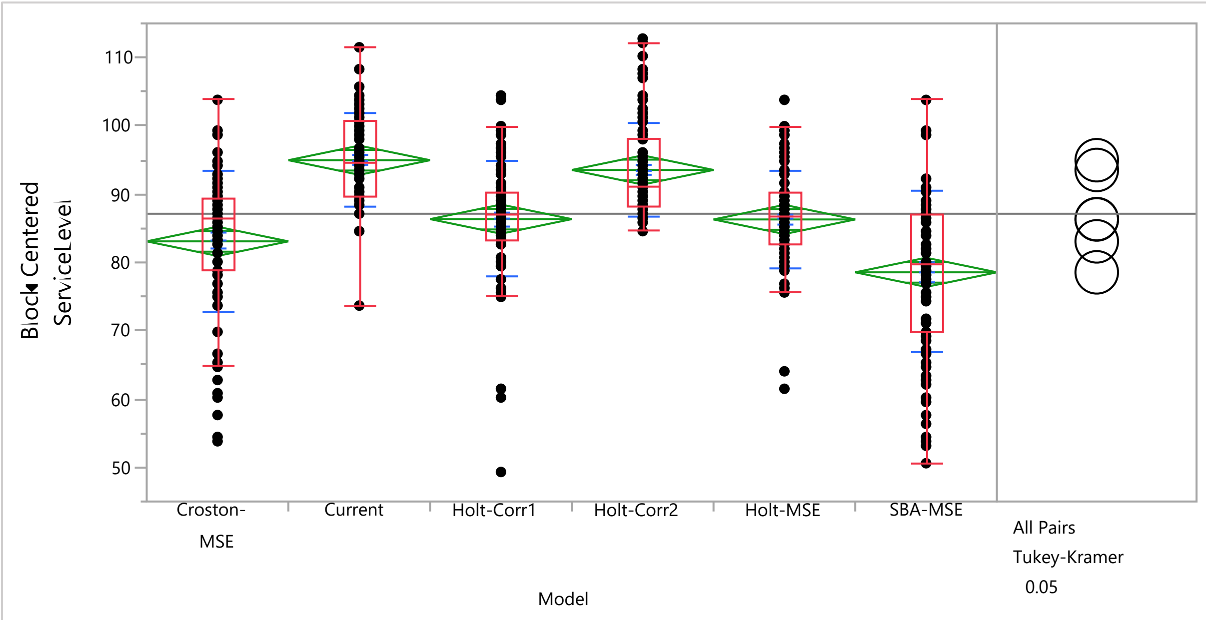

Figure A.70: Box Plots of "Service Level" for "Smooth Demand Pattern"-Case Study

Average fill rates of the models were also statistically compared and analyzed. Based on Levene's statistics, the null hypothesis that the variances are equal was rejected at p-value of <0.0001. Accordingly, the Welch's test was conducted and the null hypothesis was rejected at a p-value of <0.0001. Results of the Tukey's test showed that there is statistical evidence that SBA-MSE achieved a significantly lower fill rate compared to Current, Holt-Corr2, Holt-Corr1 and Holt-MSE. Moreover, Croston-MSE achieved a significantly lower fill rate compared to Current, Holt-Corr2, Holt-Corr1 and Holt-MSE.

Results also showed that Holt-Corr2 achieved a significantly higher fill rate compared to Holt-MSE, Holt-Corr1, Croston-MSE and SBA-MSE. No statistical difference was found between Holt-Corr2 and Current. All the proposed forecasting-inventory models except for Holt-Corr2 achieved statistically fill rate levels compared to Current. Box plots of achieved fill-rates across all the forecasting-inventory models are shown in Figure A.71.

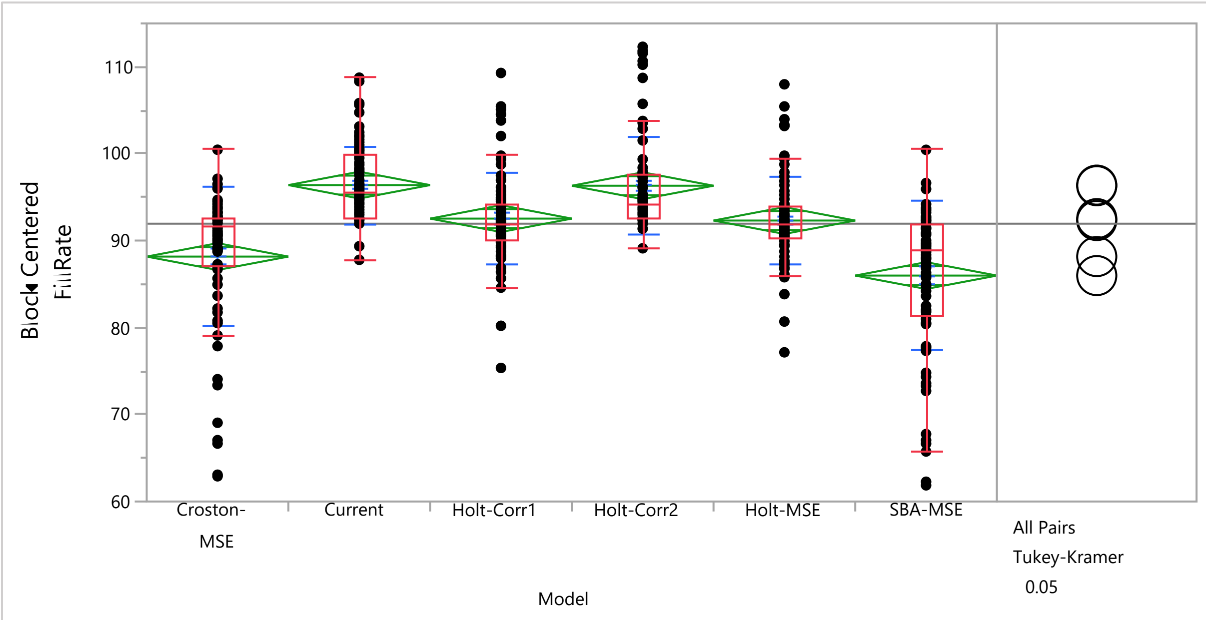

Figure A.71: Box Plots of "Fill Rate" for "Smooth Demand Pattern"-Case Study

APPENDIX B

B.1 : RESULTS OF MSE STATISTICAL ANALYSIS -DS1 (FLC)

Table B.1: Individual MSE Statistical Analysis Results- DS1 (FLC)

<table>
<tr><th>Mean Squared Error (MSE)</th><th>Interpretation</th></tr>
<tr><td><table><tr><th>Method</th><th></th><th>MSE</th></tr><tr><td>Croston</td><td>A</td><td>6.12</td></tr><tr><td>SBA</td><td>A</td><td>6.03</td></tr><tr><td>M1</td><td>B</td><td>4.06</td></tr><tr><td>Holt</td><td>B</td><td>4.00</td></tr></table></td><td>M1 and Holt achieved significantly lower MSE compared to both SBA and Croston. No difference was captured between M1 and Holt nor between SBA and Croston.</td></tr>
<tr><td><table><tr><th>Method</th><th></th><th>MSE</th></tr><tr><td>Croston</td><td>A</td><td>6.12</td></tr><tr><td>SBA</td><td>A</td><td>6.03</td></tr><tr><td>Holt</td><td>B</td><td>4.00</td></tr><tr><td>M2</td><td>C</td><td>3.71</td></tr></table></td><td>M2 achieved significantly lower MSE compared to all the methods. Holt achieved significantly lower MSE compared to both SBA and Croston. No statistical difference was captured between SBA and Croston.</td></tr>
<tr><td><table><tr><th>Method</th><th></th><th>MSE</th></tr><tr><td>Croston</td><td>A</td><td>6.12</td></tr><tr><td>SBA</td><td>A</td><td>6.03</td></tr><tr><td>M3</td><td>B</td><td>4.16</td></tr><tr><td>Holt</td><td>C</td><td>4.00</td></tr></table></td><td>Holt achieved significantly lower MSE compared to all the methods. M3 achieved significantly lower MSE compared to both SBA and Croston. No statistical difference was captured between SBA and Croston.</td></tr>
<tr><td><table><tr><th>Method</th><th></th><th>MSE</th></tr><tr><td>Croston</td><td>A</td><td>6.12</td></tr><tr><td>SBA</td><td>A</td><td>6.03</td></tr><tr><td>Holt</td><td>B</td><td>4.00</td></tr><tr><td>M4</td><td>C</td><td>3.68</td></tr></table></td><td>M4 achieved significantly lower MSE compared to all the methods. Holt achieved significantly lower MSE compared to both SBA and Croston. No statistical difference was captured between SBA and Croston.</td></tr>
<tr><td><table><tr><th>Method</th><th></th><th>MSE</th></tr><tr><td>M3</td><td>A</td><td>4.16</td></tr><tr><td>M1</td><td>A</td><td>4.06</td></tr><tr><td>M2</td><td>B</td><td>3.71</td></tr><tr><td>M4</td><td>B</td><td>3.68</td></tr></table></td><td>M2 and M4 achieved significantly lower MSE compared to both M3 and M1. No difference was captured between M3 and M1 nor between M2 and M4.</td></tr>
</table>

B.2 : RESULTS OF MSE STATISTICAL ANALYSIS -DS2 (FLC)

Test	F Ratio	DFNum	DFDen	Prob > F
O'Brien[.5]	83.9658	6	4193	<.0001*
Brown-Forsythe	189.0207	6	4193	<.0001*
Levene	252.4324	6	4193	<.0001*
Bartlett	337.8952	6	.	<.0001*

Welch's Test

Welch Anova testing Means Equal, allowing Std Devs Not Equal

F Ratio	DFNum	DFDen	Prob > F
645.6093	6	1850.6	<.0001*

Figure B.1: Levene's Test for Equal Variances and Welch's Test for MSE- DS2 (FLC)

Table B.2: Individual MSE Statistical Analysis Results- DS2 (FLC)

Mean Squared Error (MSE)	Interpretation
Method / **MSE** Croston A 0.99 SBA B 0.93 M1 C 0.85 Holt D 0.84	All the methods are significantly different from one another. The lowest MSE was achieved by Holt while the highest MSE was achieved by Croston.
Method / **MSE** Croston A 0.99 SBA B 0.93 Holt C 0.84 M2 D 0.82	All the methods are significantly different from one another. The lowest MSE was achieved by M2 while the highest MSE was achieved by Croston.
Method / **MSE** Croston A 0.99 SBA B 0.93 Holt C 0.84 M3 D 0.82	All the methods are significantly different from one another. The lowest MSE was achieved by M3 while the highest MSE was achieved by Croston.
Method / **MSE** Croston A 0.99 SBA B 0.93 Holt C 0.84 M4 D 0.80	All the methods are significantly different from one another. The lowest MSE was achieved by M4 while the highest MSE was achieved by Croston.
Method / **MSE** M1 A 0.85 M3 B 0.82 M2 C 0.82 M4 D 0.80	All the methods are significantly different from one another. The lowest MSE was achieved by M4 while the highest MSE was achieved by

B.3 : RESULTS OF MSE STATISTICAL ANALYSIS -DS3 (FLC)

Test	F Ratio	DFNum	DFDen	Prob > F
O'Brien[.5]	98.3830	6	4193	<.0001*
Brown-Forsythe	163.2730	6	4193	<.0001*
Levene	211.4275	6	4193	<.0001*
Bartlett	268.4831	6	.	<.0001*

Welch's Test

Welch Anova testing Means Equal, allowing Std Devs Not Equal

F Ratio	DFNum	DFDen	Prob > F
208.2540	6	1849.5	<.0001*

Figure B.2: Levene's Test for Equal Variances and Welch's Test for MSE- DS3 (FLC)

Table B.3: Individual MSE Statistical Analysis Results- DS3 (FLC)

Mean Squared Error (MSE)	Interpretation
Method / **MSE** Croston A 0.33 SBA B 0.31 Holt C 0.30 M1 D 0.29	All the methods are significantly different from one another. The lowest MSE was achieved by M1 while the highest MSE was achieved by Croston.
Method / **MSE** Croston A 0.33 SBA B 0.31 Holt C 0.30 M2 D 0.29	All the methods are significantly different from one another. The lowest MSE was achieved by M2 while the highest MSE was achieved by Croston.
Method / **MSE** Croston A 0.33 SBA B 0.31 Holt C 0.30 M3 D 0.29	All the methods are significantly different from one another. The lowest MSE was achieved by M3 while the highest MSE was achieved by Croston.
Method / **MSE** Croston A 0.33 SBA B 0.31 Holt C 0.30 M4 D 0.29	All the methods are significantly different from one another. The lowest MSE was achieved by M4 while the highest MSE was achieved by Croston.
Level / **Mean** M3 A 0.29 M1 B 0.29 M2 B 0.29 M4 C 0.29	The lowest MSE was achieved by M4 while the highest MSE was achieved by M3. No statistical difference was captured between M1 and M2.

B.4 : RESULTS OF MSE STATISTICAL ANALYSIS -DS1 (RAMP-REG)

Test	F Ratio	DFNum	DFDen	Prob > F
O'Brien[.5]	131.9515	6	4193	<.0001*
Brown-Forsythe	109.9330	6	4193	<.0001*
Levene	156.2825	6	4193	<.0001*
Bartlett	258.1290	6	.	<.0001*

Welch's Test

Welch Anova testing Means Equal, allowing Std Devs Not Equal

F Ratio	DFNum	DFDen	Prob > F
1226.2590	6	1850.5	<.0001*

Figure B.3: Levene's Test for Equal Variances and Welch's Test for MSE-DS1 (Ramp-Reg)

Table B.4: Individual MSE Statistical Analysis Results- DS1 (Ramp-Reg)

Mean Squared Error (MSE)	Interpretation
Method / **MSE** SBA A 9.27 Croston B 8.50 M1 C 6.37 Holt D 6.01	All the methods are significantly different from one another. The lowest MSE was achieved by Holt while the highest MSE was achieved by Croston.
Method / **MSE** SBA A 9.27 Croston B 8.50 Holt C 6.01 M2 C 5.85	M2 and Holt achieved significantly lower MSE compared to both SBA and Croston. No statistical difference was captured between Holt and M2. The highest MSE was achieved by SBA.
Method / **MSE** SBA A 9.27 Croston B 8.50 M3 C 6.02 Holt C 6.01	M3 and Holt achieved significantly lower MSE compared to both SBA and Croston. No statistical difference was captured between Holt and M3. The highest MSE was achieved by SBA.
Method / **MSE** SBA A 9.27 Croston B 8.50 Holt C 6.01 M4 C 5.86	M4 and Holt achieved significantly lower MSE compared to both SBA and Croston. No statistical difference was captured between Holt and M4. The highest MSE was achieved by SBA.
Method / **MSE** M1 A 6.37 M3 B 6.02 M4 C 5.86 M2 C 5.85	M2 and M4 achieved significantly lower MSE compared to both M1 and M3. No statistical difference was captured between M2 and M4. The highest MSE was achieved by M1.

B.5 : RESULTS OF MSE STATISTICAL ANALYSIS -DS2 (RAMP-REG)

Test	F Ratio	DFNum	DFDen	Prob > F
O'Brien[.5]	38.0807	6	4193	<.0001*
Brown-Forsythe	65.2582	6	4193	<.0001*
Levene	75.6240	6	4193	<.0001*
Bartlett	130.6905	6	.	<.0001*

Welch's Test

Welch Anova testing Means Equal, allowing Std Devs Not Equal

F Ratio	DFNum	DFDen	Prob > F
393.5675	6	1851.6	<.0001*

Figure B.4: Levene's Test for Equal Variances and Welch's Test for MSE-DS2 (Ramp-Reg)

Table B.5: Individual MSE Statistical Analysis Results- DS2 (Ramp-Reg)

Mean Squared Error (MSE)	Interpretation
Method | **MSE** M1 | A | 1.53 SBA | A | 1.53 Croston | B | 1.50 Holt | C | 1.47	Holt achieved significantly lower MSE compared to all the methods. Croston achieved significantly lower MSE compared to both SBA and M1. No statistical difference was captured between SBA and M1.
Method | **MSE** SBA | A | 1.53 Croston | B | 1.50 Holt | C | 1.47 M2 | D | 1.44	All the methods are significantly different from one another. The lowest MSE was achieved by M2 while the highest MSE was achieved by SBA.
Method | **MSE** SBA | A | 1.53 Croston | B | 1.50 Holt | C | 1.47 M3 | D | 1.45	All the methods are significantly different from one another. The lowest MSE was achieved by M3 while the highest MSE was achieved by SBA.
Method | **MSE** SBA | A | 1.53 Croston | B | 1.50 Holt | C | 1.47 M4 | D | 1.44	All the methods are significantly different from one another. The lowest MSE was achieved by M4 while the highest MSE was achieved by SBA.
Method | **MSE** M1 | A | 1.53 M3 | B | 1.45 M2 | B | 1.44 M4 | B | 1.44	M1 achieved significantly higher MSE compared to all the new methods .

B.6 : RESULTS OF MSE STATISTICAL ANALYSIS -DS3 (RAMP-REG)

Test	F Ratio	DFNum	DFDen	Prob > F
O'Brien[.5]	40.3864	6	4193	<.0001*
Brown-Forsythe	61.5446	6	4193	<.0001*
Levene	78.7780	6	4193	<.0001*
Bartlett	184.2114	6	.	<.0001*

Welch's Test

Welch Anova testing Means Equal, allowing Std Devs Not Equal

F Ratio	DFNum	DFDen	Prob > F
88.8930	6	1851.7	<.0001*

Figure B.5: Levene's Test for Equal Variances and Welch's Test for MSE-DS3 (Ramp-Reg)

Table B.6: Individual MSE Statistical Analysis Results- DS3 (Ramp-Reg)

<table>
<tr><th>Mean Squared Error (MSE)</th><th>Interpretation</th></tr>
<tr><td><table><tr><th>Method</th><th></th><th>MSE</th></tr><tr><td>Holt</td><td>A</td><td>0.58</td></tr><tr><td>M1</td><td>A</td><td>0.57</td></tr><tr><td>Croston</td><td>B</td><td>0.55</td></tr><tr><td>SBA</td><td>B</td><td>0.55</td></tr></table></td><td>SBA and Croston achieved significantly lower MSE compared to both M1 and Holt. No difference was captured between M1 and Holt nor between SBA and Croston.</td></tr>
<tr><td><table><tr><th>Method</th><th></th><th>MSE</th></tr><tr><td>Holt</td><td>A</td><td>0.58</td></tr><tr><td>M2</td><td>A</td><td>0.57</td></tr><tr><td>Croston</td><td>B</td><td>0.55</td></tr><tr><td>SBA</td><td>B</td><td>0.55</td></tr></table></td><td>SBA and Croston achieved significantly lower MSE compared to both M2 and Holt. No difference was captured between M2 and Holt nor between SBA and Croston.</td></tr>
<tr><td><table><tr><th>Method</th><th></th><th>MSE</th></tr><tr><td>Holt</td><td>A</td><td>0.58</td></tr><tr><td>M3</td><td>A</td><td>0.57</td></tr><tr><td>Croston</td><td>B</td><td>0.55</td></tr><tr><td>SBA</td><td>B</td><td>0.55</td></tr></table></td><td>SBA and Croston achieved significantly lower MSE compared to both M3 and Holt. No difference was captured between M3 and Holt nor between SBA and Croston.</td></tr>
<tr><td><table><tr><th>Method</th><th></th><th>MSE</th></tr><tr><td>Holt</td><td>A</td><td>0.58</td></tr><tr><td>M4</td><td>B</td><td>0.57</td></tr><tr><td>Croston</td><td>C</td><td>0.55</td></tr><tr><td>SBA</td><td>C</td><td>0.55</td></tr></table></td><td>SBA and Croston achieved significantly lower MSE compared to M4 and Holt. M4 achieved significantly lower MSE compared to Holt. No statistical difference was captured between SBA and Croston.</td></tr>
<tr><td><table><tr><th>Method</th><th></th><th>MSE</th></tr><tr><td>M1</td><td>A</td><td>0.57</td></tr><tr><td>M3</td><td>A</td><td>0.57</td></tr><tr><td>M2</td><td>A</td><td>0.57</td></tr><tr><td>M4</td><td>B</td><td>0.57</td></tr></table></td><td>M4 achieved significantly lower MSE compared to all the other new methods</td></tr>
</table>

B.7 : RESULTS OF MSE STATISTICAL ANALYSIS -DS1 (REG-DROP)

Test	F Ratio	DFNum	DFDen	Prob > F
O'Brien[.5]	144.9293	6	4193	<.0001*
Brown-Forsythe	85.8523	6	4193	<.0001*
Levene	285.1253	6	4193	<.0001*
Bartlett	237.0899	6	.	<.0001*

Welch's Test

Welch Anova testing Means Equal, allowing Std Devs Not Equal

F Ratio	DFNum	DFDen	Prob > F
336.3148	6	1832.5	<.0001*

Figure B.6: Levene's Test for Equal Variances and Welch's Test for MSE-DS1 (Reg.-Drop)

Table B.7: Individual MSE Statistical Analysis Results-DS1 (Reg.-Drop)

<table>
<tr><th>Mean Squared Error (MSE)</th><th>Interpretation</th></tr>
<tr><td>

Method		MSE
Croston	A	4.22
SBA	B	3.87
M1	C	2.82
Holt	D	2.69

</td><td>All the methods are significantly different from one another. The lowest MSE was achieved by Holt while the highest MSE was achieved by Croston.</td></tr>
<tr><td>

Method		MSE
Croston	A	4.22
SBA	B	3.87
M2	C	2.90
Holt	D	2.69

</td><td>All the methods are significantly different from one another. The lowest MSE was achieved by Holt while the highest MSE was achieved by Croston.</td></tr>
<tr><td>

Method		MSE
Croston	A	4.22
SBA	B	3.87
M3	C	3.12
Holt	D	2.69

</td><td>All the methods are significantly different from one another. The lowest MSE was achieved by Holt while the highest MSE was achieved by Croston.</td></tr>
<tr><td>

Method		MSE
Croston	A	4.22
SBA	B	3.87
Holt	C	2.69
M4	C	2.65

</td><td>M4 and Holt achieved significantly lower MSE compared to both SBA and Croston. No statistical difference was captured between Holt and M4. The highest MSE was achieved by SBA.</td></tr>
<tr><td>

Method		MSE
M3	A	3.12
M2	B	2.90
M1	B	2.82
M4	C	2.65

</td><td>The lowest MSE was achieved by M4 while the highest MSE was achieved by M3. No statistical difference was captured between M1 and M2.</td></tr>
</table>

B.8 : RESULTS OF MSE STATISTICAL ANALYSIS -DS2 (REG-DROP)

Test	F Ratio	DFNum	DFDen	Prob > F
O'Brien[.5]	81.9014	6	4193	<.0001*
Brown-Forsythe	143.4974	6	4193	<.0001*
Levene	162.4572	6	4193	<.0001*
Bartlett	245.5277	6	.	<.0001*

Welch's Test

Welch Anova testing Means Equal, allowing Std Devs Not Equal

F Ratio	DFNum	DFDen	Prob > F
571.1315	6	1845.8	<.0001*

Figure B.7: Levene's Test for Equal Variances and Welch's Test for MSE-DS2 (Reg.-Drop)

Table B.8: Individual MSE Statistical Analysis Results-DS2 (Reg.-Drop)

Mean Squared Error (MSE)	Interpretation
Method **MSE** Croston A 0.83 SBA B 0.78 Holt C 0.62 M1 D 0.57	All the methods are significantly different from one another. The lowest MSE was achieved by M1 while the highest MSE was achieved by Croston.
Method **MSE** Croston A 0.83 SBA B 0.78 Holt C 0.62 M2 D 0.56	All the methods are significantly different from one another. The lowest MSE was achieved by M2 while the highest MSE was achieved by Croston.
Method **MSE** Croston A 0.83 SBA B 0.78 Holt C 0.62 M3 C 0.61	M3 and Holt achieved significantly lower MSE compared to both SBA and Croston. No statistical difference was captured between Holt and M3. The highest MSE was achieved by Croston.
Method **MSE** Croston A 0.83 SBA B 0.78 Holt C 0.62 M4 D 0.56	All the methods are significantly different from one another. The lowest MSE was achieved by M4 while the highest MSE was achieved by Croston.
Method **MSE** M3 A 0.610 M1 B 0.569 M2 C 0.564 M4 D 0.556	All the methods are significantly different from one another. The lowest MSE was achieved by M4 while the highest MSE was achieved by M3.

B.9 : RESULTS OF MSE STATISTICAL ANALYSIS -DS3 (REG-DROP)

Test	F Ratio	DFNum	DFDen	Prob > F
O'Brien[.5]	83.7354	6	4193	<.0001*
Brown-Forsythe	104.1576	6	4193	<.0001*
Levene	176.0803	6	4193	<.0001*
Bartlett	273.3717	6	.	<.0001*

Welch's Test

Welch Anova testing Means Equal, allowing Std Devs Not Equal

F Ratio	DFNum	DFDen	Prob > F
337.1075	6	1848.4	<.0001*

Figure B.8: Levene's Test for Equal Variances and Welch's Test for MSE-DS3 (Reg.-Drop)

Table B.9: Individual MSE Statistical Analysis Results-DS3 (Reg.-Drop)

Mean Squared Error (MSE)	Interpretation
Method — **MSE** Croston A 0.26 SBA B 0.24 Holt C 0.20 M1 D 0.19	All the methods are significantly different from one another. The lowest MSE was achieved by M1 while the highest MSE was achieved by Croston.
Methods — **MSE** Croston A 0.26 SBA B 0.24 Holt C 0.20 M2 D 0.19	All the methods are significantly different from one another. The lowest MSE was achieved by M2 while the highest MSE was achieved by Croston.
Method — **MSE** Croston A 0.26 SBA B 0.24 Holt C 0.20 M3 C 0.20	M3 and Holt achieved significantly lower MSE compared to both SBA and Croston. No statistical difference was captured between Holt and M3. The highest MSE was achieved by Croston.
Method — **MSE** Croston A 0.26 SBA B 0.24 Holt C 0.20 M4 D 0.19	All the methods are significantly different from one another. The lowest MSE was achieved by M4 while the highest MSE was achieved by Croston.
Method — **MSE** M3 A 0.20 M2 B 0.19 M1 B 0.19 M4 C 0.19	The lowest MSE was achieved by M4 while the highest MSE was achieved by M3. No statistical difference was captured between M1 and M2.

B.10 : DATA SET ONE (DS1): SLIGHTLY INTERMITTENT (FLC)- PARAMETRIC ANALYSES

Table B.10: Slightly Intermittent Data Set Prob^{LC} of 1, 0.9 and 0.6

LC	***Parameters***	**Methods**					
		M2			***M4***		
Ramp	$Prob^{LC}$	1.00	1.00	1.00	1.00	1.00	1.00
	γ^{LC}	0.001	0.02	0.001	0.001	0.02	0.001
Reg.	$Prob^{LC}$	0.90	0.90	0.90	0.90	0.90	0.90
	γ^{LC}	0.02	0.02	0.001	0.02	0.02	0.001
Drop	$Prob^{LC}$	0.60	0.60	0.60	0.60	0.60	0.60
	γ^{LC}	0.20	0.20	0.02	0.20	0.20	0.02
Results	**MSE**	0.82	0.84	0.82	0.80	0.83	0.80
		M1					
	Prob.	1.00	1.00	1.00			
	γ	0.001	0.02	0.2			
Results	**MSE**	0.83	0.85	0.88			

Table B.11: Slightly Intermittent Data Set $Prob^{LC}$ of 0.95, 0.9 and 0.5

LC	***Parameters***	**Methods**					
		M2			***M4***		
Ramp	$Prob^{LC}$	0.95	0.95	0.95	0.95	0.95	0.95
	γ^{LC}	0.001	0.02	0.001	0.001	0.02	0.001
Reg.	$Prob^{LC}$	0.90	0.90	0.90	0.90	0.90	0.90
	γ^{LC}	0.02	0.02	0.001	0.02	0.02	0.001
Drop	$Prob^{LC}$	0.50	0.50	0.50	0.50	0.50	0.50
	γ^{LC}	0.20	0.20	0.02	0.20	0.20	0.02
Results	**MSE**	0.81	0.84	0.81	0.80	0.83	0.80
		M1					
	Prob.	0.95	0.95	0.95			
	γ	0.001	0.02	0.2			
Results	**MSE**	0.82	0.85	0.88			

Table B.12: Slightly Intermittent Data Set $Prob^{LC}$ of 0.9, 0.8 and 0.6

LC	***Parameters***	**Methods**					
		M2			***M4***		
Ramp	$Prob^{LC}$	0.90	0.90	0.90	0.90	0.90	0.90
	γ^{LC}	0.001	0.02	0.001	0.001	0.02	0.001
Reg.	$Prob^{LC}$	0.80	0.80	0.80	0.80	0.80	0.80
	γ^{LC}	0.02	0.02	0.001	0.02	0.02	0.001
Drop	$Prob^{LC}$	0.60	0.60	0.60	0.60	0.60	0.60
	γ^{LC}	0.20	0.20	0.02	0.20	0.20	0.02
Results	**MSE**	0.81	0.85	0.81	0.80	0.84	0.80
		M1					
	Prob.	0.90	0.90	0.90			
	γ	0.001	0.02	0.2			
Results	**MSE**	0.82	0.86	0.88			

B.11 : DATA SET TWO (DS2): MODERATELY INTERMITTENT (FLC)-PARAMETRIC ANALYSES

Table B.13: Moderately Intermittent Data Set Prob^{LC} of 1, 0.9 and 0.6

LC	***Parameters***	**Methods**					
		M2			***M4***		
Ramp	$Prob^{LC}$	1.00	1.00	1.00	1.00	1.00	1.00
	γ^{LC}	0.001	0.02	0.001	0.001	0.02	0.001
Reg.	$Prob^{LC}$	0.90	0.90	0.90	0.90	0.90	0.90
	γ^{LC}	0.02	0.02	0.001	0.02	0.02	0.001
Drop	$Prob^{LC}$	0.60	0.60	0.60	0.60	0.60	0.60
	γ^{LC}	0.20	0.20	0.02	0.20	0.20	0.02
Results	**MSE**	3.71	3.90	3.68	3.70	3.90	3.68
		M1					
	Prob.	1.00	1.00	1.00			
	γ	0.001	0.02	0.2			
Results	**MSE**	4.05	4.06	4.03			

Table B.14: Moderately Intermittent Data Set Prob^{LC} of 0.95, 0.9 and 0.5

LC	***Parameters***	**Methods**					
		M2			***M4***		
Ramp	$Prob^{LC}$	0.95	0.95	0.95	0.95	0.95	0.95
	γ^{LC}	0.001	0.02	0.001	0.001	0.02	0.001
Reg.	$Prob^{LC}$	0.90	0.90	0.90	0.90	0.90	0.90
	γ^{LC}	0.02	0.02	0.001	0.02	0.02	0.001
Drop	$Prob^{LC}$	0.50	0.50	0.50	0.50	0.50	0.50
	γ^{LC}	0.20	0.20	0.02	0.20	0.20	0.02
Results	**MSE**	3.76	3.95	3.78	3.75	3.95	3.76
		M1					
	Prob.	0.95	0.95	0.95			
	γ	0.001	0.02	0.2			
Results	**MSE**	3.94	4.10	4.03			

Table B.15: Moderately Intermittent Data Set Prob^{LC} of 0.9, 0.8 and 0.6

LC	***Parameters***	**Methods**					
		M2			***M4***		
Ramp	$Prob^{LC}$	0.90	0.90	0.90	0.90	0.90	0.90
	γ^{LC}	0.001	0.02	0.001	0.001	0.02	0.001
Reg.	$Prob^{LC}$	0.80	0.80	0.80	0.80	0.80	0.80
	γ^{LC}	0.02	0.02	0.001	0.02	0.02	0.001
Drop	$Prob^{LC}$	0.60	0.60	0.60	0.60	0.60	0.60
	γ^{LC}	0.20	0.20	0.02	0.20	0.20	0.02
Results	**MSE**	3.78	3.96	3.82	3.79	3.97	3.81
		M1					
	Prob.	0.90	0.90	0.90			
	γ	0.001	0.02	0.2			
Results	**MSE**	3.93	4.14	4.03			

B.12 : DATA SET TWO (DS2): HIGHLY INTERMITTENT (FLC)- PARAMETRIC ANALYSES

Table B.16: Highly Intermittent Data Set $\mathbf{Prob^{LC}}$ of 1, 0.9 and 0.6

LC	***Parameters***	**Methods**					
		M2			***M4***		
Ramp	$Prob^{LC}$	1.00	1.00	1.00	1.00	1.00	1.00
	γ^{LC}	0.001	0.02	0.001	0.001	0.02	0.001
Reg.	$Prob^{LC}$	0.90	0.90	0.90	0.90	0.90	0.90
	γ^{LC}	0.02	0.02	0.001	0.02	0.02	0.001
Drop	$Prob^{LC}$	0.60	0.60	0.60	0.60	0.60	0.60
	γ^{LC}	0.20	0.20	0.02	0.20	0.20	0.02
Results	**MSE**	0.29	0.29	0.29	0.29	0.29	0.29
		M1					
	Prob.	1.00	1.00	1.00			
	γ	0.001	0.02	0.2			
Results	**MSE**	0.29	0.29	0.30			

Table B.17: Highly Intermittent Data Set Prob^{LC} of 0.95, 0.9 and 0.5

LC	***Parameters***	**Methods**					
		M2			***M4***		
Ramp	$Prob^{LC}$	0.95	0.95	0.95	0.95	0.95	0.95
	γ^{LC}	0.001	0.02	0.001	0.001	0.02	0.001
Reg.	$Prob^{LC}$	0.90	0.90	0.90	0.90	0.90	0.90
	γ^{LC}	0.02	0.02	0.001	0.02	0.02	0.001
Drop	$Prob^{LC}$	0.50	0.50	0.50	0.50	0.50	0.50
	γ^{LC}	0.20	0.20	0.02	0.20	0.20	0.02
Results	**MSE**	0.29	0.29	0.29	0.28	0.29	0.29
		M1					
	Prob.	0.95	0.95	0.95			
	γ	0.001	0.02	0.2			
Results	**MSE**	0.29	0.29	0.30			

Table B.18: Highly Intermittent Data Set Prob^{LC} of 0.9, 0.8 and 0.6

LC	***Parameters***	**Methods**					
		M2			***M4***		
Ramp	$Prob^{LC}$	0.90	0.90	0.90	0.90	0.90	0.90
	γ^{LC}	0.001	0.02	0.001	0.001	0.02	0.001
Reg.	$Prob^{LC}$	0.80	0.80	0.80	0.80	0.80	0.80
	γ^{LC}	0.02	0.02	0.001	0.02	0.02	0.001
Drop	$Prob^{LC}$	0.60	0.60	0.60	0.60	0.60	0.60
	γ^{LC}	0.20	0.20	0.02	0.20	0.20	0.02
Results	**MSE**	0.28	0.29	0.28	0.28		0.28
		M1					
	Prob.	0.90	0.90	0.90			
	γ	0.001	0.02	0.2			
Results	**MSE**	0.29	0.29	0.30			

B.13 : ELECTRONICS DATA SET - PARAMETRIC ANALYSES

Table B.19: The Electronics Data Set (FLC) $Prob^{LC}$ of 1, 0.9 and 0.6

LC	***Parameters***	**Methods**					
		M2			***M4***		
Ramp	$Prob^{LC}$	1.00	1.00	1.00	1.00	1.00	1.00
	γ^{LC}	0.001	0.02	0.001	0.001	0.02	0.001
Reg.	$Prob^{LC}$	0.90	0.90	0.90	0.90	0.90	0.90
	γ^{LC}	0.02	0.02	0.001	0.02	0.02	0.001
Drop	$Prob^{LC}$	0.60	0.60	0.60	0.60	0.60	0.60
	γ^{LC}	0.20	0.20	0.02	0.20	0.20	0.02
Results	**MSE**	7.77	7.79	7.34	7.80	7.82	7.32
		M1					
	Prob.	1.00	1.00	1.00			
	γ	0.001	0.02	0.2			
Results	**MSE**	8.13	8.01	8.11			

Table B.20: The Electronics Data Set (Ramp-Reg.) $Prob^{LC}$ of 1, 0.9

LC	***Parameters***	**Methods**					
		M2			***M4***		
Ramp	$Prob^{LC}$	1.00	1.00	1.00	1.00	1.00	1.00
	γ^{LC}	0.001	0.02	0.001	0.001	0.02	0.001
Reg.	$Prob^{LC}$	0.90	0.90	0.90	0.90	0.90	0.90
	γ^{LC}	0.02	0.02	0.001	0.02	0.02	0.001
Results	**MSE**	13.72	13.84	13.72	13.18	13.28	13.15
		M1					
	Prob.	1.00	1.00	1.00			
	γ	0.001	0.02	0.2			
Results	**MSE**	14.42	14.55	14.63			

Table B.21: The Electronics Data Set (Reg.-Drop) Prob^{LC} of 0.9, 0.6

LC	***Parameters***	**Methods**					
		M2			***M4***		
Reg.	$Prob^{LC}$	0.90	0.90	0.90	0.90	0.90	0.90
	γ^{LC}	0.02	0.02	0.001	0.02	0.02	0.001
Drop	$Prob^{LC}$	0.60	0.60	0.60	0.60	0.60	0.60
	γ^{LC}	0.20	0.20	0.02	0.20	0.20	0.02
Results	**MSE**	2.02	2.08	2.07	1.80	1.86	1.86
		M1					
	Prob.	1.00	1.00	1.00			
	γ	0.001	0.02	0.2			
Results	**MSE**	2.05	2.02	2.09			

Table B.22: The Electronics Data Set (FLC) Prob^{LC} of 0.95, 0.9 and 0.5

LC	***Parameters***	**Methods**					
		M2			***M4***		
Ramp	$Prob^{LC}$	0.95	0.95	0.95	0.95	0.95	0.95
	γ^{LC}	0.001	0.02	0.001	0.001	0.02	0.001
Reg.	$Prob^{LC}$	0.90	0.90	0.90	0.90	0.90	0.90
	γ^{LC}	0.02	0.02	0.001	0.02	0.02	0.001
Drop	$Prob^{LC}$	0.50	0.50	0.50	0.50	0.50	0.50
	γ^{LC}	0.20	0.20	0.02	0.20	0.20	0.02
Results	**MSE**	7.80	7.80	7.40	7.85	7.84	7.38
		M1					
	Prob.	0.95	0.95	0.95			
	γ	0.001	0.02	0.2			
Results	**MSE**	7.81	7.92	8.11			

Table B.23: The Electronics Data Set (Ramp-Reg.) $Prob^{LC}$ of 0.95, 0.9

LC	***Parameters***	**Methods**					
		M2			***M4***		
Ramp	$Prob^{LC}$	0.95	0.95	0.95	0.95	0.95	0.95
	γ^{LC}	0.001	0.02	0.001	0.001	0.02	0.001
Reg.	$Prob^{LC}$	0.90	0.90	0.90	0.90	0.90	0.90
	γ^{LC}	0.02	0.02	0.001	0.02	0.02	0.001
Results	**MSE**	13.72	13.84	13.72	13.39	13.43	13.36
		M1					
	Prob.	0.95	0.95	0.95			
	γ	0.001	0.02	0.2			
Results	**MSE**	14.11	14.41	14.63			

Table B.24: The Electronics Data Set (Reg.-Drop) $Prob^{LC}$ of 0.9, 0.5

LC	***Parameters***	**Methods**					
		M2			***M4***		
Reg.	$Prob^{LC}$	0.90	0.90	0.90	0.90	0.90	0.90
	γ^{LC}	0.02	0.02	0.001	0.02	0.02	0.001
Drop	$Prob^{LC}$	0.50	0.50	0.50	0.50	0.50	0.50
	γ^{LC}	0.20	0.20	0.02	0.20	0.20	0.02
Results	**MSE**	2.04	2.14	2.13	1.82	1.91	1.91
		M1					
	Prob.	0.95	0.95	0.95			
	γ	0.001	0.02	0.2			
Results	**MSE**	2.02	2.02	2.09			

Table B.25: The Electronics Data Set (FLC) Prob^{LC} of 0.9, 0.8 and 0.6

LC	*Parameters*	Methods					
		M2			*M4*		
Ramp	$Prob^{LC}$	0.90	0.90	0.90	0.90	0.90	0.90
	γ^{LC}	0.001	0.02	0.001	0.001	0.02	0.001
Reg.	$Prob^{LC}$	0.80	0.80	0.80	0.80	0.80	0.80
	γ^{LC}	0.02	0.02	0.001	0.02	0.02	0.001
Drop	$Prob^{LC}$	0.60	0.60	0.60	0.60	0.60	0.60
	γ^{LC}	0.20	0.20	0.02	0.20	0.20	0.02
Results	**MSE**	8.21	8.13	8.10	8.35	8.25	8.19
		M1					
	Prob.	0.90	0.90	0.90			
	γ	0.001	0.02	0.2			
Results	**MSE**	7.76	7.89	8.11			

Table B.26: The Electronics Data Set (Ramp-Reg.) Prob^{LC} of 0.9 and 0.8

LC	*Parameters*	Methods					
		M2			*M4*		
Ramp	$Prob^{LC}$	0.90	0.90	0.90	0.90	0.90	0.90
	γ^{LC}	0.001	0.02	0.001	0.001	0.02	0.001
Reg.	$Prob^{LC}$	0.80	0.80	0.80	0.80	0.80	0.80
	γ^{LC}	0.02	0.02	0.001	0.02	0.02	0.001
Results	**MSE**	13.87	13.84	14.05	13.75	13.57	13.91
		M1					
	Prob.	0.90	0.90	0.90			
	γ	0.001	0.02	0.2			
Results	**MSE**	14.12	14.38	14.62			

Table B.27: The Electronics Data Set (Reg.-Drop) Prob^{LC} of 0.8 and 0.6

LC	***Parameters***	**Methods**					
		M2			***M4***		
Reg.	$Prob^{LC}$	0.80	0.80	0.80	0.80	0.80	0.80
	γ^{LC}	0.02	0.02	0.001	0.02	0.02	0.001
Drop	$Prob^{LC}$	0.60	0.60	0.60	0.60	0.60	0.60
	γ^{LC}	0.20	0.20	0.02	0.20	0.20	0.02
Results	**MSE**	2.14	2.08	2.18	1.89	1.94	2.00
		M1					
	Prob.	0.90	0.90	0.90			
	γ	0.001	0.02	0.2			
Results	**MSE**	2.03	2.03	2.09			

APPENDIX C

C.1 : STATISTICAL ANALYSIS OF ON-HAND INVENTORY -DS1 (FLC)

Test	F Ratio	DFNum	DFDen	Prob > F
O'Brien[.5]	41.2392	6	4193	<.0001*
Brown-Forsythe	58.1917	6	4193	<.0001*
Levene	94.4007	6	4193	<.0001*
Bartlett	169.9889	6	.	<.0001*

Welch's Test

Welch Anova testing Means Equal, allowing Std Devs Not Equal

F Ratio	DFNum	DFDen	Prob > F
3453.8313	6	1834.4	<.0001*

Figure C.1: Levene's Test for Equal Variances and Welch's Test for DS1 (FLC)

Table C.1: Each of the New Methods Models Compared to Holt, SBA and Croston Models-DS1 (FLC)

<table>
<tr><th>Inventory Measure</th><th>Statistical Difference?</th><th>Statistical Comparison</th><th>Interpretation</th></tr>
<tr><td rowspan="5">Mean On-hand Inventory</td><td>YES</td><td><table><tr><th>Model</th><th></th><th>On-hand</th></tr><tr><td>Croston-MSE</td><td>A</td><td>9.74</td></tr><tr><td>SBA-MSE</td><td>A</td><td>9.70</td></tr><tr><td>M1-MSE</td><td>B</td><td>5.63</td></tr><tr><td>Holt-MSE</td><td>C</td><td>5.19</td></tr></table></td><td>Holt-MSE achieved significantly lower on-hand inventory levels. M1-MSE achieved significantly lower on-hand inventory compared to SBA-MSE and Croston. No difference was detected between SBA and Croston.</td></tr>
<tr><td>YES</td><td><table><tr><th>Model</th><th></th><th>On-hand</th></tr><tr><td>Croston-MSE</td><td>A</td><td>9.74</td></tr><tr><td>SBA-MSE</td><td>A</td><td>9.70</td></tr><tr><td>Holt-MSE</td><td>B</td><td>5.19</td></tr><tr><td>M2-MSE</td><td>C</td><td>4.60</td></tr></table></td><td>M2-MSE achieved significantly lower on-hand inventory levels. Holt-MSE achieved significantly lower on-hand inventory compared to SBA-MSE and Croston-MSE. No difference was detected between SBA-MSE and Croston-MSE.</td></tr>
<tr><td>YES</td><td><table><tr><th>Model</th><th></th><th>On-hand</th></tr><tr><td>Croston-MSE</td><td>A</td><td>9.74</td></tr><tr><td>SBA-MSE</td><td>A</td><td>9.70</td></tr><tr><td>M3-MSE</td><td>B</td><td>5.47</td></tr><tr><td>Holt-MSE</td><td>C</td><td>5.19</td></tr></table></td><td>Holt-MSE achieved significantly lower on-hand inventory levels. M3-MSE achieved significantly lower on-hand inventory compared to SBA-MSE and Croston-MSE. No difference was detected between SBA-MSE and Croston-MSE.</td></tr>
<tr><td>YES</td><td><table><tr><th>Model</th><th></th><th>On-hand</th></tr><tr><td>Croston-MSE</td><td>A</td><td>9.74</td></tr><tr><td>SBA-MSE</td><td>A</td><td>9.70</td></tr><tr><td>Holt-MSE</td><td>B</td><td>5.19</td></tr><tr><td>M4-MSE</td><td>C</td><td>4.42</td></tr></table></td><td>M4-MSE achieved significantly lower on-hand inventory levels. Holt-MSE achieved significantly lower on-hand inventory compared to SBA-MSE and Croston-MSE. No difference was detected between SBA-MSE and Croston-MSE.</td></tr>
<tr><td>YES</td><td><table><tr><th>Model</th><th></th><th>On-hand</th></tr><tr><td>M1-MSE</td><td>A</td><td>5.63</td></tr><tr><td>M3-MSE</td><td>A</td><td>5.47</td></tr><tr><td>M2-MSE</td><td>B</td><td>4.60</td></tr><tr><td>M4-MSE</td><td>C</td><td>4.42</td></tr></table></td><td>M4-MSE achieved significantly lower on-hand inventory levels. M2-MSE achieved significantly lower on-hand inventory compared to M1-MSE and M3-MSE. No difference was detected between M1-MSE and M3-MSE.</td></tr>
</table>

C.2 : STATISTICAL ANALYSIS OF ON-HAND INVENTORY –DS2 (FLC)

Test	F Ratio	DFNum	DFDen	Prob > F
O'Brien[.5]	25.1324	6	4193	<.0001*
Brown-Forsythe	31.8746	6	4193	<.0001*
Levene	32.7484	6	4193	<.0001*
Bartlett	41.2128	6	.	<.0001*

Welch's Test

Welch Anova testing Means Equal, allowing Std Devs Not Equal

F Ratio	DFNum	DFDen	Prob > F
3134.8738	6	1859.8	<.0001*

Figure C.2: Levene's Test for Equal Variances and Welch's Test for DS2 (FLC)

Table C.2: Each of the New Methods Models Compared to Holt, SBA and Croston Models-DS2 (FLC)

Inventory Measure	Statistical Difference?	Statistical Comparison: Model	Grouping	On-hand	Interpretation
Mean On-hand Inventory	YES	Croston-MSE	A	3.18	All the models were significantly different than one another. Holt-MSE achieved the lowest on-hand inventory level.
		SBA-MSE	B	2.93	
		M1-MSE	C	2.41	
		Holt-MSE	D	2.33	
	YES	Croston-MSE	A	3.18	All the models were significantly different than one another. M2-MSE achieved the lowest on-hand inventory level.
		SBA-MSE	B	2.93	
		Holt-MSE	C	2.33	
		M2-MSE	D	2.16	
	YES	Croston-MSE	A	3.18	All the models were significantly different than one another. M3-MSE achieved the lowest on-hand inventory level.
		SBA-MSE	B	2.93	
		Holt-MSE	C	2.33	
		M3-MSE	D	2.14	
	YES	Croston-MSE	A	3.18	All the models were significantly different than one another. M4-MSE achieved the lowest on-hand inventory level.
		SBA-MSE	B	2.93	
		Holt-MSE	C	2.33	
		M4-MSE	D	2.08	
	YES	M1-MSE	A	2.41	M4-MSE achieved significantly lower on-hand inventory level compared to all the methods. No difference was detected between M3-MSE and M2-MSE. M1-MSE achieved the highest on-hand level.
		M2-MSE	B	2.16	
		M3-MSE	B	2.14	
		M4-MSE	C	2.08	

C.3 : STATISTICAL ANALYSIS OF ON-HAND INVENTORY –DS3 (FLC)

Test	F Ratio	DFNum	DFDen	Prob > F
O'Brien[.5]	32.4637	6	4193	<.0001*
Brown-Forsythe	51.5936	6	4193	<.0001*
Levene	54.1087	6	4193	<.0001*
Bartlett	44.2751	6	.	<.0001*

Welch's Test

Welch Anova testing Means Equal, allowing Std Devs Not Equal

F Ratio	DFNum	DFDen	Prob > F
355.0251	6	1858.5	<.0001*

Figure C.3: Levene's Test for Equal Variances and Welch's Test for DS3 (FLC)

Table C.3: Individual Statistical Comparisons of Models- DS3 (FLC)

<table>
<tr><th>Inventory Measure</th><th>Statistical Difference?</th><th>Statistical Comparison</th><th>Interpretation</th></tr>
<tr><td rowspan="5">Mean On-hand Inventory</td><td>YES</td><td><table><tr><th>Model</th><th></th><th>On-hand</th></tr><tr><td>Croston-MSE</td><td>A</td><td>1.54</td></tr><tr><td>SBA-MSE</td><td>A</td><td>1.52</td></tr><tr><td>Holt-MSE</td><td>B</td><td>1.40</td></tr><tr><td>M1-MSE</td><td>C</td><td>1.30</td></tr></table></td><td>M1-MSE achieved significantly lower on-hand inventory levels. Holt-MSE achieved significantly lower on-hand inventory compared to SBA-MSE and Croston. No difference was detected between SBA and Croston.</td></tr>
<tr><td>YES</td><td><table><tr><th>Model</th><th></th><th>On-hand</th></tr><tr><td>Croston-MSE</td><td>A</td><td>1.54</td></tr><tr><td>SBA-MSE</td><td>A</td><td>1.52</td></tr><tr><td>Holt-MSE</td><td>B</td><td>1.40</td></tr><tr><td>M2-MSE</td><td>C</td><td>1.30</td></tr></table></td><td>M2-MSE achieved significantly lower on-hand inventory levels. Holt-MSE achieved significantly lower on-hand inventory compared to SBA-MSE and Croston. No difference was detected between SBA and Croston.</td></tr>
<tr><td>YES</td><td><table><tr><th>Model</th><th></th><th>On-hand</th></tr><tr><td>Croston-MSE</td><td>A</td><td>1.54</td></tr><tr><td>SBA-MSE</td><td>A</td><td>1.52</td></tr><tr><td>Holt-MSE</td><td>B</td><td>1.40</td></tr><tr><td>M3-MSE</td><td>C</td><td>1.31</td></tr></table></td><td>M3-MSE achieved significantly lower on-hand inventory levels. Holt-MSE achieved significantly lower on-hand inventory compared to SBA-MSE and Croston. No difference was detected between SBA and Croston.</td></tr>
<tr><td>YES</td><td><table><tr><th>Model</th><th></th><th>On-hand</th></tr><tr><td>Croston-MSE</td><td>A</td><td>1.54</td></tr><tr><td>SBA-MSE</td><td>A</td><td>1.52</td></tr><tr><td>Holt-MSE</td><td>B</td><td>1.40</td></tr><tr><td>M4-MSE</td><td>C</td><td>1.23</td></tr></table></td><td>M4-MSE achieved significantly lower on-hand inventory levels. Holt-MSE achieved significantly lower on-hand inventory compared to SBA-MSE and Croston. No difference was detected between SBA and Croston.</td></tr>
<tr><td>YES</td><td><table><tr><th>Level</th><th></th><th>Mean</th></tr><tr><td>M3-MSE</td><td>A</td><td>1.31</td></tr><tr><td>M1-MSE</td><td>A</td><td>1.30</td></tr><tr><td>M2-MSE</td><td>A</td><td>1.30</td></tr><tr><td>M4-MSE</td><td>B</td><td>1.23</td></tr></table></td><td>M4-MSE achieved the lowest on-hand inventory level. No difference was detected between M1-MSE, M2-MSE and M3-MSE.</td></tr>
</table>

C.4 : STATISTICAL ANALYSIS OF ON-HAND INVENTORY -DS1 (RAMP-REG)

Test	F Ratio	DFNum	DFDen	Prob > F
O'Brien[.5]	17.3410	6	4193	<.0001*
Brown-Forsythe	18.3859	6	4193	<.0001*
Levene	26.1262	6	4193	<.0001*
Bartlett	46.9746	6	.	<.0001*

Welch's Test

Welch Anova testing Means Equal, allowing Std Devs Not Equal

F Ratio	DFNum	DFDen	Prob > F
269.9460	6	1856.7	<.0001*

Figure C.4: Levene's Test for Equal Variances and Welch's Test for DS1 (Ramp-Reg)

Table C.4: Individual Statistical Comparisons of Models- DS1 (Ramp-Reg)

Inventory Measure	Statistical Difference?	Statistical Comparison	Interpretation
Mean On-hand Inventory	YES	**Model** / **On-hand** Holt-MSE A 7.33 M1-MSE B 7.21 Croston-MSE C 7.10 SBA-MSE C 7.07	Holt-MSE achieved significantly higher on-hand inventory levels compared to all models. M1-MSE achieved significantly higher on-hand inventory compared to SBA-MSE. No difference was detected between SBA-MSE and Croston-MSE.
	YES	**Model** / **On-hand** Holt-MSE A 7.33 Croston-MSE B 7.10 SBA-MSE B 7.07 M2-MSE C 6.91	M2-MSE achieved the lowest on-hand inventory levels. Holt-MSE achieved significantly higher on-hand inventory compared to all models. No difference was detected between SBA-MSE and Croston-MSE.
	YES	**Model** / **On-hand** Holt-MSE A 7.33 M3-MSE B 7.20 Croston-MSE B C 7.10 SBA-MSE C 7.07	Holt-MSE achieved significantly higher on-hand inventory levels compared to all models. There was no evidence to support that Croston-MSE achieved significantly different inventory levels compared to neither SBA-MSE nor M3-MSE. SBA-MSE achieved significantly lower on-hand level compare to both Holt-MSE and M3-MSE
	YES	**Model** / **On-hand** Holt-MSE A 7.33 Croston-MSE B 7.10 SBA-MSE B 7.07 M4-MSE C 6.64	M4-MSE achieved the lowest on-hand inventory levels. Holt-MSE achieved significantly higher on-hand inventory compared to all models. No difference was detected between SBA-MSE and Croston-MSE.
	YES	**Model** / **On-hand** M1-MSE A 7.21 M3-MSE A 7.20 M2-MSE B 6.91 M4-MSE C 6.64	M4-MSE achieved the lowest on-hand inventory levels. M2-MSE achieved significantly lower on-hand inventory levels compared to both M1-MSE and M3-MSE. No difference was detected between M1-MSE and M3-MSE.

C.5 : STATISTICAL ANALYSIS OF ON-HAND INVENTORY -DS2 (RAMP-REG)

Test	F Ratio	DFNum	DFDen	Prob > F
O'Brien[.5]	15.7259	6	4193	<.0001*
Brown-Forsythe	31.2428	6	4193	<.0001*
Levene	35.9373	6	4193	<.0001*
Bartlett	48.2255	6	.	<.0001*

Welch's Test

Welch Anova testing Means Equal, allowing Std Devs Not Equal

F Ratio	DFNum	DFDen	Prob > F
50.1556	6	1857.5	<.0001*

Figure C.5: Levene's Test for Equal Variances and Welch's Test for DS2 (Ramp-Reg)

Table C.5: Individual Statistical Comparisons of Models - DS2 (Ramp-Reg)

Inventory Measure	Statistical Difference?	Statistical Comparison	Interpretation
Mean On-hand Inventory	YES	**Model** **On-hand** Holt-MSE A 3.37 M1-MSE A 3.32 Crotson-MSE B 3.26 SBA-MSE B 3.24	SBA-MSE and Croston-MSE performed similarly and achieved significantly lower on-hand inventory levels compared to both M1-MSE and Holt-MSE. No difference was detected between M1-MSE and Holt-MSE.
	YES	**Model** **On-hand** M2-MSE A 3.37 Holt-MSE A 3.37 Croston-MSE B 3.26 SBA-MSE B 3.24	SBA-MSE and Croston-MSE performed similarly and achieved significantly lower on-hand inventory levels compared to both M2-MSE and Holt-MSE. No difference was detected between M2-MSE and Holt-MSE.
	YES	**Model** **On-hand** Holt-MSE A 3.37 M3-MSE B 3.29 Crotson-MSE C 3.26 SBA-MSE C 3.24	Holt-MSE achieved significantly higher on-hand inventory levels compared to all models. M3-MSE achieved higher inventory levels compared to SBA-MSE and Croston-MSE. No statistical difference was captured between SBA-MSE and Croston-MSE.
	YES	**Model** **On-hand** Holt-MSE A 3.37 M4-MSE B 3.29 Crotson-MSE B C 3.26 SBA-MSE C 3.24	Holt-MSE achieved significantly higher on-hand inventory levels compared to all models. M3-MSE achieved higher inventory levels compared to SBA-MSE No statistical difference was captured between SBA-MSE and Croston-MSE nor between M4-MSE and Croston-MSE.
	YES	**Model** **On-hand** M2-MSE A 3.35 M1-MSE B 3.31 M4-MSE B 3.28 M3-MSE B 3.27	M2-MSE achieved significantly higher on-hand inventory levels compared to all models. No statistical difference was captured between M1-MSE, M4-MSE and M3-MSE

C.6 : STATISTICAL ANALYSIS OF ON-HAND INVENTORY -DS3 (RAMP-REG)

Test	F Ratio	DFNum	DFDen	Prob > F
O'Brien[.5]	18.6315	6	4193	<.0001*
Brown-Forsythe	29.4653	6	4193	<.0001*
Levene	32.6107	6	4193	<.0001*
Bartlett	55.6681	6	.	<.0001*

Welch's Test

Welch Anova testing Means Equal, allowing Std Devs Not Equal

F Ratio	DFNum	DFDen	Prob > F
11.7767	6	1858.5	<.0001*

Figure C.6: Levene's Test for Equal Variances and Welch's Test for DS3 (Ramp-Reg)

Table C.6: Individual Statistical Comparisons of Models - DS3 (Ramp-Reg)

<table>
<tr><th>Inventory Measure</th><th>Statistical Difference?</th><th>Statistical Comparison</th><th>Interpretation</th></tr>
<tr><td rowspan="5">Mean On-hand Inventory</td><td>YES</td><td><table><tr><th>Model</th><th></th><th>On-hand</th></tr><tr><td>Holt-MSE</td><td>A</td><td>1.95</td></tr><tr><td>M1-MSE</td><td>A B</td><td>1.91</td></tr><tr><td>SBA-MSE</td><td>B</td><td>1.89</td></tr><tr><td>Croston-MSE</td><td>B</td><td>1.89</td></tr></table></td><td>Holt-MSE achieved significantly higher on-hand levels compared to SBA-MSE and Croston-MSE. No difference was captured between M1-MSE and the rest of the models.</td></tr>
<tr><td>YES</td><td><table><tr><th>Model</th><th></th><th>On-hand</th></tr><tr><td>Holt-MSE</td><td>A</td><td>1.95</td></tr><tr><td>M2-MSE</td><td>A</td><td>1.95</td></tr><tr><td>SBA-MSE</td><td>B</td><td>1.89</td></tr><tr><td>Croston-MSE</td><td>B</td><td>1.89</td></tr></table></td><td>SBA-MSE and Croston-MSE performed similarly and achieved significantly lower on-hand inventory levels compared to both M2-MSE and Holt-MSE. No difference was detected between M2-MSE and Holt-MSE.</td></tr>
<tr><td>YES</td><td><table><tr><th>Model</th><th></th><th>On-hand</th></tr><tr><td>Holt-MSE</td><td>A</td><td>1.95</td></tr><tr><td>M3-MSE</td><td>A B</td><td>1.92</td></tr><tr><td>SBA-MSE</td><td>B</td><td>1.89</td></tr><tr><td>Croston-MSE</td><td>B</td><td>1.89</td></tr></table></td><td>Holt-MSE achieved significantly higher on-hand levels compared to SBA-MSE and Croston-MSE. No difference was captured between M3-MSE and the rest of the models.</td></tr>
<tr><td>YES</td><td><table><tr><th>Model</th><th></th><th>On-hand</th></tr><tr><td>Holt-MSE</td><td>A</td><td>1.95</td></tr><tr><td>M4-MSE</td><td>A B</td><td>1.93</td></tr><tr><td>SBA-MSE</td><td>B</td><td>1.89</td></tr><tr><td>Croston-MSE</td><td>B</td><td>1.89</td></tr></table></td><td>Holt-MSE achieved significantly higher on-hand levels compared to SBA-MSE and Croston-MSE. No difference was captured between M4-MSE and the rest of the models.</td></tr>
<tr><td>NO</td><td><table><tr><th>Model</th><th></th><th>On-hand</th></tr><tr><td>M2-MSE</td><td>A</td><td>1.95</td></tr><tr><td>M4-MSE</td><td>A B</td><td>1.93</td></tr><tr><td>M3-MSE</td><td>B</td><td>1.92</td></tr><tr><td>M1-MSE</td><td>B</td><td>1.91</td></tr></table></td><td>M2-MSE achieved significantly higher on-hand levels compared to M1-MSE and M3-MSE. No difference was captured between M4-MSE and the rest of the models.</td></tr>
</table>

C.7 : STATISTICAL ANALYSIS OF ON-HAND INVENTORY -DS1 (REG.-DROP)

Test	F Ratio	DFNum	DFDen	Prob > F
O'Brien[.5]	65.7434	6	4193	<.0001*
Brown-Forsythe	63.8440	6	4193	<.0001*
Levene	123.3623	6	4193	<.0001*
Bartlett	82.6464	6	.	<.0001*

Welch's Test

Welch Anova testing Means Equal, allowing Std Devs Not Equal

F Ratio	DFNum	DFDen	Prob > F
126.4280	6	1853.8	<.0001*

Figure C.7: Levene's Test for Equal Variances and Welch's Test for DS1 (Reg.-Drop)

Table C.7: Individual Statistical Comparisons of Models - DS1 (Reg.-Drop)

Inventory Measure	Statistical Difference?	Statistical Comparison	Interpretation
Mean On-hand Inventory	YES	**Model** **On-hand** SBA-MSE A 4.89 Croston-MSE A 4.71 M1-MSE B 4.07 Holt-MSE C 3.73	Holt-MSE achieved the lowest on-hand inventory levels. M1-MSE achieved significantly lower on-hand inventory levels compared to both SBA-MSE and Croston-MSE. No difference was detected between SBA-MSE and Croston-MSE.
	YES	**Model** **On-hand** SBA-MSE A 4.89 Croston-MSE A 4.71 M2-MSE B 3.94 Holt-MSE B 3.73	SBA-MSE and Croston-MSE performed similarly and achieved significantly lower on-hand inventory levels compared to both M2-MSE and Holt-MSE. No difference was detected between M2-MSE and Holt-MSE.
	YES	**Model** **On-hand** SBA-MSE A 4.89 Croston-MSE A 4.71 M3-MSE B 4.07 Holt-MSE C 3.73	Holt-MSE achieved the lowest on-hand inventory levels. M3-MSE achieved significantly lower on-hand inventory levels compared to both SBA-MSE and Croston-MSE. No difference was detected between SBA-MSE and Croston-MSE.
	YES	**Model** **On-hand** SBA-MSE A 4.89 Croston-MSE A 4.71 M4-MSE B 3.85 Holt-MSE B 3.73	Holt-MSE achieved the lowest on-hand inventory levels. M4-MSE achieved significantly lower on-hand inventory levels compared to both SBA-MSE and Croston-MSE. No difference was detected between SBA-MSE and Croston-MSE
	YES	**Model** **On-hand** M3-MSE A 4.07 M1-MSE A 4.07 M2-MSE A B 3.94 M4-MSE B 3.85	M4-MSE achieved the lowest on-hand inventory levels compared to M1-MSE and M3-MSE. No statistical difference was detected between M1-MSE and M3-MSE. No evidence was found to indicate that M2-MSE performed differently compared to all the models.

C.8 : STATISTICAL ANALYSIS OF ON-HAND INVENTORY -DS2 (REG.-DROP)

Test	F Ratio	DFNum	DFDen	Prob > F
O'Brien[.5]	72.0868	6	4193	<.0001*
Brown-Forsythe	91.6564	6	4193	<.0001*
Levene	94.3229	6	4193	<.0001*
Bartlett	103.2111	6	.	<.0001*

Welch's Test

Welch Anova testing Means Equal, allowing Std Devs Not Equal

F Ratio	DFNum	DFDen	Prob > F
358.1194	6	1851.4	<.0001*

Figure C.8: Levene's Test for Equal Variances and Welch's Test for DS2 (Reg.-Drop)

Table C.8: Individual Statistical Comparisons of Models - DS2 (Reg.-Drop)

Inventory Measure	Statistical Difference?	Statistical Comparison	Interpretation
Mean On-hand Inventory	YES	**Model** **On-hand** SBA-MSE A 2.23 Croston-MSE A 2.22 M1-MSE B 1.81 Holt-MSE B 1.78	Holt-MSE and M1-MSE achieved significantly lower on-hand inventory levels compared to both SBA-MSE and Crotson-MSE. . No statistical difference was detected between Croston-MSE and SBA-MSE.
	YES	**Model** **On-hand** SBA-MSE A 2.23 Croston-MSE A 2.22 Holt-MSE B 1.81 M2-MSE C 1.72	M2-MSE achieved the lowest on-hand inventory levels compared to all models. Holt-MSE carried significantly lower on hand inventory levels compared to both Croston-MSE and SBA-MSE. No statistical difference was detected between Croston-MSE and SBA-MSE.
	YES	**Model** **On-hand** SBA-MSE A 2.23 Croston-MSE A 2.22 Holt-MSE B 1.81 M3-MSE B 1.77	SBA-MSE and Croston-MSE performed similarly and achieved significantly higher on-hand inventory levels compared to both M3-MSE and Holt-MSE. No difference was detected between M3-MSE and Holt-MSE.
	YES	**Model** **On-hand** SBA-MSE A 2.23 Croston-MSE A 2.22 Holt-MSE B 1.81 M4-MSE C 1.68	M4-MSE achieved the lowest on-hand inventory levels compared to all models. Holt-MSE carried significantly lower on hand inventory levels compared to both Croston-MSE and SBA-MSE. No statistical difference was detected between Croston-MSE and SBA-MSE.
	YES	**Model** **On-hand** M1-MSE A 1.78 M3-MSE A 1.77 M2-MSE B 1.72 M4-MSE C 1.68	M4-MSE achieved the lowest on-hand inventory levels compared to all models. M2-MSE carried significantly lower on hand inventory levels compared to both M1-MSE and M3-MSE. No statistical difference was detected between M1-MSE and M3-MSE.

C.9 : STATISTICAL ANALYSIS OF ON-HAND INVENTORY -DS3 (REG.-DROP)

Test	F Ratio	DFNum	DFDen	Prob > F
O'Brien[.5]	51.6739	6	4193	<.0001*
Brown-Forsythe	41.3494	6	4193	<.0001*
Levene	54.7246	6	4193	<.0001*
Bartlett	87.3349	6	.	<.0001*

Welch's Test

Welch Anova testing Means Equal, allowing Std Devs Not Equal

F Ratio	DFNum	DFDen	Prob > F
82.1361	6	1851.6	<.0001*

Figure C.9: Levene's Test for Equal Variances and Welch's Test for DS3 (Reg.-Drop)

Table C.9: Individual Statistical Comparisons of Models - DS3 (Reg.-Drop)

Inventory Measure	Statistical Difference?	Statistical Comparison	Interpretation
Mean On-hand Inventory	YES	**Model** — **On-hand** Croston-MSE A 1.37 SBA-MSE A 1.35 Holt-MSE A 1.32 M1-MSE B 1.24	M1-MSE achieved the lowest on-hand inventory level. No difference was detected between SBA-MSE, Croston-MSE and Holt-MSE.
	YES	**Model** — **On-hand** Croston-MSE A 1.37 SBA-MSE A 1.35 Holt-MSE A 1.32 M2-MSE B 1.20	M2-MSE achieved the lowest on-hand inventory level. No difference was detected between SBA-MSE, Croston-MSE and Holt-MSE.
	YES	**Model** — **On-hand** Croston-MSE A 1.37 SBA-MSE A 1.35 Holt-MSE A B 1.32 M3-MSE B 1.27	M3-MSE achieved the lowest on-hand inventory levels compared to SBA-MSE and Croston-MSE. No statistical difference was detected between SBA-MSE and Croston-MSE. No evidence was found to indicate that Holt-MSE performed differently compared to all the models.
	YES	**Model** — **On-hand** Croston-MSE A 1.37 SBA-MSE A 1.35 Holt-MSE A 1.32 M4-MSE B 1.17	M4-MSE achieved the lowest on-hand inventory level. No difference was detected between SBA-MSE, Croston-MSE and Holt-MSE.
	YES	**Model** — **On-hand** M3-MSE A 1.27 M1-MSE A 1.24 M2-MSE B 1.20 M4-MSE B 1.17	M4-MSE and M2-MSE performed similarly and achieved significantly lower on-hand inventory levels compared to both M1-MSE and M3-MSE. No difference was detected between M1-MSE and M3-MSE

C.10 : STATISTICAL ANALYSIS OF ON-HAND INVENTORY - THE ELECTRONICS DATA SET (ALL SKUS)

Test	F Ratio	DFNum	DFDen	Prob > F
O'Brien[.5]	1.5957	6	3325	0.1441
Brown-Forsythe	5.9948	6	3325	<.0001*
Levene	8.4394	6	3325	<.0001*
Bartlett	39.5899	6	.	<.0001*

Welch's Test

Welch Anova testing Means Equal, allowing Std Devs Not Equal

F Ratio	DFNum	DFDen	Prob > F
25.1085	6	1472.4	<.0001*

Figure C.10: Levene's Test for Equal Variances and Welch's Test for the Electronics Data Set (All SKUs)

Table C.10: Individual Statistical Comparisons of Models - the Electronics Data Set (All SKUs)

Inventory Measure	Statistical Difference?	Statistical Comparison	Interpretation
Mean On-hand Inventory	YES	**Model** **On-hand** Croston-MSE A 5.37 SBA-MSE A B 5.10 Holt-MSE A B 5.04 M1-MSE B 4.92	M1-MSE achieved significantly lower on-hand inventory levels compared to Croston-MSE. No significant difference was found between SBA-MSE and Holt-MSE compared to any of the models.
	YES	**Model** **On-hand** Croston-MSE A 5.37 SBA-MSE A 5.10 Holt-MSE A 5.04 M2-MSE B 4.46	M2-MSE achieved significantly lower on-hand inventory levels compared to all the models.
	YES	**Model** **On-hand** Croston-MSE A 5.37 SBA-MSE A B 5.10 Holt-MSE A B 5.04 M3-MSE B 4.92	M3-MSE achieved significantly lower on-hand inventory levels compared to Croston-MSE. No significant difference was found between SBA-MSE and Holt-MSE compared to any of the models.
	YES	**Model** **On-hand** Croston-MSE A 5.37 SBA-MSE A 5.10 Holt-MSE A 5.04 M4-MSE B 4.28	M4-MSE achieved significantly lower on-hand inventory levels compared to all the models.
	YES	**Model** **On-hand** M3-MSE A 4.92 M1-MSE A 4.92 M2-MSE B 4.46 M4-MSE B 4.28	M4-MSE and M2-MSE performed similarly and achieved significantly lower on-hand inventory levels compared to both M1-MSE and M3-MSE. No difference was detected between M1-MSE and M3-MSE

C.11 : STATISTICAL ANALYSIS OF ON-HAND INVENTORY - THE ELECTRONICS DATA SET (FLC)

Test	F Ratio	DFNum	DFDen	Prob > F
O'Brien[.5]	0.9103	6	2492	0.4863
Brown-Forsythe	3.4301	6	2492	0.0022*
Levene	4.5793	6	2492	0.0001*
Bartlett	18.1778	6	.	<.0001*

Welch's Test

Welch Anova testing Means Equal, allowing Std Devs Not Equal

F Ratio	DFNum	DFDen	Prob > F
14.9979	6	1105.2	<.0001*

Figure C.11: Levene's Test for Equal Variances and Welch's Test for the Electronics Data Set (FLC)

Table C.11: Individual Statistical Comparisons of Models - the Electronics Data Set (FLC)

Inventory Measure	Statistical Difference?	Statistical Comparison	Interpretation
Mean On-hand Inventory	YES	**Model** **On-hand** Croston-MSE A 5.01 Holt-MSE A 4.89 M1-MSE A 4.80 SBA-MSE A 4.78	No significant difference was found between any of the models.
	YES	**Level** **Mean** Croston-MSE A 5.01 Holt-MSE A 4.89 SBA-MSE A 4.78 M2-MSE B 4.37	M2-MSE achieved significantly lower on-hand inventory levels compared to all the models.
	YES	**Model** **On-hand** Croston-MSE A 5.01 Holt-MSE A 4.89 M3-MSE A 4.79 SBA-MSE A 4.78	No significant difference was found between any of the models.
	YES	**Level** **Mean** Croston-MSE A 5.01 Holt-MSE A 4.89 SBA-MSE A B 4.78 M4-MSE B 4.60	M4-MSE achieved significantly lower on-hand inventory levels compared to Croston-MSE and Holt-MSE. No significant difference was found between SBA-MSE and any of the models
	YES	**Level** **Mean** M1-MSE A 4.80 M3-MSE A 4.79 M4-MSE A B 4.60 M2-MSE B 4.37	M2-MSE achieved significantly lower on-hand inventory levels compared to M1-MSE and M3-MSE. No significant difference was found between M4-MSE and any of the models

C.12 : STATISTICAL ANALYSIS OF ON-HAND INVENTORY - THE ELECTRONICS DATA SET (RAMP-REG.)

Test	F Ratio	DFNum	DFDen	Prob > F
O'Brien[.5]	1.0817	6	490	0.3722
Brown-Forsythe	0.6219	6	490	0.7128
Levene	0.9099	6	490	0.4874
Bartlett	5.9714	6	.	<.0001*

Welch's Test

Welch Anova testing Means Equal, allowing Std Devs Not Equal

F Ratio	DFNum	DFDen	Prob > F
2.0901	6	217.26	0.0555

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Ratio	Prob > F
Model	6	25.595	4.266	2.4638	0.0236*
PN	70	26980.978	385.443	222.6187	<.0001*
Error	420	727.189	1.731		
C. Total	496	27733.762			

Figure C.12: Levene's Test for Equal Variances and Welch's Test for the Electronics Data Set (Ramp-Reg.)

Table C.12: Individual Statistical Comparisons of Models- the Electronics Data Set (Ramp-Reg.)

Inventory Measure	Statistical Difference?	Statistical Comparison	Interpretation
Mean On-hand Inventory	NO	**Model** A **On-hand** Croston-MSE A 7.89 SBA-MSE A 7.87 Holt-MSE A 7.84 M1-MSE A 7.81	All the models performed similarly, no statistical evidence that any of the considered models achieved lower On-hand levels of inventory.
	NO	**Model** **On-hand** Croston-MSE A 7.89 SBA-MSE A 7.87 Holt-MSE A 7.84 M2-MSE A 7.53	All the models performed similarly, no statistical evidence that any of the considered models achieved lower On-hand levels of inventory.
	NO	**Model** **On-hand** Croston-MSE A 7.89 SBA-MSE A 7.87 Holt-MSE A 7.84 M3-MSE A 7.69	All the models performed similarly, no statistical evidence that any of the considered models achieved lower On-hand levels of inventory.
	YES	**Level** **On-hand** Croston-MSE A 7.89 SBA-MSE A 7.87 Holt-MSE A 7.84 M4-MSE B 7.21	M4-MSE outperformed all the models by carrying significantly lower on-hand levels. No difference was captured between the other models themselves.
	YES	**Model** **On-hand** M1-MSE A 7.81 M3-MSE A B 7.69 M2-MSE A B 7.53 M4-MSE B 7.21	M4-MSE outperformed M1-MSE by carrying significantly lower on-hand levels.

C.13 : STATISTICAL ANALYSIS OF ON-HAND INVENTORY - THE ELECTRONICS DATA SET (REG-DROP)

Test	F Ratio	DFNum	DFDen	Prob > F
O'Brien[.5]	2.4787	5	282	0.0322*
Brown-Forsythe	2.4000	5	282	0.0374*
Levene	5.1211	5	282	0.0002*
Bartlett	13.7340	5	.	<.0001*

Welch's Test

Welch Anova testing Means Equal, allowing Std Devs Not Equal

F Ratio	DFNum	DFDen	Prob > F
3.5960	5	129.77	0.0044*

Figure C.13: Levene's Test for Equal Variances and Welch's Test for the Electronics Data Set (Reg-Drop)

Table C.13: Individual Statistical Comparisons of Models - the Electronics Data Set (Reg-Drop)

Inventory Measure	Statistical Difference?	Statistical Comparison	Interpretation
Mean On-hand Inventory	YES	**Model** / **On-hand** Holt-MSE A 5.89 Croston-MSE A B 4.54 SBA-MSE B 4.45 M1-MSE B 3.89	Holt-MSE achieved significantly higher on-hand levels compared to both SBA-MSE and M1-MSE. No statistical difference was found between Croston-MSE and the rest of the models.
	YES	**Model** / **On-hand** Holt-MSE A 5.89 Croston-MSE A B 4.54 SBA-MSE A B 4.45 M2-MSE B 3.93	Holt-MSE achieved significantly higher on-hand levels compared to M2-MSE. No statistical difference was found between SBA-MSE, Croston-MSE and the rest of the models.
	YES	**Model** / **On-hand** Holt- MSE A 5.89 Croston-MSE B 4.54 SBA- MSE B 4.45 M3-MSE B 3.92	Holt-MSE achieved significantly higher on-hand levels compared to the rest of the models.
	YES	**Level** / **Mean** Holt-MSE A 5.89 Croston-MSE A B 4.54 SBA-MSE A B 4.45 M4-MSE B 3.91	Holt-MSE achieved significantly higher on-hand levels compared to M4-MSE. No statistical difference was found between SBA-MSE, Croston-MSE and the rest of the models.
	NO	**Level** / **Mean** M2-MSE A 3.93 M3-MSE A 3.92 M4-MSE A 3.91 M1-MSE A 3.89	No difference was captured between the proposed models