THE REPUBLIC OF TURKEY
BAHCESEHIR UNIVERSITY

DEMAND FORECASTING IN MOBILE PHONE INDUSTRY

Master Thesis

ZEYNEP ÖRNEK

ISTANBUL, 2018

THE REPUBLIC OF TURKEY
BAHCESEHIR UNIVERSITY

GRADUATE SCHOOL OF NATURAL AND APPLIED SCIENCES
INDUSTRIAL ENGINEERING

DEMAND FORECASTING
IN MOBILE PHONE INDUSTRY

Master Thesis

ZEYNEP ÖRNEK

Thesis Supervisor: ASST. PROF. ADNAN ÇORUM

ISTANBUL, 2018

THE REPUBLIC OF TURKEY
BAHCESEHIR UNIVERSITY

GRADUATE SCHOOL OF NATURAL AND APPLIED SCIENCES
INDUSTRIAL ENGINEERING

Name of the thesis: Demand Forecasting in Mobile Phone Industry

Name/Last Name of the Student: Zeynep ÖRNEK
Date of the Defense of Thesis: 26.01.2018

The thesis has been approved by the Graduate School of Natural And Applied Sciences.

Prof. Dr. Nafız ARICA
Graduate School Director
Signature

I certify that this thesis meets all the requirements as a thesis for the degree of Master of Arts.

Asst. Prof. Adnan ÇORUM
Program Coordinator
Signature

This is to certify that we have read this thesis and we find it fully adequate in scope, quality and content, as a thesis for the degree of Master of Arts.

Examining Committee Members	Signature
Thesis Supervisor Asst. Prof. Adnan ÇORUM	-----------------------------------
Member Asst. Prof. Ethem ÇANAKOĞLU	------------------------------------
Member Asst. Prof. Mehtap Dursun USTA	------------------------------------

ACKNOWLEDGEMENTS

Firstly, I thank to my mother and my brother for their unquestioning support that they have always gave me.

I thank to Sebahattin Yaman, Muzaffer Gölcü and Osman Varoğlu who helped me to choose incredible thesis subject and always encouraged me about my academic life.

And, of course, I thank to my supervisor Asst. Prof. Adnan Çorum and Asst. Prof. Okan Şakar for their guidance, patience and continuous support throughout this study.

İstanbul, 2018 Zeynep ÖRNEK

ABSTRACT

DEMAND FORECASTING
IN MOBILE PHONE INDUSTRY

ZEYNEP ÖRNEK

Industrial Engineering

Thesis Supervisor: Asst. Prof. Adnan Çorum

January 2018, 103 pages

The ever-changing developments in information and communication technologies in the globalizing world, the ever-increasing product variety in the sectors and the constant exacerbation of competition have led businesses to search for ways to achieve sustainable competitive advantage.

At the beginning of this kind of search is the management of all production, marketing and procurement processes with high performance from the strategic direction. In order to achieve sustainable competitive advantage especially for the enterprises in the mobile phone sector, it is very important for them to successfully predict the future strategic decisions to be taken within the scope of "supply chain management" (SCM) and "inventory management".

Quantitative and qualitative research models are employed together in this study, which the main objective is to determine effective demand forecasting method in order to provide full-time optimization of the SCM and inventory management processes of the enterprises in the mobile phone sector.

Within the scope of the research, similar researches abroad and domestically conducted for the basic concept and topic of the research have been searched and examined. Thus, the theoretical frame and method of the thesis have been tried to be determined. In the second phase of the study, the data of two telephone models subject to demand forecasting within the scope of this research by employing Negative Binomial Regression (NBR) Analysis, time series analysis and machine learning method. The quantitative findings obtained by using the listed methods have been tried to be interpreted in the light of qualitative information and findings obtained as a result of the literature review.

As a result of the research; Through NBR and time series analyzes, demand estimates for the mobile phone industry including weekly and monthly periods have been reached, which will enable more reliable sales forecasts for the future of the mobile phone industry. In addition, the optimum number of phones that mobile phone operators have stored in their stock before offering the sale is determined as a result of research. Another result of the study is that; the more precise and clear quantitative method for demand forecast method in mobile phone sector comparing the traditional methods is “machine learning” method.

Finally, in the research, the optimum amount of stocking and potential sales on a weekly and monthly basis were predicted by using random forest algorithm for a new mobile phone product offered for sale to national and global markets and another mobile phone pre-marketed.

Keywords: Mobile Phone Sector, SCM, Inventory Management, Demand Forecasting, Machine Learning Method

ÖZET

MOBİL TELEFON ENDÜSTRİSİNDE TALEP PLANLAMASI

Zeynep Örnek

Endüstri Mühendisliği

Tez Danışmanı: Yrd. Doç. Dr. Adnan Çorum

Ocak 2018, 103 sayfa

Küreselleşen dünyada bilişim ve iletişim teknolojilerinde her geçen gün yaşanan gelişmeler, sektörlerde giderek artan ürün çeşitlilikleri verekabetin sürekli şiddetlenmesi işletmeleri sürdürebilir rekabet avantajı sağlamaya yönelik arayışlara yöneltmiştir.

Bu tür arayışların en başında ise işletmelerin stratejik yönden tüm üretim, pazarlama ve tedarik süreçlerini yüksek performansla yönetmeleri gelmektedir.Özellikle mobil telefon sektöründeki işletmeler açısından yeni ekonomik düzende sürdürebilir rekabet avantajı elde edebilmek için "tedarik zinciri yönetimi" (TZY) ve "envanter yönetimi" kapsamında almaları gereken stratejik kararları, geleceği başarılı bir şekilde tahmin ederek oluşturmaları oldukça önemlidir.

Temel amacı, mobil telefon sektöründeki işletmelerin TZY ve envanter yönetimi süreçlerinde tam zamanlı optimizasyonu sağlamak üzere etkili talep tahmini yöntemi belirlemek olan bu araştırmada nitel ve nicel araştırma yöntemler birlikte kullanılmıştır.

Araştırma kapsamında öncelikle araştırmanın temel kavram ve konusuna yönelik daha önce yurt dışında ve yurt içinde yapılmış benzer araştırmalar toplanmış ve incelenmiştir. Böylece tezin teorik çerçevesi ve yöntemi belirlenmeye çalışılmıştır. Araştırmanın ikinci aşamasında bu araştırma kapsamında talep tahminine konu edilen iki telefon modeline ait toplanan nicel veriler; kantatif talep tahmin yöntemi olarak literatürde anılan NBR modeli, zaman serileri analizi ve makine öğrenme yöntemi kullanılarak analiz edilmiştir. Sayılan yöntemler kullanılarak ulaşılan nicel bulgular ise, literatür incelemesi sonucunda ulaşılan nitel bilgi ve bulgular ışığında yorumlanmaya çalışılmıştır.

Araştırma sonucunda; NBR ve zaman serisi analizleri aracılığıyla ulaşılan bulgular, mobil telefon sektöründeki işletmelerin geleceği için daha güvenilir satış tahminlerini yapmalarını sağlayacak nitelikte haftalık ve aylık periyotlar içeren talep tahminlerine ulaşılmıştır. Bunun yanı sıra mobil telefon işletmelerinin satışa sunmadan önce stoklarında depoladıkları telefonların optimum sayısı araştırma sonucunda belirlenmiştir. Araştırmanın diğer bir sonucu da mobil telefon sektöründe geleneksel yöntemlerle yapılan talep tahminlerine göre çok daha net ve doğruluk düzeyi yüksek talep tahmininde bulunmaya olanak veren kantatif talep tahmin yönteminin ise "makine öğrenmesi" yönteminin, "random forest algoritması" olduğu tespit edilmiştir.

Araştırmada son olarak, random forest algoritması kullanılarak ulusal ve küresel pazarlara satışa sunulan yeni bir mobil telefon ürünü ile önceden satışa sunulan başka bir mobil telefonun, optimum düzeyde olması gereken stoklama ve potansiyel satış

miktarlarını, haftalık ve aylık periyotta belirleyecek nitelikte kesin ve net bulgulara ulaşılmıştır.

Anahtar Kelimeler: Mobil Telefon Sektörü, TZY, Envanter Yönetimi, Talep Tahmini, Makine Öğrenme Yöntemi

CONTENTS

TABLES

FIGURES

ABBREVIATIONS

CB	:	Competative Brand.
MAD	:	Mean Absolute Deviation
MAE	:	Mean Absolute Error
NBR	:	Negative Binomial Regression
p.m.	:	Previous Month
p.w.	:	Previous Week
RAE	:	Relative Absolute Error
RMSE	:	Root Mean Squared Error
S. P.	:	Sales Price
S.V.	:	Sales Volume
SCM	:	Supply Chain Management
TDK	:	Türk Dil Kurumu
TL	:	Turkish Lira (TRY)
WEKA	:	Waikato Environment for Knowledge Analysis

1. INTRODUCTION

The ever-changing developments in information and communication technologies in the globalizing world, increasing product diversity in the sectors and the constant exacerbation of competition are leading to various quests for businesses to provide sustainable competitive advantage. At the beginning of this kind of search is the management of all production, marketing and procurement processes with high performance from the strategic perspective.

Indeed, today's businesses are experiencing rapid changes and transformations both inside and outside. In order to survive in the new economic regime and be competitive, it is necessary to make strategic decisions under "supply chain management" (SCM) and "inventory management". Taking these decisions successfully by predicting the future will give them considerable gains.

The “demand forecast” success especially in terms of businesses operating in the mobile phone sector examined in this thesis, is highly critical in production, marketing and SCM processes generally, and especially in the context of inventory and order management. The most important reason for this is the constant growth of the mobile phone industry worldwide and the rapid increase in demand. As a matter of fact, it is seen that the number of smartphone usage which makes it easy to enter the internet and to make it mobile in the world has increased incredibly.

As a matter of fact, by the year 2017, when the world population is calculated as 7 billion 476 million, approximately 4 billion 917 million (66 percent of the world population) mobile phone users are in the World (DGO, 2017:3-4). By 2017, the number of laptop and PC usage as a means of connecting internets worldwide has increased by 45 percent compared to 2016, while the use of mobile phones for the same purpose has increased by 50 percent (DGO, 2017:6). Moreover, the increase in the number of mobile phones connecting to the internet in the previous year increased by 30 percent around the world, while the increase in the number of connections via PC and laptop decreased by 20 percent compared to the previous year (DGO, 2017:9).

In Turkey, as of 2017, 48 million people constituting 60 percent of the country's population are internet users and the number of people connecting to Internet via mobile phones is 71 million. In addition, in the period between 2016 and 2017, connecting Internet by computers in Turkey decreased by 29 percent to 36 percent, while mobile web traffic increased by 33 percent to 61 percent (DGO, 2017:3-4).

This kind of statistics and data show that today mobile phone sector is an extremely dynamic and innovative sector that both in the world and in Turkey, where demand is changing every day according to the new models and competition is fierce. That's why all businesses that want to survive in the industry have to make "demand forecasts" within inventory, sales and order management very precisely. For this and similar reasons, defining "supply chain management", "inventory management" and "demand forecasting" concept, which are discussed in this thesis, will be the first priority.

From a literary perspective, it appears that the SCM concept is defined as the process of "integrating retailers, wholesalers, manufacturers and suppliers to produce and distribute products in the right quantity, in the right place and on time to meet customer service level requirements" (Mangan et al., 2008:12-13; Ungan, 2011:13; Nebol et al., 2014:11).

SCM in general consists of various processes and subsystems, although it shows changes according to sectors and businesses. These include managerial processes for demand forecasting, raw material supply, storage, transportation, ordering, sales, and similar operations for production, sales or marketing (Stevenson, 2012:76-77). Among these, it is stated in the literature that subsystems with the most strategic designation and value under SCM are "demand management" and "inventory management" (Kobu, 2005; Beamon, 1998; Lambert and Cooper, 2000; Bowersox et al., 2002; Croxton et al.2002; Feng et al. 2008; Tilford, 2009; Rexhausen et al., 2012; Stevenson, 2012; Krajewski et al. 2013).

In the literature, the concept of "inventory" is most simply defined as "a stock or warehouse where various goods are stored" (Kamauff, 2009: 187). Most of the goods contained in an operator's inventory consist of goods or business-related goods in which the operator is located (Stevenson, 2012:556). It is possible to define the concept of inventory management as "effective management of stocking level in enterprises, management of storage activities such as how to maintain stocks, when stocks should be renewed and to determine order / production quantities" (Monks, 1996; Kobu, 2006; Nahmias, 2009; Yüksel, 2010).

In terms of businesses, the general objective of inventory management is to ensure that the required amount of goods or part is available at the desired time and place at the desired amount (Bowersox, 2002; Kobu, 2006; Schuh, 2006; Kumar and Suresh, 2008; Nahmias, 2009; Yüksel, 2010; Yenersoy, 2011). For a successful inventory management, having the right material in the right place at the right time and at the right cost Shows the success of inventory management (Kumar and Suresh, 2008; Nahmias, 2009; Stevenson, 2012). Thus, the success of "demand forecasting" under the SCM has a lot of precautionary measures in terms of the reduction of all costs in the business, the increase of production and marketing performance (Ülgen and Mirze, 2007; Nahmias, 2009; Yüksel, 2010; Yenersoy, 2011).

In the literature, the concept of "forecasting" is defined as "trying to predict the future in order to plan the decisions to be made and the operations to be carried out for business management" (Tek, 1999:296; Tilford, 2009:16). The concept of demand management is defined as "the ability of businesses to understand customer demand and balance this demand with supply chain capacity" (Lambert and Cooper, 2000:18).

As the definition implies, demand management is concerned with the ability of businesses to estimate accurately customer desires and needs (Lapide, 2008:14). A well-implemented demand management has considerable strategic importance and value in terms of ensuring customer satisfaction, increasing sales and ensuring the effectiveness of inventory management (Leenders et al., 2002; Rexhausen et al., 2012; Stevenson, 2012; Krajewski et al., 2013).

When the literature is examined, there are many studies pointing out that making forecasts with high accuracy in terms of business production processes, SCM process and stages, as well as strategic considerations will provide considerable gains to the enterprises (Fitzgerald et al., 1991; Stewart, 1995; Stewart, 1995; Beamon (1999), Bagchi (1996) Bowersox et al., 2002; Kehoe and Boughton (2001; Gunasekar et al. (2001); Gunasekaran et al. (2004); Lockamy et al., (1999), Stewart, 1995, Beamon and McCormack, 2004, Gunasekaran and Kobu, 2007, Deshpande, (2012; Rexhausen et al., 2012).

Many similar researches in the literature emphasize that successful "demand forecasting" in terms of inventory management will provide considerable and strategic benefits to businesses (Balkhi and Benkherouf, 2004; Teng and Chang, 2005; Teng et al., 2005; Sana, 2008; Sarkar et al., 2011; Bose, 2002; Singh and Singh, 2011; Majumder and Bera, 2013; Dem et al., 2014).

However, in today's rapidly growing and developing "mobile phone industry" it is becoming increasingly difficult to make successful estimates in the context of increasing production, procurement, sales, marketing, ordering and customer satisfaction (Stevenson, 2012:76-77). This is because the development of demand estimates in terms of businesses operating in this sector consists of multi-stage processes and applications, including both precursors and formal calculations and statistical estimates. In addition, demand forecasting that businesses have been using for many years can often yield inaccurate and statistically meaningless results in such a dynamic sector. (Mangan et al., 2008; Nebol et al., 2014; Stevenson, 2012).

Indeed, the mobile phone sector is a "high-tech-based production" sector (Decker, Gnibba and Yukawa, 2010). Another feature of the sector is that mobile phones manufactured and sold in this sector are included in the "Short sales season and products with a short lifespan" group (Graefe and Armstrong, 2011). In addition, it is often difficult to predict potential sales in the sector, because of the high uncertainty of demand for these products (Goodwin et al., 2012; Berbain, Bourbonnais, Vallin, 2011). Because of these reasons in mobile phone sector, traditional demand forecasting methods such as "time series analysis" are often inadequate and ineffective (Semco et al., 2013, Boese, 2015, Chen, Tzu and Liang, 2017).

In recent years, enterprises have faced such dilemmas in demand forecasting, and have been increasingly turning to the use of "machine learning" methods in "artificial intelligence" product technologies to solve problems that require "forecasting" and "estimate" (Dunham, 2003; Bahrololum, Salahi and Khalegni, 2009 Farid and Rahman, 2010; Jemili, Zaghdoud and Ahmed, 2007; Zhang and Zhu, 2010 Bace and Mell, 2011; Vural and Sağıroğlu, 2011; Zhang et al., 2012; Mu, Chen ve Zhang, 2012; Alazab, Hobbs, Abawajy and Alazab, 2012; Sharma ve Nema, 2013; Amos, Turner and White (2013); Faragher and Harle (2013; Wu and Hung (2014); Guinness (2015); Sağbaş and Ballı (2015).

"Machine Learning" in the literature; is a technique of creating computer software to produce better results using past experiences or sample data (Alpaydın, 2011:13). As can be understood from the description, machine learning allows to detect the hidden complex pattern between databases and to make new predictions and estimates by taking advantage of statistics and computational power for meaningful pattern extraction (Xiang, Yong and Meng, 2008: 918-924, Vural and Sagiroglu, 2011; Zhang et al., 2012; ICT, 2017).

It is not possible, however, to have a computer program, or algorithm, to forecast and predict where, how, and how much of a new product (such as a new mobile phone) will be sold on the market (Scarfone and Mell, 2007:80-94; Bace and Mell, 2011:4-5). It is stated in the literature that "machine learning method" which analyzes such problems according to "relationship rule" will have very effective results in solving similar problems. (Fader and Hardie, 2005; Liu, Yi and Yang, 2007; Alpaydın, 2011; Xiang, Yong and Meng, 2008; ICT, 2017).

Therefore, in order to solve a problem whose algorithm is not known in the above-mentioned manner, the "machine learning" method for making an inference according to the “relationship rule" by looking at the collected data is a very effective way of achieving accurate predictions. (Kendall, 1999; Çalış, Gazdağı and Yıldız, 2013). (Liu, Yi and Yang, 2007: 1561-1568).

However, as a result of the literature review, it has not been found (by the knowledge of the researcher) among the researches on SCM and demand forecasts under inventory management that the researcher using the "machine learning" method was used. For this reason, it is considered that this research which aims to make demand forecasting in SCM and inventory management in the "mobile phone sector", including a model newly introduced to the market, will make a significant contribution to the literature.

The main purpose of the study is to determine the effective demand forecasting methodology to provide full-time optimization of the mobile phone industry inventory management processes. To increase the accuracy of estimates made by qualitative estimation methods (expert opinion) and quantitative estimation methods (delphi method) which are frequently used in the mobile phone sector of the researcher; (delta) between "forecasting demand" and "actual sales" in such traditional methods in the sector, and, more importantly, proposing a more effective demand forecasting method for the mobile phone sector.

Within the scope of this research, which primarily aims and goals are introduced, firstly the literature has been examined and qualitative data about the basic concepts of thesis have been collected at the theoretical level and the methods used in the researches about "demand forecasting" under SCM and inventory management have been examined. Finally, in the second part of the thesis, in the context of the research, there has been a review in the literature about whether "multi-regression analysis" and "machine learning methods" used in demand forecasting should be used in this study.

In the third part of the thesis, the purpose, scope, model, hypotheses of the research, population and sample and methods used in gathering and analyzing research data were tried to be explained. In the chapter, explanations are given in the context of descriptive tables about the machine learning method used in the research and also in the literature.

In the fourth part of the thesis, the findings of the demand forecasts made by SPSS and WEKA programs were interpreted in the context of descriptive tables. In this context, correlations and multiple regression findings in this section were evaluated together with machine learning findings, and finally the findings were discussed in the literature.

In the fifth and last section of the thesis, quantitative findings reached within the scope of the research were interpreted in the light of the qualitative information reached in the theoretical sections and some results were tried to be reached. Finally, some suggestions have been made to the researchers who are planning to work in the same subject and in the same way with this thesis and with the enterprises in the mobile telephone sector.

.

2. LITERATURE REVIEW

Findings of the literature on the basic concepts of this research, which aim to determine the effective demand forecasting method to provide full-time optimization in the inventory management processes of the mobile phone industry, are briefly summarized under the following headings.

2.1 THEORETICAL FRAMEWORK

This research is primarily concerned with the concepts of supply chain management, inventory management, and demand forecasting, and the underlying research concepts are described based on the literature.

2.1.1 Supply Chain Management in Enterprises (SCM)

The ever-changing developments in information and communication technologies in the globalizing world, increasing product diversity in the sectors and continuously increasing global competition conditions drive businesses to various quests to provide a sustainable competitive advantage (Tengilimoğlu and Yiğit, 2013).

Supply Chain Management (SCM) has become an increasingly strategic and managerial space for all businesses to achieve a high-quality output, increase customer satisfaction and increase the organizational efficiency of the business to gain a competitive advantage globally (Rexhausen et al. 2012).

In the literature, the concept of "supply chain" is defined as "processes in which raw materials are procured by enterprises to use in production, raw materials are converted into semi-finished or final products, and these products are delivered to the end user" (Mangan et al., 2008:12-13). In the supply chain, there is information/product, and fund flows between various subsystems throughout the chain. Customers, retailers, wholesalers/distributors, manufacturers and input suppliers in such schemes come together to meet customer needs directly or indirectly (Uzun and Karataş, 2012; Acar and Köseoğlu, 2014).

SCM is defined as the process of integrating retailers, wholesalers, manufacturers, and suppliers to produce and distribute products in the right quantity, in the right place and on time to meet customer service level requirements (Ungan, 2011:13; Nebol et al., 2014:11).

From a literary perspective, it is possible to come up with many definitions similar to the SCM description mentioned above: For example, Quinn (1997: 5) defines the concept of SCM as "all processes related to products from the raw material stage to the end user.".According to Kopczak (1997: 9) it is "a set of elements covering suppliers, producers, distributors, retailers and providing the flow of materials, products, and information between them." Shin et al. (2000: 18) define "the art of managing raw materials, goods and products forwards, cash backward, knowledge for both directions" (Lambert and Cooper, 2000: 14).

The last point reached in the processes and practices of SCM, which has undergone various development processes, is the development of different types of SCM models according to "product" and "customer." (Vonderembse et al., 2006). Undoubtedly, at the forefront of such new models and applications are the information and communication sectors, which are composed of high-tech production systems such as the mobile communication sector. (Mangan et al., 2008; Nebol et al., 2014). To ensure the sustainable competitive advantage of the enterprises operating in such sectors, effective management of the processes and practices of SCM is significant and vital. (Stewart, 1995; Rexhausen et al., 2012).

On the other hand, although it shows some changes according to the sectors, in general, in today's enterprises, the stages of SCM consists of sub-systems and administrative processes listed (1) demand management; (2) distribution management; (3) supplier relationship management; (4) customer relationship management; (5) purchase; (6) new product development; (7) inventory management; (8) process management; (9) capacity planning; (10) site selection. (Bowersox et al., 2002).

The most important processes and subsystems within the scope of SCM are "demand management" and "inventory management" processes and applications. (Lambert and Cooper, 2000; Croxton et al.2002; Feng et al. 2008; Tilford, 2009; Rexhausen et al. 2012). For example, according to Beamon (1998), the two processes will be operated and managed in a harmonious manner, which will provide the maximum benefit expected from all the processes and processes. (Krajewski et al. 2013).

Finally, it should be said that in sectors where competition is intensified globally, in terms of an economic regime in which new developments and changes are taking place every day, every hour and minute, in both internal and external environment of enterprises, effective inventory management practices under the scope of SCM has quite a significant importance (Stevenson, 2012:76-77).

Also, with demand forecasting managed under SCM, being successful in the inventory management processes contributes to increasing the production and sales performance of the enterprises, to increase the product quality and to obtain the sustainable competitive advantage of the enterprises. (Leenders et al. 2002; Lockamy and McCormack, 2004; Gunasekaran and Kobu, 2007).

Because of these kinds of contributions and gains mentioned in the literature, demand estimation and inventory management are covered under the scope of this research. A model for accurate and successful demand forecasting for businesses to be successful in SCM, managing inventory and order have been tried to be developed.

2.1.2 Inventory (Stock) Management Processes in Businesses

The most important and most fundamental of the SCM practices that are carried out regarding strategic management in the enterprises is undoubtedly the "inventory management" processes and applications (Koçel, 2015: 270). "Inventory management" based on logistics management and accounting management is at the forefront of the basic concepts discussed in this thesis.

The word "inventory," which is transliterated into Turkish as a counterpart to the words "stock" and "inventory" in English, is used in this same meaning (TDK, 2017). In fact, the term "stock" is used to describe the physical and monetary elements of the SCM and the production process, while the term "inventory" is used to express the inventory of goods that are physically counted at the end of the year in accounting (Kobu, 2005: 341).

A stock or a warehouse where the inventory goods are stored, as the word implies. For that reason, most of the items on an enterprises’ inventory are comprised of sectors, products, or business-related commodities that the enterprise is in (Kamauff, 2009: 187).For example, manufacturing firms stock raw materials, purchased parts, partially finished products and spare parts for finished products and machines; a healthcare facility holds medical supplies, spare parts of medical devices and other logistics procurement supplies in stock. What will be the problem and the primary success criterion here is the art of responding correctly to these questions; keeping what, how long, how much and in which depot will be more ergonomic and profitable? (Stevenson, 2012:556).

In this sense, it is possible to define the concept of inventory management in terms of adequate follow-up of inventory levels in enterprises, management of storage activities, determination of when stock should be renewed, and management of applications such as determination of order / production quantities (Monks, 1996; Kobu, 2006; Nahmias, 2009; Yüksel, 2010).

It is understood from the definition that the general aim of inventory management and systems is to ensure that the required parts are available at the desired time and place at the desired quantity (Bowersox, 2002). Inventory control systems that will serve this purpose vary depending on factors such as the structure of business/organization, product structure, management approaches. (Kobu, 2006; Schuh, 2006; Kumar and Suresh, 2008; Nahmias, 2009; Yüksel, 2010; Yenersoy, 2011):

Generally, regarding businesses, the types of inventories are considered as raw materials, semi-finished goods, auxiliary material stocks and final products (Aghezzaf, 2006). They also prefer to have safety stocks so that they are not adversely affected by uncertainties in the system, such as demand, duration of supply and operating supply (Kumar and Suresh, 2008; Nahmias, 2009; Yüksel, 2010; Yenersoy, 2011).

The general inventory costs for a business are a long list: Order / production preparation cost (per cycle); Purchase / production (variable) cost (per unit);Cost of availability (per unit); Storage cost; Cost of capital; Insurance and tax costs; Deterioration, aging and waste costs; System costs; non-possession cost (per unit) (Tersine, 1994; Eroğlu, 2002; Nahmias, 2009; Yenersoy, 2011; Stevenson, 2012).

On the other hand, for a successful inventory management, it is necessary to keep the right material in the right place at the right time and the right cost (Stevenson, 2012). Since the success of the demand forecasting will affect the decrease or increase of all the costs mentioned above, it is significant and essential to predict highly accurate regarding SCM and the success of the inventory management for the performance of the enterprise (Kumar and Suresh, 2008; Nahmias, 2009).

Inventory management in all sectors and businesses is seen as the most basic and most important SCM operation management process. Because the success of inventory management affects all production operations, marketing, and even financing processes (Ülgen and Mirze, 2007: 290). The businesses also must improve strategies that will reduce storage costs to the most considerable extent by balancing businesses with satisfactory production efficiency and customer demand. (Collier, 2009: 186).

Finally, it should be said that to correctly configure the inventory management functions in the system, the processes related directly with each other such as ordering, purchasing, warehousing, distribution and inventory control within these functions should be performed with the most accurate estimations (Aytekin, 2009: 113). Therefore, the "accurate demand forecast" in inventory management under the scope of SCM in the enterprises has strategic meaning and prevention. (Aghezzaf, 2006; Rexhausen et al. 2012).

2.1.3 Order Policies in Inventory Management

The main aim of inventory management is providing customer services at a satisfactory level while keeping the stock prices within reasonable limits (Kumar ve Suresh, 2008). There are two primary considerations of inventory management about this aim. The first one is the level of customer services, in other words having the right amount of goods at the right place, at the right time. The other one is ordering and transportation costs (Lockamy and McCormack, 2004; Gunasekaran and Kobu, 2007).

The enterprises keep various inventory ordering policies to overcome these two main considerations. These kinds of policies provide background for inventory managers to give their decisions about two main issues; “when the orders should be given” and “what amount of orders should be given” (Nahmias, 2009; Yenersoy, 2011).

“The optimum ordering amount” which gains importance in this sense reflects the balance between transportation costs and ordering costs. Depending on the change in orders, one of the costs increases while the other one decreases. For example, if the amount of order is relatively small, the average inventory becomes low, and the transportation costs become low, too. Whereas, the small amount of order will require frequent orders and then it will increase the annual ordering costs. Inversely, giving orders in higher amounts but lower frequency may decrease annual ordering costs which in turn yields the average stock levels would be higher and then causes an increase in transportation costs. Consequently, the ideal solution is not a big amount of order or a small amount of order but a balance between these two (Stevenson, 2012:558-562).

Three main ordering models are widely used currently and identified as “basic economic ordering quantity model,” “Quantity decrease model” and “economic production quantity model” (Stevenson, 2012:562-566). These models suggest continuous inventory tracking to know when the order is re-ordered.

For this, four key determinants are used to determine the amount of reorder points maintained under order models: 1. Demand rate (usually based on an estimate). 2. Term time. 3. The grade of the tally and the term time variability. 4. Acceptable end of stock risk for management is the risk level (Stevenson, 2012:574).

Finally, it should be said that to reduce the risk of becoming stuck at the term time (safe stock) for ordering within a forecasting model, it is necessary to carry additional stock, called safety stock. Because re-order point safety will vary according to the quantity (Stevenson, 2012:578).

2.1.4 Demand Management and Forecasting in Enterprises

All economic activities are based on the demand of the consumer. Without considering the demand level of the society to which it will be addressed, an enterprise in production will have to produce in inappropriate quantities (Nahmias, 2009; Yüksel, 2010; Yenersoy, 2011). In this new economic regime where competition is intensified, such problems are being tried to be solved by sufficient "demand management" applications.

In this context, businesses do not want to produce more than they can sell, nor do they want to produce under their selling capacity. Businesses that produce more than they can afford to sell have to cope with too much inventory cost and have to sell their remaining products at meager prices. Businesses that produce less than their suppliers can miss out on more profit, and their brand values and corporate reputations are damaged.

In the literature, the concept of "forecasting" is defined as "trying to predict the future to plan the decisions to be made and the operations to be carried out for business management." Demand forecasting is the function of estimating the number of goods and services that consumers will demand in the future (Tilford, 2009:16). In another source, demand forecasting is defined as "estimating sales of a given product within a certain future time" (Tek, 1999:296).

The concept of demand management in the literature is defined as "the ability of businesses to understand customer demand and balance this demand with supply chain capacity" (Lambert and Cooper, 2000:18). As the definition implies, demand management is concerned with the ability of businesses to accurately estimate customer needs and needs (Lapide, 2008:14).

Demand forecasts are the most critical inputs that must be reached in many business decisions.As a matter of fact, according to Croxton et al. (2002), demand management is the most crucial element of supply chain management. According to Raxhausen et al. (2012), well-implemented demand management has considerable strategic importance and value regarding ensuring customer satisfaction, increasing sales and ensuring the effectiveness of inventory management.

So, according to the literature, it can be said that the amount of production in terms of the enterprises is a fundamental balance issue, and the only way to achieve this balance is to make a "demand forecast" in a correct and full time within the scope of successful "demand management" (Krajewski vd., 2013).

The development of demand estimates is a multi-stage process with both premise and precise estimates (Kress and Snyder, 1994:6). This is the basis for determining the level of production of the enterprise. Demand estimates are often made by businesses for which the product will be produced, what the consumer will demand from that product, and where the likelihood of such a claim is likely to occur (Lapide, 2007).

However, management in the business requires different estimates of the future level of activity based on the interest and focal points of the various stages. Different estimates such as market forecast, financial forecast, stock forecast, sales forecast, order forecast and production forecast are developed in this way (Schroeder, 1989:71).

The selection of demand forecasting techniques that businesses will use, especially in strategic decision making; it is very important to take into account such factors as the time and interval covered by the estimates, the long or short term of decisions to be made according to the results of the estimates, the accessibility to the data, the quality of the data obtained and the ease of understanding and application of the technique (Klassen and Flores, 2001:172).

In such cases, the available capacity can often meet most of the demand volume. Product features and demand model affects the type of forecast to be done, and the time it takes to cover. In particular, if demand trends are expected to be increasing in a long period compared to demand forecasts, it is necessary to make a forecast for a period that allows planning for the necessary expansion or equipment. This time interval varies from a few months to a few years (Rexhausen et al., 2012).

In this context, the demand forecasts to be made in the enterprises are grouped into "time periods" in four ways.The first is "Long-term forecasts" (maybe five or more years), the second is "Medium-term forecasts" (which may cover a period of up to five years starting from six months); "Short-term estimates" (three months, up to six months), and fourth "Very short-term estimates" (weekly, even daily) (Feng et al., 2008:16).

Finally, it should be said that the precise estimates are significant regarding supply chain and inventory management. Incorrect estimates can cause deficiencies and oversights throughout the supply chain (Leenders vd., 2002).

Excessively optimistic estimates may cause a material and capacity overruns that may increase costs. Both the shortcomings in the supply chain and the excesses have a negative impact not only on customer service but also on profits. Moreover, incorrect estimates may cause temporary increases and decreases in orders in the supply chain (Stevenson, 2012:76-77).

2.1.5 Methods Used in Demand Forecasting and Machine Learning Method

The wide variety of goods and services produced in the new economic era; the differentiation demands of consumer goods, intermediate goods, capital goods from one another; the limited availability of the available statistics and the wide variation in reliability ratings of these statistics make it impossible to use a single demand forecasting method.

As noted in the literature, businesses need information on existing situations and plans for the future to collect the ideas and judgments of normal persons. (Monks, 1987; 268; Render and Stair, 2000; 157). Moreover, while choosing the most appropriate method for estimating the demand to be made, it is said in the literature that two main factors to consider are "cost" and "accuracy." Other factors to consider when choosing an estimation technique include the existence of historical data; the time required to collect, analyze and forecast the data and the existence of the computer software (Fildes and Hastings, 1994:13).

Demand forecasting models that are shaped according to these variables are mainly classified into two groups. The first of these is qualitative, namely qualitative demand forecasting techniques, while the other groups are called quantitative, namely quantitative demand forecasting models. The first group of qualitative techniques can be used if the numerical data for the case to be estimated cannot be obtained, the uncertainty and the variability of the data are excessive (Stevenson, 2012:424).

For example, expert opinions, individual experience and judgments, and subjective factors can be addressed. The inputs of qualitative estimation techniques, which provide for the handling of such subjective factors, can be obtained from various sources. These sources of information can be customers, salespeople, managers, technical staff or experts from outside the business (Stevenson, 2012:425). The main qualitative techniques used in the decision-making process can be grouped into four groups: Delphi technique, market research, expert group opinion and sales force mix (Demir and Gümüşoğlu, 2003:497).

Quantitative demand forecasting techniques in the second group are divided into two subgroups as time series and causal techniques (regression analysis) (Sanders and Manrodt, 2003:513). In the time series analysis in the first group, the past data for the variable to be estimated is analyzed to obtain a particular data trend. Time Series Analysis is based on the assumption of future predictions based on the observation of the past (Tütek and Gümüşoğlu, 2000:197).

On the other hand, in some recent researches, "Machine Learning" method is seen to be used in demand forecasts for different sectors. It will be appropriate to describe briefly the method of machine learning that is used in the demand forecasts made within the scope of this research.

"Machine Learning" in the literature; is a technique of creating computer software to produce better results using experiences or sample data (ICT, 2017). Machine learning is a system that studies the work and construction of algorithms that can be learned as a structural function and can be predicted through the data (Fader and Hardie, 2005).

In another source, "machine learning" is defined as writing descriptive or predictive inferences using descriptive data or using experience (Alpaydın, 2011:13).

It is clear from the definitions that machine learning takes advantage of the statistics and computers to determine the hidden complex patterns between databases and to extract meaningful patterns (Xiang, Yong, and Meng, 2008: 918-924). For example, search engines such as Google and Yandex on the internet offer alternative search criteria, and the introduction of a new search suggests an example for machine learning applications. Likewise, in countries where different languages are spoken, the automatic translation of such a search engine to a different language in a different language is an example of machine learning applications. (Vural and Sağıroğlu, 2011; Zhang et al., 2012; ICT, 2017).

However, it should be said immediately that the algorithm must be known so that any problem can be solved by the computer (Bace and Mell, 2011:4-5). The concept of the algorithm is defined as a sequence of commands that will be applied to translate "input to output" in the computer software language (Vural and Sağıroğlu, 2011: 89-103). It does not have the chance to use these types of software, which have effective results in many issues and problems. For example, it is not possible to have an algorithm written to estimate and predict where, how, and how much of a new product will be sold to the market (Scarfone and Mell, 2007:80-94).

Because there are hundreds of factors that can cause such a problem. Even if there was an algorithm for this problem, it would be possible to write a separate computer program for it and to get an exact result on it, which would often be impossible due to the lack of data constraints and past sales data (Bace and Mell, 2011:4-5). Here, the "relationship rule" in the statistics and philosophical science enters the circuit. To explain the rule with an example; If a customer buys product X and also buys product Y, then it is said that the customer who buys X is a candidate to buy Y (Cristianni et al., 2000).

It is stated in the literature that the "machine learning method" which is designed according to the association rule in the solution of these and similar problems will have very effective results (Fader and Hardie, 2005; Liu, Yi and Yang, 2007; Alpaydın, 2011; Xiang, Yong and Meng, 2008; ICT, 2017). Therefore, in order to solve a problem whose algorithm is unknown, the "machine learning" method is very useful in making an inference based on collected data. It is also possible to say that it is a very efficient method in terms of reaching specific predictions (Kendall, 1999; Çalış, Gazdağı and Yıldız, 2013).

Finally, it should be said that this method could be used in many different areas. Generally, however, this method produces solutions to problems by making deductions or estimates from existing examples and data. This allows the method to be used in demand forecasting and to achieve satisfactory results (Liu, Yi and Yang, 2007: 1561-1568).

As can be seen, demand forecasting methods and techniques, which play a crucial role in making strategic decisions in all management and production processes today, continue to be developed and widely used. Clearly, even in this respect, it is possible to say that this research, which aims to make demand forecasting using the "machine learning" method, will make an essential contribution to the literature.

2.2 LITERATURE REVIEW OF RESEARCH HYPOTHESES

In this part of the study, the relationships between dependent and independent variables in the hypotheses developed within the scope of the research were tried to be examined within the framework of previous research in the literature. In this context, in the literature review, firstly, the research about the application of demand forecasting in terms of inventory management processes and applications maintained under SCM have been examined.

When the literature is examined, there are many studies indicating that it is very important to make predictions with high accuracy in demand forecasting in terms of production processes and SCM processes and stages (Fitzgerald et al., 1991; Stewart, 1995; Stewart, 1995; Beamon (1999), Bagchi (1996) Bowersox et al., 2002; Lockamy and McCormack, 2004; Gunasekaran and Kobu, 2007).

For example, Bowersox et al., (2002) pointed out that all of the applications and activities in the SCM process have great importance and significance in terms of the performance of the enterprises; especially “demand management” and “inventory management” applications have more strategic importance and value due to the fact that they affect production directly compared to all other SCM subsystems.

Kehoe and Boughton (2001) compared inventory management systems based on traditional and knowledge-based estimates with each other. In this context, the performance of the changing and transforming SCM systems with electronic markets entering the economic systems via the internet has been analyzed by the developed regression model. As a result of the research, it is revealed that the new computer-aided SCM systems are more successful than traditional SCM systems and that the most critical performance indicator that explains this success is "the success of demand forecasting."

Under the SCM, Gunasakaran conducted three types of research that looked at the success of demand forecasting and made essential contributions to the literature. Gunesekaran et al. (2001) and Gunesekaran (2004) research and Gunesekaran and Kobu (2007) research have reached some results which will shed light on the relation between these administrative areas.

Gunasekaran et al. (2001) argued that the supply chain performance of firms is directly related to demand forecasts based on decisions to be made at strategic, tactical and operational level. After 3 years of research by the same researchers, it has been determined that the biggest contribution to "SCM performance" measured by dividing into five classes is the "demand planning" and "delivery planning" variables (Gunasekaran et al., 2004).

Gunasekaran and Kobu (2007) found that demand forecasting models based on algorithms on calculations made by various computer programs and inventory management systems supported by modern technologies (e.g., machine learning methods based on artificial intelligence) are very effective on SCM performance in enterprises.

In addition, in the literature, it is seen that, in some research, the effect of demand forecasting is investigated in terms of the reduction of stock costs and duration of customer demands within strategic SCM applications (Deshpande, 2012; Rexhausen et al., 2012).

Deshpande (2012), for instance, has found that full-time deliveries based on actual demand and order forecast plans under the strategic SCM practices have a positive impact on reducing business inventory costs, reducing response time to satisfy customer requests, and increasing customer satisfaction.

Similarly, Rexhausen et al. (2012) investigated the effectiveness of demand management on SCM performance and argued that the right demand estimates in terms of all SCM processes were the most important factors enhancing performance.

In the second stage of the literature review aimed at developing research hypotheses, the research that investigated the roles and functions of demand forecasting in terms of enterprises' inventory management practices and processes were examined.In this context, it can be seen from the literature that the number of research focusing on demand forecasting within inventory management has increased considerably.

In this context, it is seen that the meaning and the importance of "forecasting of demand" are discussed in terms of inventory management in some research in the literature (Balkhi and Benkherouf, 2004, Teng and Chang, 2005, Teng et al., 2005, Sana, 2008;Sarkar et al., 2011).

With a general evaluation, these studies mostly refer to the "demand forecast success" of the enterprises on the basis of various "reasons for uncertainty” such as: "Situations of lack of stocks caused by the production environment" (Salameh and Jaber, 2000)."Claiming after-action event" (Bayındır et al., 2007). "Reducing defects in production, quality control and control errors" (Hayek and Salameh, 2001; Liao, 2007) and "allowing delays in payments" (Pentico et al., 2009; Teng and Chang, 2009). "Commercial credit policies launched by businesses" (Darwish, 2008; Jaber et al., 2008; Mahata, 2012).

In the literature, it seems that some research emphasize the necessity of making demand forecasting under the name of "continuous surveillance" in the models known as "probable inventory models", which include cases where the demand uncertainty is represented by a probability distribution (Axsater, 1993; Chen, 1999; Hariga, 2010; Yang et al. 2011).

It is also emphasized that in the literature, the demand forecasts of the enterprises in terms of inventory management success have been changed depending on the demand forecast time and / or stock quantity (Bayındır et al., 2006; Ben-Daya et al., 2008; Ertogral, 2011).In some studies, it was emphasized that estimates made in terms of inventory management were generally "blurry" in other words, not clear (Bose, 2002; Singh and Singh, 2011; Majumder and Bera, 2013; Dem et al., 2014).

As a result of the literature review, it has been understood that "demand forecasting" has become very important in terms of increasing SCM and inventory management performance, due to technological developments in the globalized world, global competition increases in markets, and product and service suppliers presenting to a new product market every day.

2.3 LITERATURE REVIEW FOR THE RESEARCH METHOD

As emphasized in previous sections of the study; each enterprise must make some managerial decisions at strategic, tactical, and operational levels based on accurate estimates of the success of its day-to-day operations.If the estimates made are not correct, programs will be produced that will provide very little or too much resource, too little or too much output, false output or incorrect timing of output, all of which will lead to additional costs and dissatisfied customers (Stevenson, 2012:76-77).

Various demand forecasting methods are used in "demand forecasts," which are designed especially to be based on SCM and production management, as well as on decisions to be made in inventory and order management. Essentially these methods are basically divided into two groups as "qualitative" and "quantitative" methods.

Qualitative techniques allow the addition of soft information (e.g., human factors, personal opinions, preliminary tests) to the forecasting process (Stevenson, 2012:80). "Judgment prediction" is an example of qualitative techniques based on the analysis of subjective inputs from various sources such as consumer surveys, sales staff, executive and expert panels.

The quantitative techniques in the second group mainly consist of the analysis of objective or challenging data. It is emphasized in the literature that such methods provide more clear and favorable results in the demand forecasts to be made. For this reason, information and determinations about demand forecasting methods which are used most widely in the literature and which are also preferred in the scope of this research are briefly described below.

2.3.1 Use of Time Series in Demand Forecasting

When the literature is examined, it can be said that the oldest method used in demand forecasting is "Time series analysis" method (Stevenson, 2012:76-77). An analysis of time series that tries to reflect only past experiences into the future includes examining past values and determining whether they are trends. In cases where there is no significant deviation, time series analysis also includes forecasting (Stevenson, 2012:76-77).

When the literature is examined, it is seen that the most commonly used estimation techniques in the time series analysis are "Arithmetic Mean Method", "Moving Average Method", "Weighted Moving Average Method", "Exponential Correction Method" and "Least Squares Method" (Bhattacharya, 1997:5; Stevenson, 2012:76-77).

Much research has been done in the literature on demand forecasts using the above-mentioned methods within the time series models:For example, Kirby (1966) calculated demand estimates using 23 different time series of 7.5-year monthly sales data of different sewing machine product groups from five different countries.As a result of the research, forecasts were made according to the demand season and the month of the UK market.Zhou et al. (2002) used a time series analysis method to estimate the hourly and daily water demand for the urban area of the Melbourne water supply system.

Baker and Fitzpatrick (1986) used multiple regression analyzes together with exponential correction in the prediction of daily urgent health care and routine health care claims for four districts of South Carolina.Schultz (1987) used the "exponential correction method" in predicting the irregularity of product demand in a business operating in the healthcare sector.Sani and Kingsman (1997) estimated and compared the results of different qualitative spare parts requests with simple exponential correction and moving average methods in different inventory management.Gavcar et al., (1999) tried to determine the demand estimates of paper-cardboard types used in Turkey by means of multiple regression analysis and determine the correlation between the variables.

When attention is paid to the research summarized above, it is noticed that the sectors and businesses that are subject to such research have been predicting the products and services that have been selling in the market for many years. Moreover, it is observed that in all studies no new product market has been put on the market. It is essential to understand that the products for which demand forecasting is aimed at are both "extremely long-lasting" and "medium-tech products." More importantly, it appears that past semester data for variables used in studies using time series analysis can be easily reached. (Bhattacharya, 1997:5-7).

It is proper to say that it is not possible to use "time series" in a sector where the diversity of products is changing and enriched every day, necessitating intensive technology like mobile telephone sector (Bhattacharya, 1997:5; Stevenson, 2012:76-77). Furthermore, it is not possible to use the "time series analysis" method to calculate demand estimates for new products that have not yet been marketed(Kotler, Wong, Saunders and Armstrong, 2005; Stevenson, 2012).

Because time-based data such as sales, order, or ratings for past periods of a product newly introduced into the market will not be available yet. Even so, there will not be much meaning and prospect in terms of rapid technological development and the prediction of the demand patterns of future products of such time series in an intensified competitive environment. (Kotler, Wong, Saunders and Armstrong, 2005).

Using "time series analysis" in forecasting demand for sales, order, production, SCM and inventory management of businesses that market products featured with "short life cycles" and "high tech" such as and mobile phones can often lead to unsuccessful estimates (Lynn et al., 1999; Reiner et al., 2009; Bass et al., 2001; Kahn, 2002).

As a result of the literature review, it is evaluated that in the light of these findings, using "regression" and "machine learning" methods for demand forecasting in the mobile telephone sector will give more accurate results.

2.3.2 Use of Regression Analysis in Demand Forecasting

When the literature is examined, it is seen that increasing number of regression analysis methods are used in the research on "demand forecasting" in recent periods.For example, Businger and Read (1999) used only simple regression analysis in predicting demand for maintenance-repair parts in the US Navy, and Law and Au (1999) predicted Japanese tourists' travel demand to Hong Kong with simple regression analysis.

In the literature, there are also researches that use time series analysis and regression analysis methods together in demand forecasting. For example, Bhattacharya (1974) used linear regression and moving average methods to predict telephone demand in Australia. As a result of the research, potential phone subscription sales and order quantities were estimated on the Australian market on a quarterly and annual basis.

Carlson and Umble (1980) set the last five-year sales figures as dependent variables for five different US car models (mini, small, medium, standard, and luxury) to make demand forecasts with multiple regression analysis. The independent variables in the study were variables such as "household disposable income level," "prices varying according to automobile type," "gasoline prices in the country" and "workers in the automotive sector. "Forecasts of potential sales were made in the US market with seasonal and monthly analysis findings.

Malik and Ahmad, (1981) used time series analysis and regression analysis together to estimate the food demand in Libya according to the months and years. Kamenetzky et al. (1982) have designed a study to determine the monthly and weekly demand for ambulance services of people living in Southwest Pennsylvania according. In the study, data related to the ambulance demand data of the last year, the structure of the company providing the ambulance service and the quality of the service were analyzed by multiple regression analysis and time series analysis and forecasts were made for next week and month. As a result of the research, it was determined that the ambulance demand intensified in the last week of the month and the ambulance calls in the spring and in the fall would increase.

Huss (1985) aimed at conducting and comparing the results obtained from sales forecasts of 2, 4, 6 and 7 years using linear regression analysis, time series analysis, exponential correction method and multiple regression analysis, employing past demand forecasts and current sales data of 49 firms providing electricity distribution in the USA. It has been understood that the models are more successful in the 6 and 7-year estimates in this sense, where the predictions of the research made using more than one model are inversely proportional to time. Burger et al. (2001) used different techniques such as moving average, exponential correction and multiple regression analysis in the prediction of American tourists' travel demands to Durban.

It is seen in the literature that an increasing number of multiple regression analyses are used in recent demand forecasting studies. For example, Chu and Zhang (2003) estimated sales using linear and nonlinear regression models using monthly retail sales data from 1985-1999 from the US population.

Willemain et al., (2004) used the multiple regression models to determine quantities for service parts stored and ordered in the context of SCM and inventory management, and Zotteri et al. (2005) used the logarithmic regression model for predicting the five products' integrated claims for a chain of markets in Europe. According to the literature, it is possible to say that "multiple regression" models enable efficient demand forecasting in order to reach meaningful results in SCM, inventory and sales management in various sectors - especially in manufacturing sectors, which require advanced technology (Stevenson, 2012:107).

Moreover, when this method is used together with other demand forecasting methods, accuracy levels are increased, and it is possible to reach harmonized findings (Stevenson, 2012:107). According to findings obtained as a result of the literature review, it has been understood that the "multiple regression analysis" can be used together with the "machine learning" method in the research on demand forecasting in the mobile phone sector.

2.3.3 Use of Machine Learning Method in Demand Forecasting

In the literature, it seems that there is an extremely limited number of studies using "machine learning" methods in demand forecasts made in various sectors and for different purposes.

For example, Alon et al. (2001) analyzed estimates of integrated retail sales in the US using multiple regression in time series analysis, while testing the estimates reached with the machine learning method. Similarly, Chu and Cao (2011) seem to use new methods such as "probabilistic neural networks" (an algorithm to predict the adoption of new products) and dynamic cubic neural networks (activation function and a modification mechanism for cubic architecture).Both studies have shown that such new techniques have higher accuracy of prediction performance than traditional prediction methods.

Similarly; Amos, Turner, and White (2013) used the machine learning classifiers application as a prediction model for malware detection for Android.Faragher and Harle (2013) used machine learning to predict the location of smartphones whereas Wu and Hung (2014) used machine learning to predict malicious Android applications.Sagbas and Balli (2015) tried to predict the route of transport by using smartphone detectors and machine learning methods. Guinness (2015) used the "machine learning" approach to predict the mobility contexts of smartphone sensors.

As a result of the literature review, no research among "demand forecasting" studies conducted under SCM or inventory management, has been found within the knowledge of the researcher that employs both the artificial intelligence-assisted prediction models and the "the machine learning" method.

However, when it comes to the literature, it is stated that "Machine learning" gives very practical and precise results especially in cases where there are no previous human experiences but the estimations are made to make strategic decisions with a high level of certainty. (Dunham, 2003, Harrah, Salahi and Khalegni, 2009 Farid and Rahman, 2010, Jemili, Zaghdoud and Ahmed, 2007, Zhang and Zhu, 2010 Base and Mell, 2011, Vural and Sagioglu, 2011, Zhang et al., 2012 , Chen and Zhang, 2012, Alazab, Hobbs, Abawajy and Alazab, 2012, Sharma and Nema, 2013).

Because of machine learning, a branch of artificial intelligence in solving such problems makes successful predictions by taking advantage of the statistical and computational power to determine, the currently constrained divergence, a very intricate pattern and make a rational decision.(Michie, Spiegelhalter and Taylor, 1994, Sebastiani, 2002, Nguyen and Armitage, 2008, Bitter, Elizondo and Watson, 2010, Vural and Sagioglu, 2011, Bace and Mell, 2011, Goodwin, Dyussekeneva and Meeran2012; Gong and Guan, 2012; Koc, Mazzuchi and Sarkani, 2013; Calis, Gazdag and Yıldız, 2013; Dunder et al., 2013; Sorias, 2014; Lee et al., 2015; Amasya and Bilgin, 2015; Habibi et al., 2015; ICT, 2017).

As a result, according to the research in the literature, it is evaluated that, in the mobile telephony sector with short product life, "demand forecasting" can be performed efficiently by using "machine learning method" in sales, marketing, procurement or order estimations of a product newly introduced to the market.

2.4 METHODS USED IN DEMAND FORECASTING IN THE MOBILE TELEPHONE SECTOR

In today's rapidly growing and evolving "mobile phone industry," it is becoming increasingly important to make successful estimates in the context of increasing production, sales, marketing, ordering and customer satisfaction (Stevenson, 2012:76-77).

It is seen that the general purpose of demand forecasting in the mobile phone sector is to estimate the increase in user numbers, market share estimates, pricing forecasts based on production volume, and average revenue per user (Greene, 2009). It is also observed that cross-sectional models for estimation based on relationships between different services, or multiple regression models for similar services in different markets are frequently used in this sector (Stevenson, 2012:76-77).

However, using traditional demand forecasting in this sector is often misleading and statistically meaningless. There are several reasons for this in the literature. First of all, mobile telephony sector is a "high-tech-based production" sector. The term "high-tech market," which defines the sector, refers to newly developed and rapidly growing markets; these kinds of sectors and markets are driven by technological innovations that develop themselves. So traditional demand forecasting methods in the sector lead to ineffective results. (Decker, Gnibba, and Yukawa, 2010).

Another feature of the sector is that the mobile phones produced and sold in this sector are in the "Short sales season and products with a short lifespan" group (Subrahmanyan, 2000). Businesses that market such short-lived products, or those suppliers of supply chains, find it very difficult to predict potential sales because of the high uncertainty in demand for these products (Fildes and Kumar, 2002).

Moreover, when making sales forecasts for short-lived products with traditional forecasting methods, data for many variables are needed for accurate identification and estimation (Goodwin et al., 2012). However, in the "product life cycles," there is not a long enough time series for quite short-lived products such as mobile phones (Goodwin et al., 2012).

Another reason why traditional estimation methods in the mobile phone sector do not provide adequate and precise results is the emergence of new products and technologies constantly in this sector (Graefe and Armstrong, 2011).

Fader and Hardie (2001) described market pre-evaluation as a necessary step to avoid pre-cost decisions. Ching et al. (2010) recommend the use of forecasting models ranked as "sales index, Taylor series and diffusion models" in estimates of sales of new products. However, Mentzer and Moon (2005) state that this method is not feasible if no product market has been introduced before in the same class.

According to Qian (2012), not only is it possible to analyze consumer preferences or intentions to purchase existing products by a forecasting model that describes how the consumers product choice is related to the featured of the product, but also how consumers will react to potential changes in existing products or how to respond to new products.

In some studies in the literature, it is seen that the use of more complex nonlinear models related to the life cycle of new products is recommended (Kahn, 2002).For example, Ivanov (2009) argues that using the collective wisdom of the forecasting market in the mobile phone sector would be a handy tool in predicting demand for new products. However, according to Graefe and Armstrong (2011), it is difficult for participants to predict whom the potential customers are based on demand estimates of new products, even if they are going through an appropriate training session.

Traditional demand forecasting methods are often inadequate because of the widespread innovation in the mobile phone industry, product, competition and industry (Mahajan et al. 2000; Mead and Islam, 2006). However, in the mobile phone industry, where new products are often marketed, more predictive models need to be developed to meet fast-moving markets and short product lifetimes and demands (Berbain, Bourbonnais, Vallin, 2011).

Because the rapidly evolving mobile telephony technology affects consumers' behavior, their daily lifestyle, their marketing and their commercial activities, which makes the demand forecasts difficult. Actually, Semco Jahanbin Paul Goodwin and Sheik Meeran (2013) studied in the sale forecasting of new products in mobile phone sector. The demand forecast made within the scope of the research was made in order to determine the future production capacity. It has been found that a combination of complementary methods gives the most accurate results in estimating the production capacity.

Boese (2015) made demand forecasts to estimate the optimal prices and possible market shares of communication product groups such as mobile phones. Pricing information for each mobile device group included in the sampling and parameters for the valuable information within the mobile device group were obtained. Substituting factors were then determined for the obtained parameters to develop a substitution estimation model.

Hsi-Tse Wang and Ta-Chung Wang (2016) jointly applied the gray estimation model and the Lotka-Volterra competition model to predict the diffusion and competition analysis of mobile phone companies. As a result of the research, it was determined that the Android operating system is superior to other competitive products in terms of consumer demand, and it was determined that GM (1,1), which is a gray estimation model used in the research, made a more effective prediction for the sector companies.

Chen, Tzu, and Liang (2017) focused on SCM applications in the mobile telephony sector. In this study, sales forecasts of smartphones representing the largest shipment volume and development trend are considered as research subjects. Within the scope of the research, efficient forecasting models have been developed to detect market trends in mobile devices.However, it has not been possible to develop a forecasting model that is "easy to use, accurate and low cost" as targeted in this research, which conducted traditional demand forecasting methods.

In this research which the primary objective is to develop a “demand forecasting model” that will provide the necessary sales and order optimization in SCM and inventory management in the mobile phone sector, it is understood based on the findings of the studies in the literature that employing “multiple regression “ and “machine learning” will be appropriate.

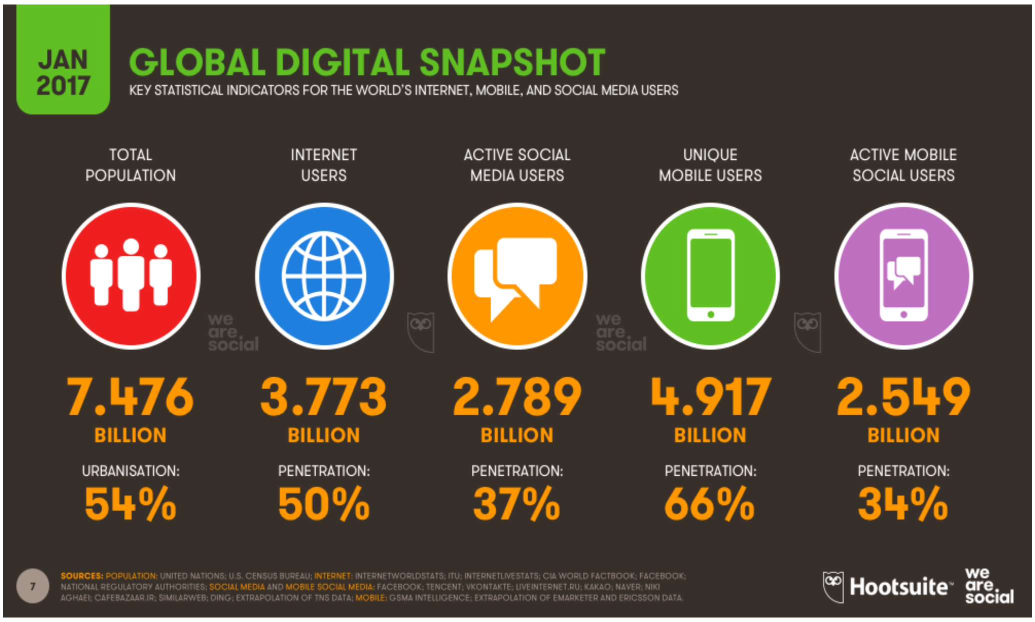
2.5 THE GLOBAL DEVELOPMENTS OF MOBİLE PHONE SECTOR

Today, the frequency of use of internet, computer and mobile phone technologies has increased at global level and these increases are continuing day by day - even every second. Such increases are undoubtedly leading to the growth of the mobile phone market both in the world and in Turkey, and thus demand forecasts are changing day by day. This makes demand and order forecasting difficult in the sector.

The Digital Global Overview (DGO), a digitalization report of the World, which is published annually by "We Are Social" a marketing agency and by the "Hootsuite Institute", provides important information to the researchers about the internet, mobile and social media user statistics in the world.

The latest data collected from 238 countries were analyzed and published in this report in January 2017 and updated information, statistics and trends related to the development of internet and digital in the globalizing world are presented in the graphics. (DGO, 2017:3-4).

Figure 2.1: Number of Internet and Social Media Users in the World



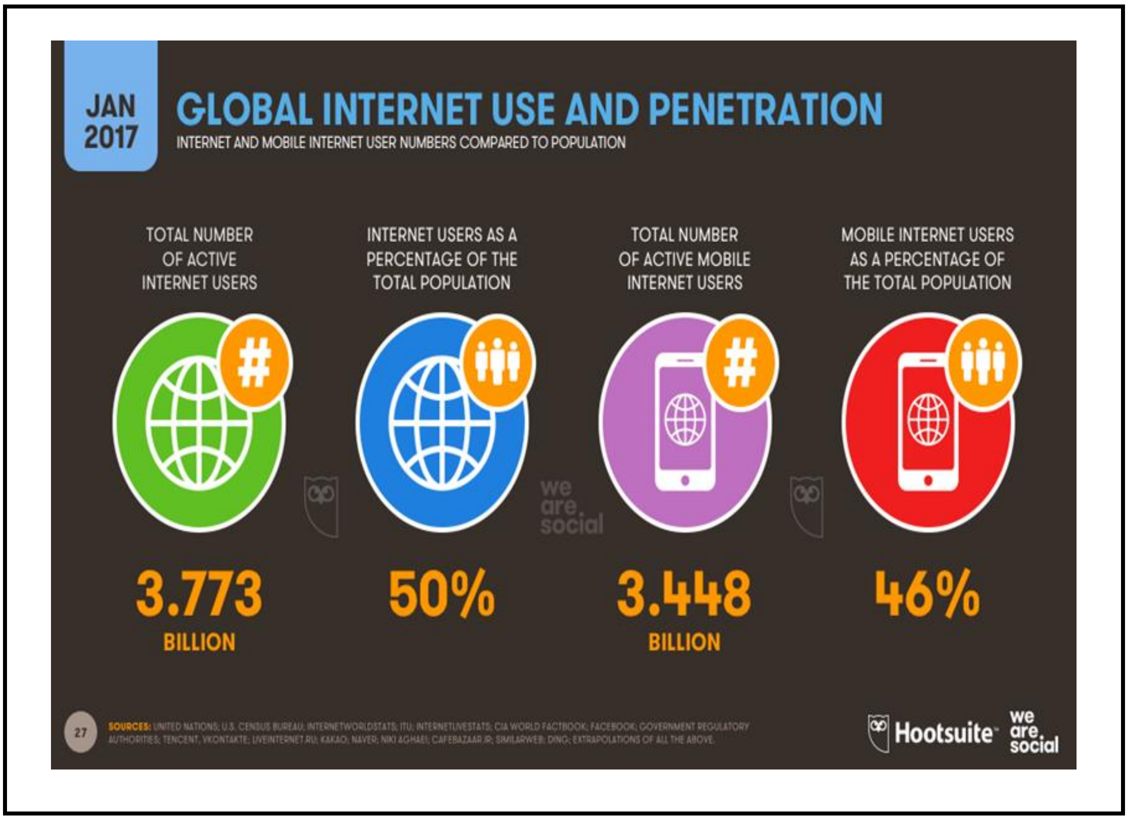
Source: https://wearesocial.com/special-reports/digital-in-2017-global-overview

As we have seen above, in the 2017 report, which the world's population calculated as 7 billion 476 million, a total of 3 billion 773 million of this population are internet users and 2 billion 789 million of them are active social media users.

What is important is that by 2017 there are around 4 billion 917 million mobile phone users (66 percent of the world population) worldwide. In addition, approximately 2 billion 560 million (34 percent of the world's population) are entering social media via mobile / smartphones.

Mobile phones, however, have gained popularity in 2007 when Appple ran the Iphone market. When it comes to 2017, approximately 5 billion people have mobile phones and it shows the size and volume of this sector.

Figure 2.2: Number of Internet Users and its Ratio to the World Population

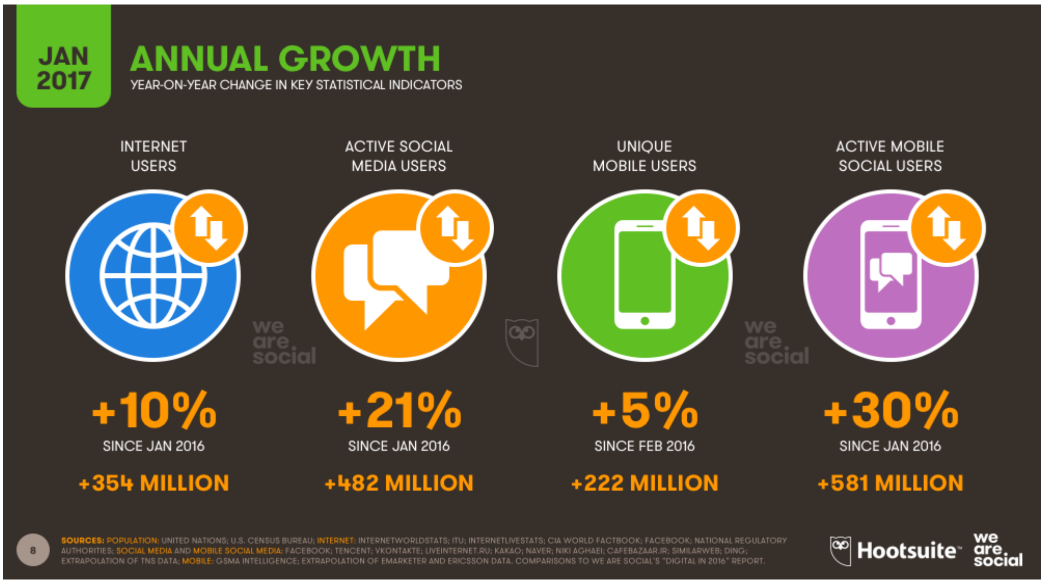


Source: https://wearesocial.com/special-reports/digital-in-2017-global-overview

As it can be seen, there are 3 billion 773 million people (50 percent of the total) of the 7 billion 476 million people living in the world by 2017 have internet connection and 3 billion 448 million of them are connected to the internet via mobile/smart phone (46 percent).

The findings, which show that 2017 will be an important milestone in Internet usage, once again reveal the rapid increase in mobile usage. How big the development of Internet is, which in 1994 alone has only 25 million users in 110 countries but has reached almost 4 billion users by 2017, 54 percent of the world's population. The fact that they have only been in existence for 23 years is a fact that demonstrates the speed of the digital revolution in the global level. This indicates that about 18 people attended the Internet for one second.

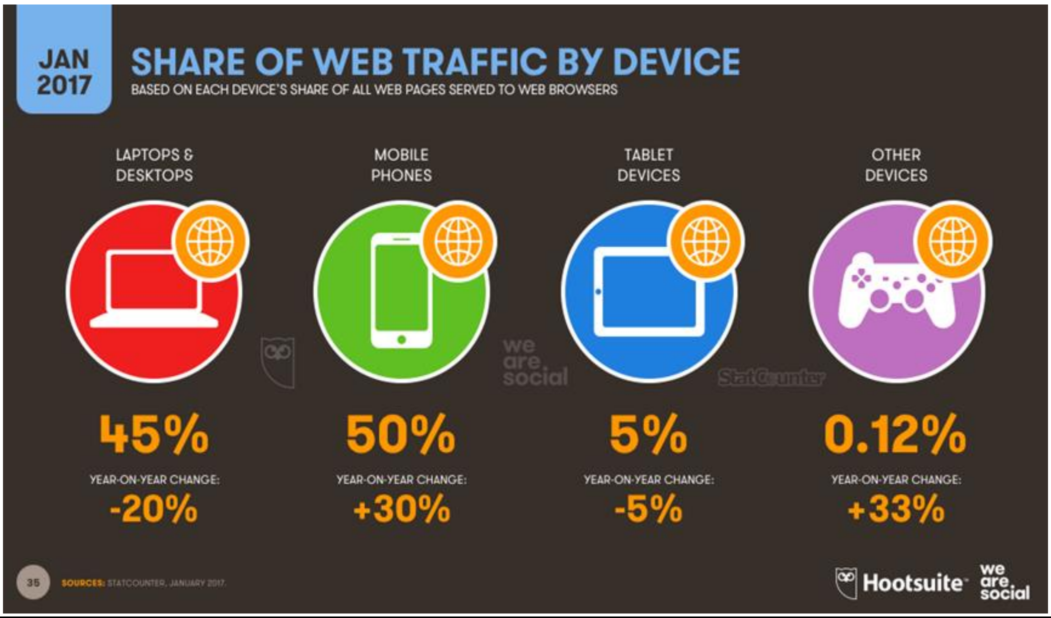
Figure 2.3: Increases in the Number of Internet-Social Media Users in the World (2016-2017)



Source: https://wearesocial.com/special-reports/digital-in-2017-global-overview

As seen figure, compared to the figures in 2016, it is seen that by 2017, the number of Internet users increased by 10 percent (354 million people); 21 percent of active social media users (482 million people) and 30 percent (581 million people) of mobile/smartphone social media users increased.

Figure 2.4: Share of Web Traffic by Device (2016-2017)

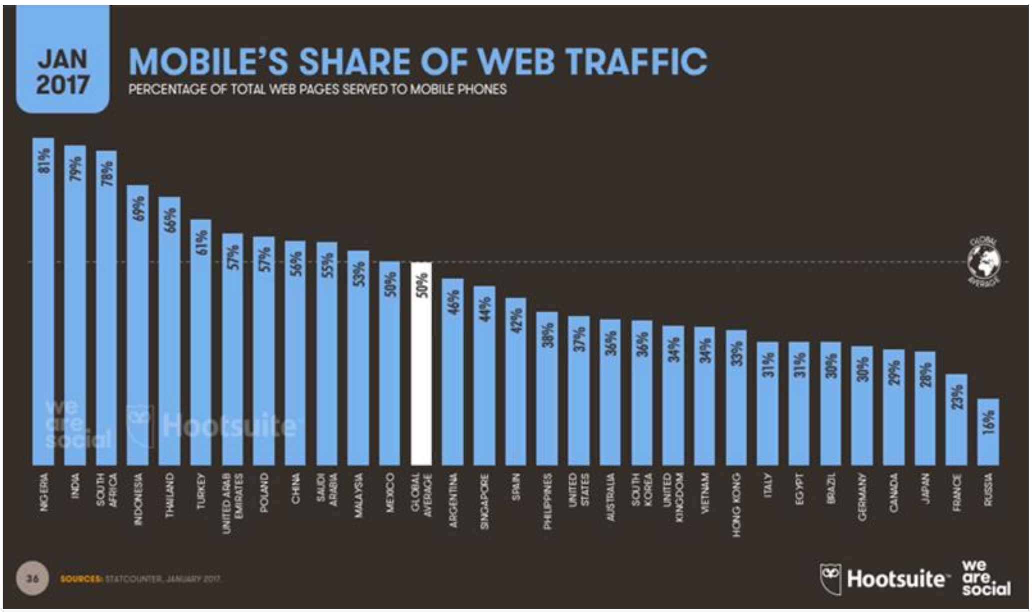


Source: https://wearesocial.com/special-reports/digital-in-2017-global-overview

As it can be seen in the figure above, worldwide usage of laptops and PCs as a means of connecting internets increased by 45 percent compared to 2016, while usage of mobile phones for the same purpose increased by 50 percent.

Moreover, while the increase in the number of mobile phones due to the connection to the internet has increased by 30 percent compared to the previous year, the increase in the number of online connections via PC and laptop has decreased by 20 percent compared to the previous year.

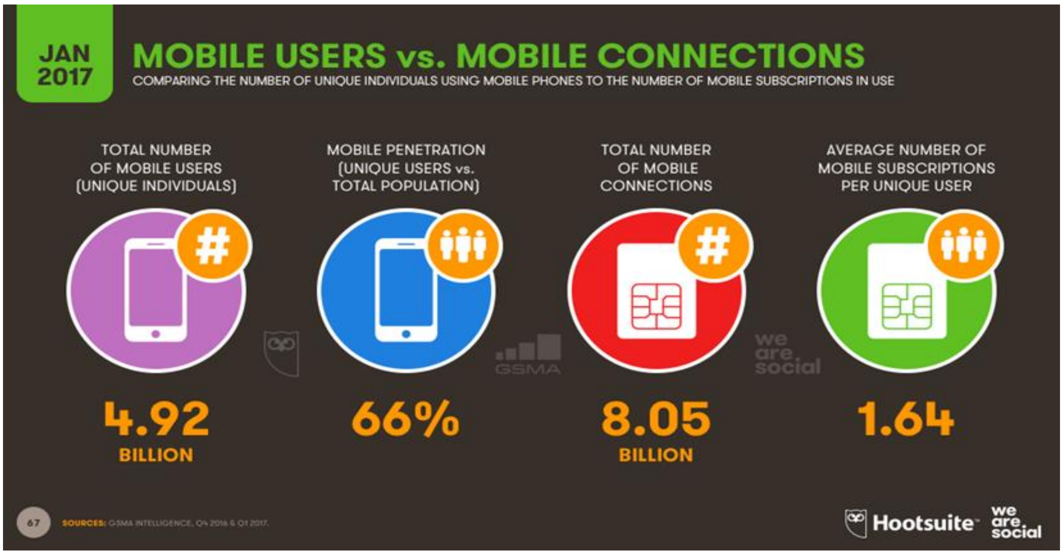
Figure 2.5: Mobile's Share of Web Traffic (2016-2017)



Source: https://wearesocial.com/special-reports/digital-in-2017-global-overview

As seen in the chart above, while 50 percent of the world population is connected to the internet by mobile phones, this ratio is 61 percent in Turkey.

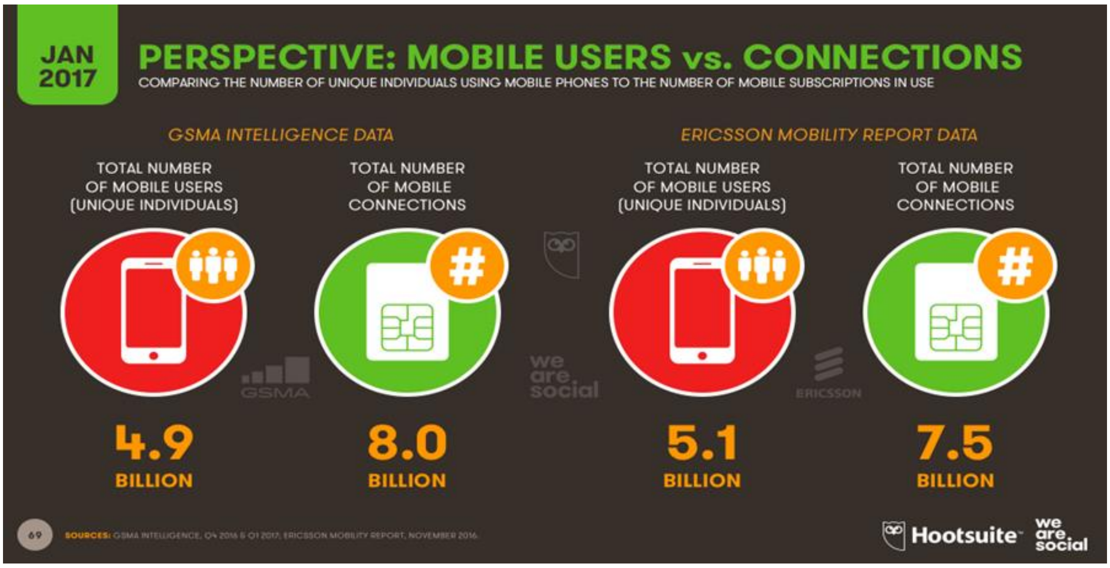
Figure 2.6: The Comparison of Mobile User of Mobile Connections



Source: https://wearesocial.com/special-reports/digital-in-2017-global-overview

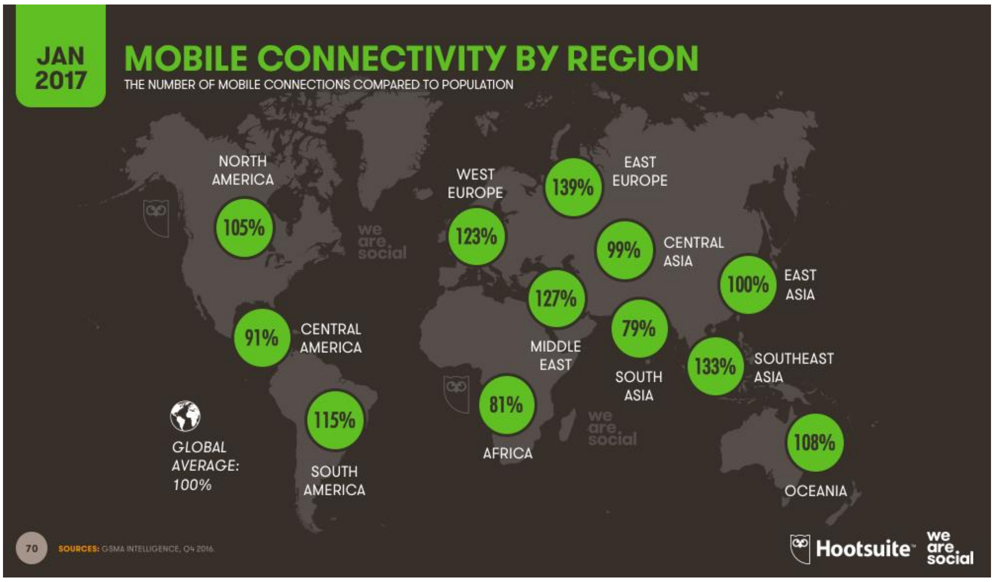
More than half of the world now uses at least one smartphone. Nearly, two-thirds of the world's population owns at least one mobile phone. More than half of the web traffic worldwide now comes from a mobile phone.

Figure 2.7: The Perspective of Mobile User Connections



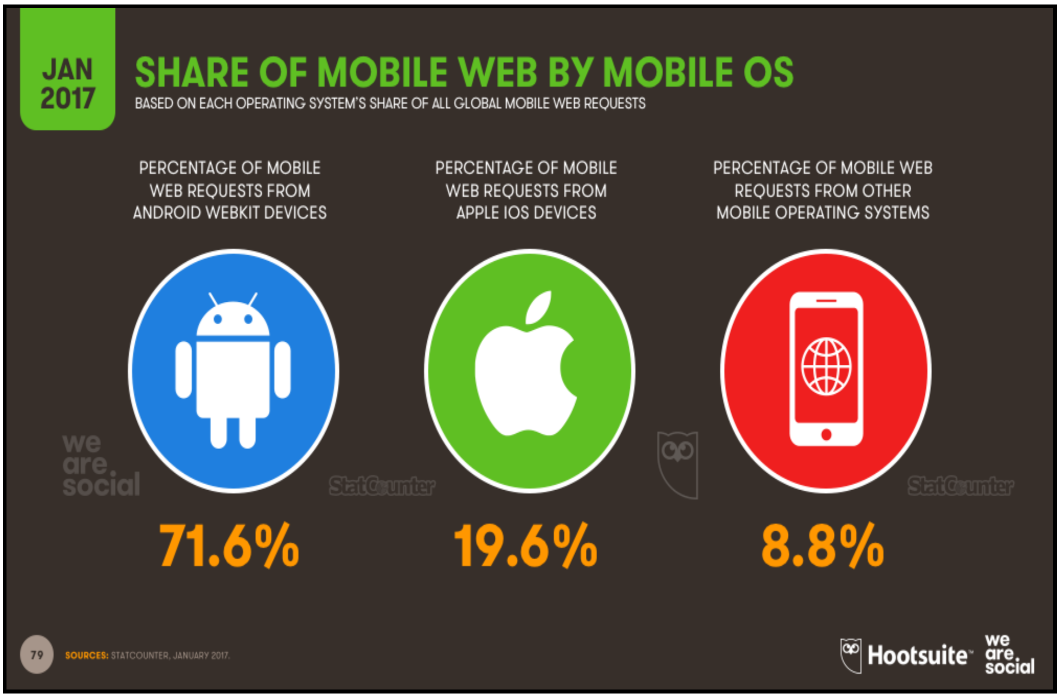
Source: https://wearesocial.com/special-reports/digital-in-2017-global-overview

Figure 2.8: Mobile Connectivity by Region



Source: https://wearesocial.com/special-reports/digital-in-2017-global-overview

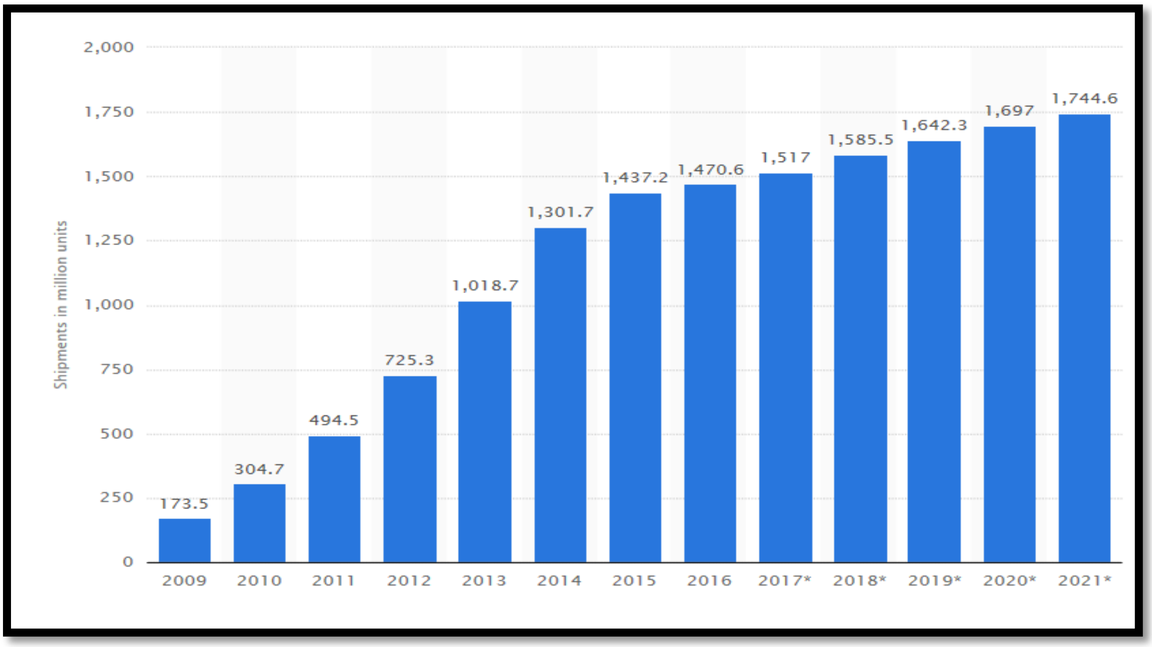
Figure 2.9: Share of Mobile Web by Mobile Operation Systems



Source: https://wearesocial.com/special-reports/digital-in-2017-global-overview

In fact, when the sales figures of mobile phones are examined, it will be seen that the usage increases experienced in mobile phone sector are similar at global level. In this sense, the chart below shows the estimated total shipment quantities from 2017 to 2021 with the total shipment figures of smart mobile phones worldwide from 2009 to 2016, as shown in the table above:

Figure 2.10: Global Smartphone Shipments Forecast From 2010 to 2021 (In Million Units)



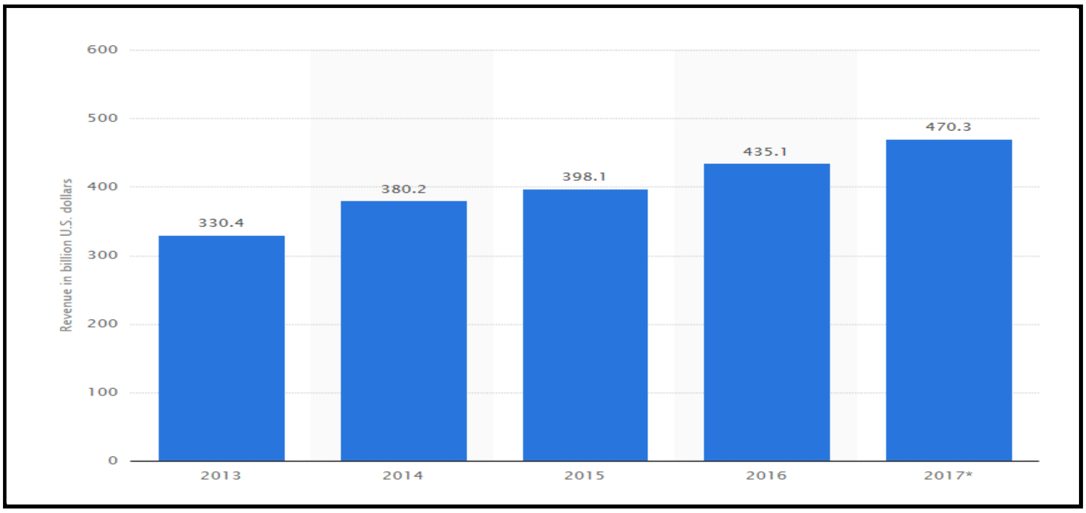
Source: https://wearesocial.com/special-reports/digital-in-2017-global-overview

As seen in the graph, according to the demands of the global markets, 173.5 million pieces of smartphones were shipped globally in 2009, with a steady growth and this figure reached 1 billion and half billion in 2016.

Although, according to 2021 forecasting this number is estimated to reach 1 billion 744 million as a requirement of the market demand, developments in the sector and in the market indicate that this number will increase much more.

Indeed, global revenue from smartphone sales from 2013 to 2017 (in billion US dollars) shows global revenue from smartphone sales between 2013 and 2017. According to the source, global revenue from smartphone sales in 2016 was $ 435.1 billion:

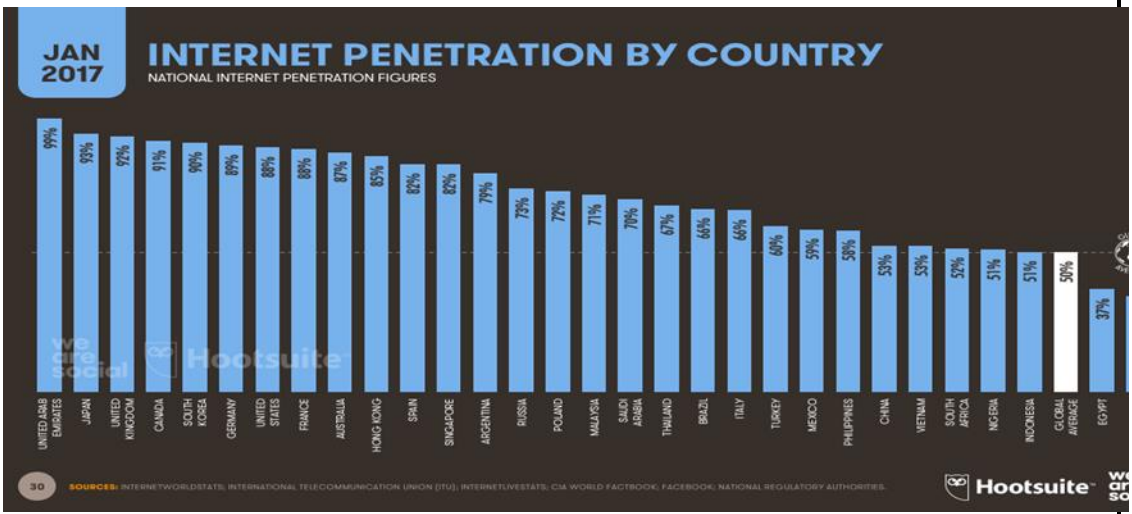
Figure 2.11: Global Revenue From Smartphone Sales From 2013 to 2017 (In Billion US Dollars)



Source: https://wearesocial.com/special-reports/digital-in-2017-global-overview

On the other hand, when the frequencies and rates of internet and mobile phone use in Turkey are examined; just as it is in the world, it is seen that the number of users entering the country with mobile / smart mobile phones in Turkey is almost doubled every year.As a matter of fact, statistics and data on internet and mobile phone usage habits change in Turkey are included in the "Digital in 2017 Global Overview" report. For example, the frequency of Internet usage in Turkey by 2017 is reflected in the report as follows:

Figure 2.12: Internet Usage Rates by Population, Countries (2017)



Source: https://wearesocial.com/special-reports/digital-in-2017-global-overview.

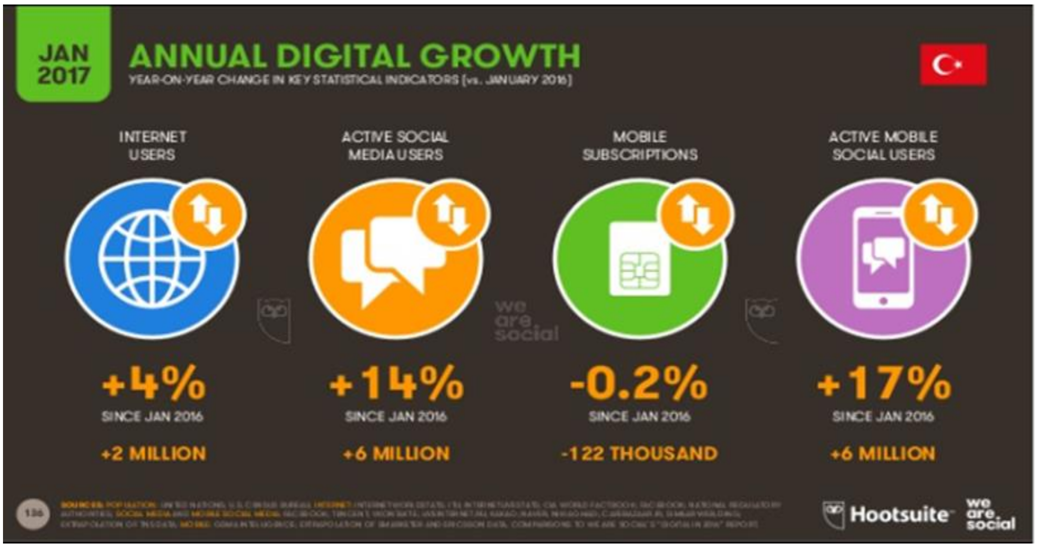
As you can see in the chart above, 50 percent of the world population has internet access by 2017. This rate was 60 percent in Turkey. Turkey has passed the world average by 10 percent.

Figure 2.12: Turkey's Internet and Social Media Usage Statistics

Source: https://wearesocial.com/special-reports/digital-in-2017-global-overview

When we look at Turkey's Internet and Social Media Usage Statistics, 48 million people constituting 60 percent of the population in Turkey are connected to the internet. The number of mobile users in Turkey is 71 million, while the number of users connected to social media via mobile phone is 42 million.

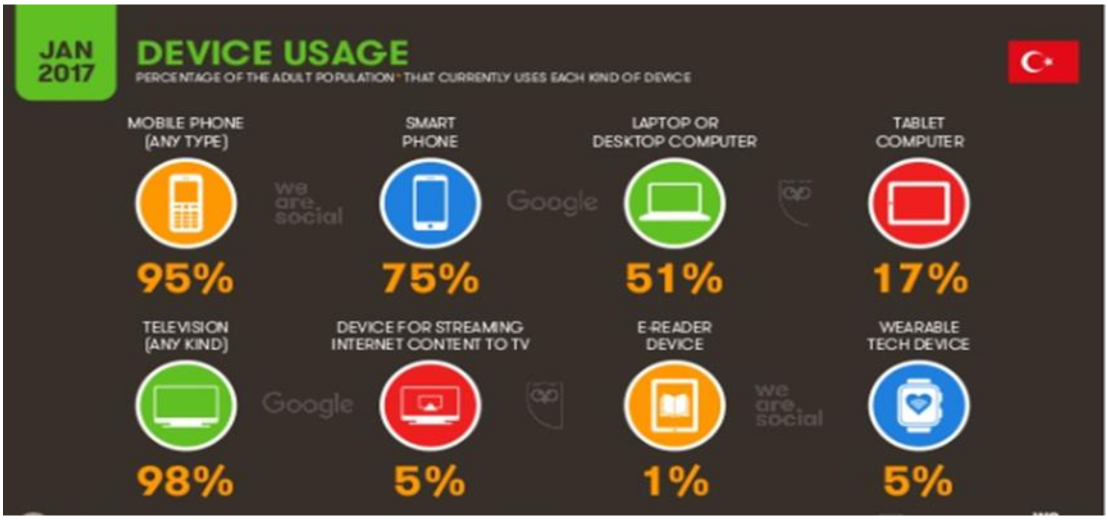
Figure 2.13: Annual Digital Growth in Turkey



Source: https://wearesocial.com/special-reports/digital-in-2017-global-overview

When we look at digital growth, we see that in Turkey since January 2016, the number of internet users has risen from 4 percent to 2 million and the number of active social media users has increased by 14 percent to 6 million. In our country, the number of people using social media via mobile has increased by 17 percent in the last one year.

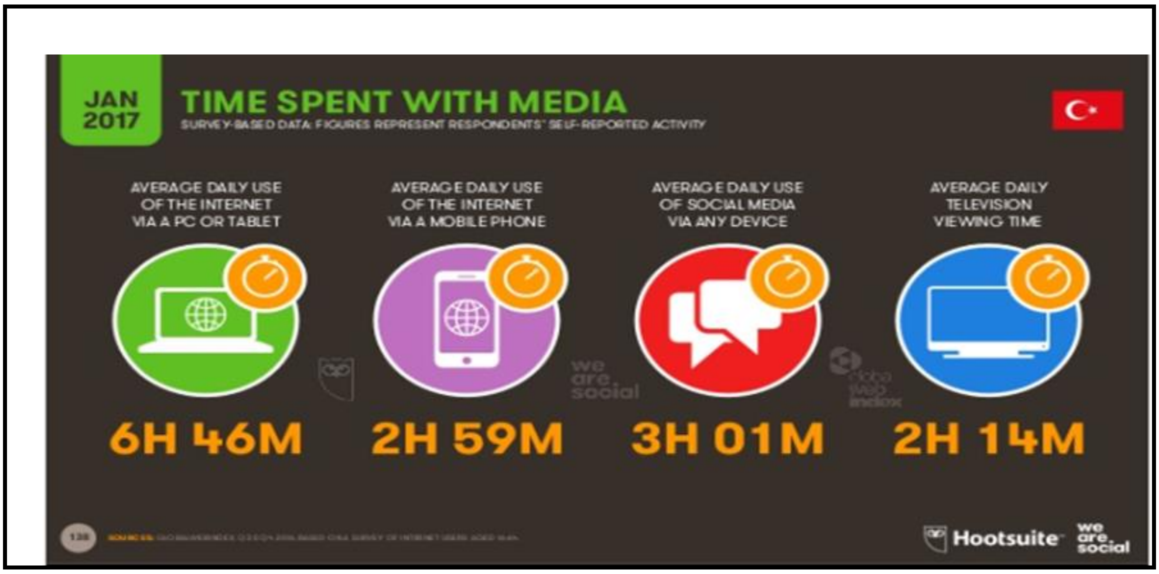
Figure 2.14: Device Usage in Turkey



Source: https://wearesocial.com/special-reports/digital-in-2017-global-overview

According to the report, 95 percent of device users in Turkey own mobile phones and 75 percent use smartphones. While the use of laptops and desktops is 51 percent, TV is still an important part of our lives with 98 percent.

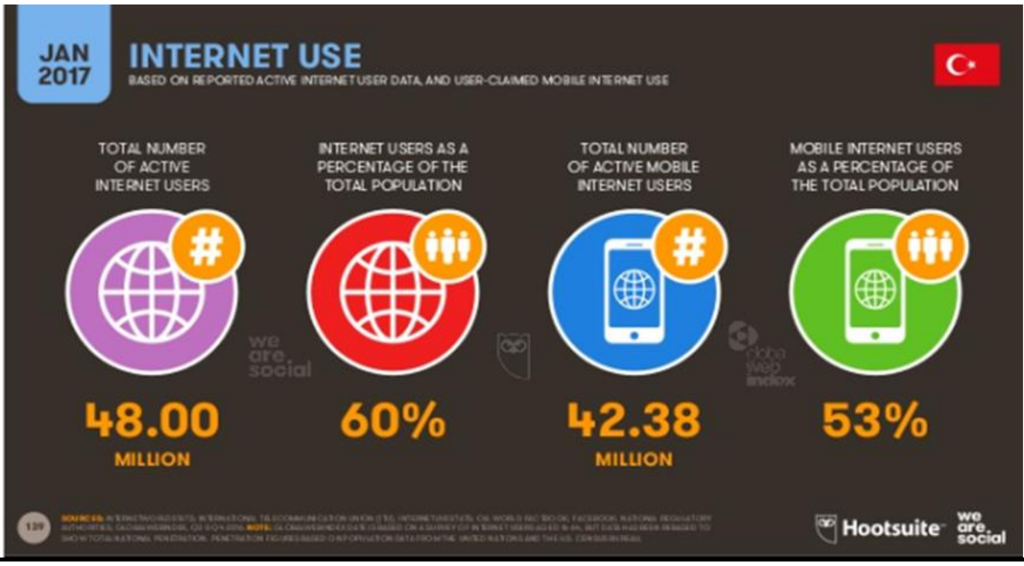
Figure 2.15: Time Spent with Media



Source: https://wearesocial.com/special-reports/digital-in-2017-global-overview

Users spend an average of 7 hours a day in front of a computer, 3 hours a day on the phone, and 3 hours on social media platforms. The average time spent on TV is 2 hours.

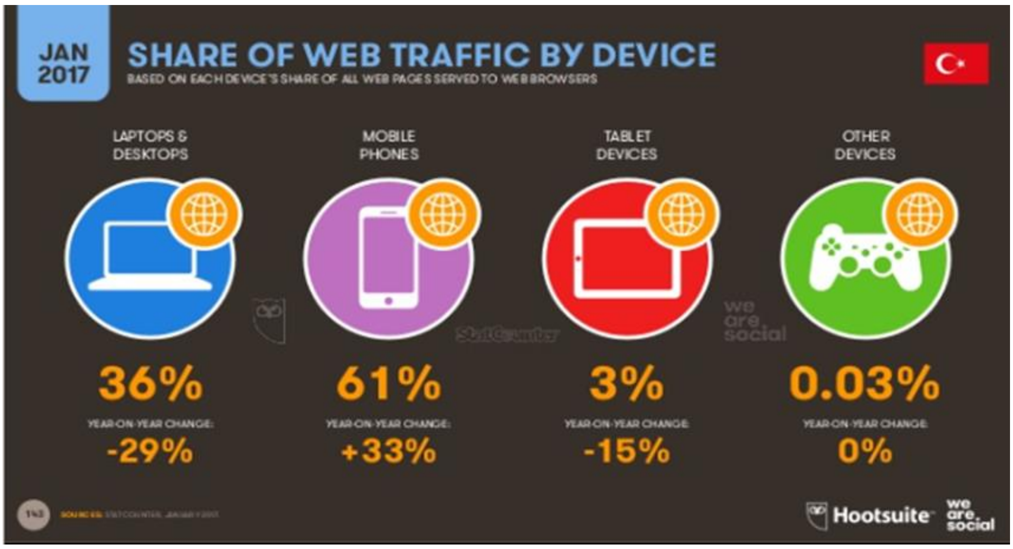
Figure 2.16: Internet Use in Turkey



Source: *https://wearesocial.com/special-reports/digital-in-2017-global-overview*

According to Turkey's web traffic; visits by computer dropped by 29 percent to 36 percent, and mobile traffic increased by 33 percent to 61 percent. This situation once again reveals the importance of mobile in terms of web traffic in Turkey.

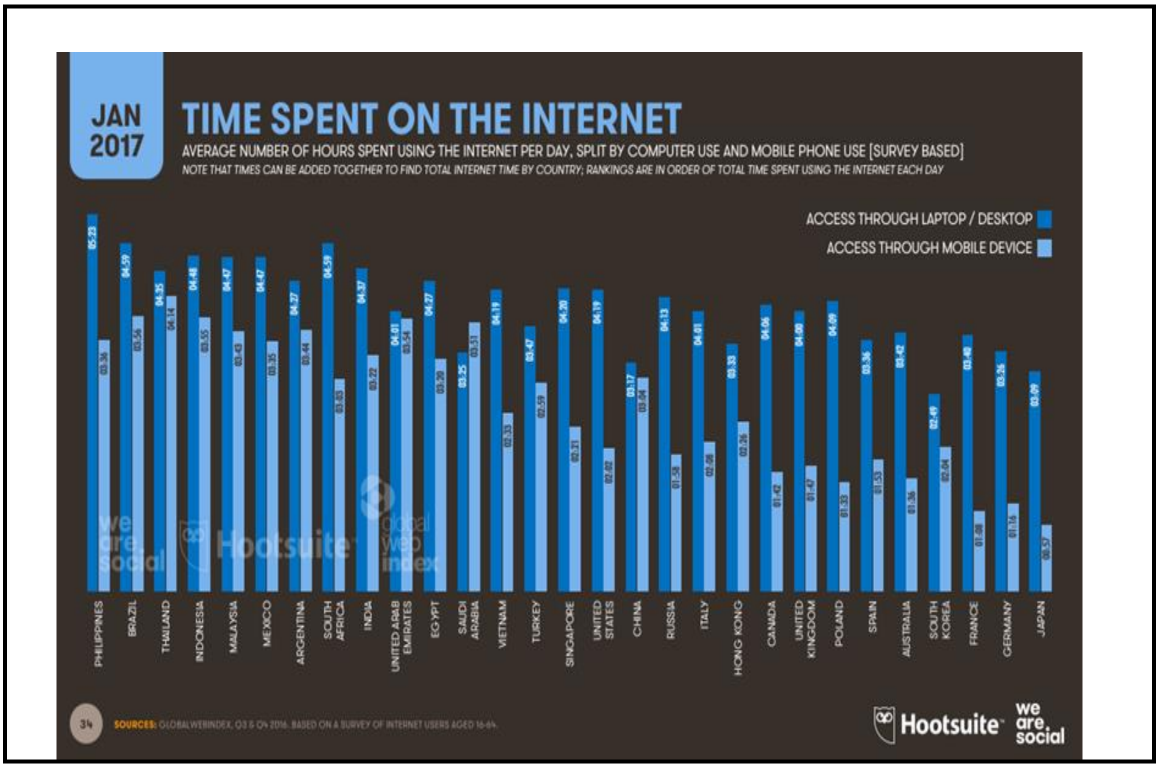
Figure 2.17: Share of Web Traffic by Device



Source: *https://wearesocial.com/special-reports/digital-in-2017-global-overview*

In parallel with this, the following graph shows the average time spent by people living in Turkey on the internet in one day with computers and mobile devices:

Figure 2.18: Countries' Internet Usage Times



Source: https://wearesocial.com/special-reports/digital-in-2017-global-overview.

As seen in the graph, Turkish people spend about 2 hours 59 minutes on the internet via mobile / smart phone. When the data of the country are compared, it is noteworthy that the time spent on the internet with mobile technologies is much higher in Turkey than in other countries. It is possible to say that this difference is due to the fact that much more time is spent in social media with mobile phones in Turkey.

Figure 2.19: Weekly Online Activities by Device

Source: https://wearesocial.com/special-reports/digital-in-2017-global-overview

As seen above, According to the evaluation of frequency of weekly internet connections in Turkey, it is seen that mobile-smart phones are used by 47 percent in the control of the mails and 79 percent in the visits to social networking sites. It is understood that mobile/smart phones are used by 71 percent for research and searching internets, 41 percent for researching a product, and 29 percent for music listening intentions. Undoubtedly, these ratios are quite high for the same purposes in terms of computer and tablet usage rates.

As a result, the mobile phone sector is highly dynamic, both in the world and in Turkey, and it is an innovative sector supported by high technology, where demand is changing every day according to new models and competition is intense. For this reason, all businesses that want to survive in the sector have to make "demand forecasts" precisely within the context of inventory, sales and order management in order to stand in this sector and to maintain its competitive advantage.

3. DATA AND METHODOLOGY

3.1 AIMS AND OBJECTIVES OF THE RESEARCH

The main purpose of the study is to determine the effective demand forecasting methodology to provide full-time optimization of the mobile phone industry inventory management processes.

The objectives of the study are: to increase the accuracy of estimates made using qualitative estimation methods and quantitative estimation methods which are frequently used in the mobile telephone industry. To reduce the difference (delta) between "forecasting demand" and "actual sales" made in such traditional methods in the sector. What matters most is to suggest the more efficient demand forecasting method for the mobile phone industry.

In addition to all these, the results of the study can contribute to making more reliable sales forecasts for the future. It is also assessed that the results may contribute to the approximate date of the decline in sales figures, depending on the early sales data.

3.2 RESEARCH METHOD

Qualitative and quantitative research methods are used together in the study. In the scope of qualitative research, similar previous researches on the basic concept and topic of the research have been collected and examined. Thus, the theoretical frame and method of the thesis have been tried to be determined.

In the scope of the study, quantitative research method was used to analyze collected quantitative data of "A" telephone model and "B" telephone model.[1] In this context, quantitative research data collected on dependent variables subject to "demand forecasting"; was analyzed by employing the “Negative Binomial Regression analysis”, "time series analysis" and "machine learning" method.

Thus, the quantitative findings obtained by using these methods mentioned in the literature as quantitative demand forecasting method have been tried to be interpreted in

[1] Selected mobile phone brands and models are coded us the letters “A, B, C…” in this study, which are the sample of this research.

the light of qualitative information and findings obtained as a result of the literature review.

3.3 RESEARCH DATA AND VARIABLES

In this thesis, the data related to sale, repair and figures belong to other rivals of two mobile phone models selected as an example produced by a domestic technology and cell phone company is examined.

The survey data covers the period from April 2016 to November 2017. Within this time period, quantitative data about "SIM activation" and the other variables that are considered to affect sales directly or indirectly were collected.

The period (daily, weekly, and monthly) and the values (number, percents, and amount) of the collected research data in the Excel format are shown in the following table:

Table 3.1: Values Related to the Independent Variables of the Study

Variables	Period	min	max	Value
S.V. of (A) Mobile Phone Model	Weekly	1	19536	Volume
Sim Activation of (A) Mobile Phone Model	Weekly	49	5058	Volume
Return to Service of (A) Mobile Phone Model	Weekly	9	2279	Volume
Average Weekly Exchange Rate	Weekly	2,8279	3,814	Ratio percent
Firstday of month stock (A) Mobile Phone Model	Daily	10	25897	Volume
S.V. of (A) Mobile Phone Model	Monthly	4500	47400	Volume
S.P. of (A) Mobile Phone Model	Monthly	1014,1	1238,7	Price (TL)
S.V. of (CB1) Mobile Phone Model	Monthly	12300	89200	Volume
S.P. of (CB1) Mobile Phone Model for P. M.	Monthly	1529	1658	Price (TL)
S.V. of (CB2) Mobile Phone Model for P. M.	Monthly	4000	13900	Volume
S.P. of (CB2) Mobile Phone Model for P. M.	Monthly	1516	1709	Price (TL)
S.V. of (CB3) Mobile Phone Model for P. M.	Monthly	6000	13600	Volume
S.P. of (CB3) Mobile Phone Model for P. M.	Monthly	1239	1295	Price (TL)
S.V. of (CB4) Mobile Phone Model or P. M.	Monthly	1000	4000	Volume
S.P. of (CB4) Mobile Phone Model for P. M.	Monthly	1287	1386	Price (TL)
S.V. of (CB5) Mobile Phone Model for P. M.	Monthly	6000	15800	Volume
S.P. of (CB5) Mobile Phone Model for P. M.	Monthly	881	975	Price (TL)
S.V. of (CB6) Mobile Phone Model for P. M.	Monthly	25100	135200	Volume
S.P. of (CB6) Mobile Phone Model for P. M.	Monthly	1183,5	1604,9	Price (TL)
S.V. of (CB7) Mobile Phone Model for P. M.	Monthly	6000	142600	Volume
S.P. of (CB7) Mobile Phone Model for P. M.	Monthly	1260	1360	Price (TL)
S.V. of (CB8) Mobile Phone Model for P. M.	Monthly	9700	31000	Volume
S.P. of (CB8) Mobile Phone Model for P. M.	Monthly	1172	1345	Price (TL)
S.V. of (CB9) Mobile Phone Model for P. M.	Monthly	17200	87300	Volume
S.P. of (CB9) Mobile Phone Model for P. M.	Monthly	993,9	1257,5	Price (TL)
S.V. of (CB10) Mobile Phone Model for P. M.	Monthly	1000	17700	Volume
S.P. of (CB10) Mobile Phone Model for P. M.	Monthly	1065	1291	Price (TL)
S.V. of (CB11) Mobile Phone Model for P. M.	Monthly	2200	22100	Volume
S.P. of (CB11) Mobile Phone Model for P. M.	Monthly	915	969	Price (TL)

**Descriptions: S.V.= Sales volume; S.P.= Sales price; P.M.= Previous month; P.M.= Previous week; (D) = A research company; (A) = Selected mobile phone model in this research (market driven mobile phone model); (B)=Selected mobile phone model in this research (new model to be marketed); (CB)=Competative brand; TL=TRY=Turkish lira.*

Within the scope of the research, there are two telephone models (dependent variables) that are subject to demand forecasting: The first is the "A" phone model and the second is the "B" phone model.

The weekly and monthly data related to sales, repair, stock and Sim activation for the years 2016-2017 were collected for these two different phone models subject to demand forecasting. As the data is subject to trade secret nature, the investigator collects this data with special permission from the related firm regarding the physical method.

In addition to these data, the sales price and sales volume of competing companies which produced mobile phones at the same level as the two models were collected for the research from the (D) named distributor company.

The collected research data were first grouped by the time periods they belonged to, and then loaded into the programs to be analyzed.

3.4 METHODS USED IN THE ANALYSIS OF RESEARCH DATA

The data for the (A) phone model and the (B) phone model were included in the analysis in three stages.

In the first stage, Negative Binomial Regression Analysis is employed to analyze the data. In the second phase of the analysis, "demand forecasts" were made in six different ways according to the "time series analysis" method. In the third and final phase of the analysis, "machine learning" method was used to try to determine which algorithm should be used in predicting demand for telephones.

Under the following headings, a brief description of these three methods was first made in the literature. Then we briefly explain why and how these methods are used.

3.4.1 Time Series Analysis Method

Time series analysis method is employed to determine the demand forecast for (A) and (B) phone model.

"Simple moving average", "Weighted Moving Average" (3 periods), "Single Exponential Smoothing", "Trend Adjusted", "Exponential Smoothing", "Trend and Seasonal Effects" and "Linear Trend" time series methods are used to estimate demand for each phone separately. The "excel" application of the Office 2016 program was used in the time series analysis according to the formulas calculated above.

The methods used in the time series analyzes are based on the following formulas and calculations:

3.4.1.1 Simple Moving Average

The Simple Moving Average will take the last several data points and average them to forecast the next period. The number of data points (or periods) selected is set by the value in the Periods cell:

Simple Moving Average

F_t = Forecast for period t (or the coming period)

p = Number of periods to be averaged

A_{t-1} = Actual demand in period t - 1 (or the previous period)

$$F_t = \frac{A_{t-1} + A_{t-2} + A_{t-3} + \dots + A_{t-p}}{p}$$

Mean Absolute Deviation (MAD)

t = Period number

A = Actual demand for the period

F = Forecast demand for the period

n = Total number of periods

$$MAD = \frac{\sum_{t=1}^{n} |A_t - F_t|}{n}$$

Mean Square Error (MSE)

$$MSE = \frac{\sum_{t=1}^{n} (A_t - F_t)^2}{n - 1}$$

3.4.1.2 Single Exponential Smoothing

The problem with the previous two methods, *Simple Moving Average* and *Weighted Moving Average* is that a large amount of historical data is required. With *Single Exponential Smoothing* the oldest piece of data is eliminated once a new piece has been added.

The forecast is calculated by using the previous forecast, as well as the previous actual value with a weighting or smoothing factor, alpha. Alpha can never to be greater than 1 and higher values of alpha put more weight on the most recent periods. Note on the equations below the similarity to the 3 period weighted moving average.

Simple Exponential Smoothing

F_t = Forecast for period t (or the coming period)

F_{t-1} = Forecast for period t - 1 (or the previous period)

A_{t-1} = Actual demand in period t - 1 (or the previous period)

α = Smoothing constant

$$F_t = \alpha * A_{t-1} + (1-\alpha) * F_{t-1}$$

and

$$F_{t-1} = \alpha * A_{t-2} + (1-\alpha) * F_{t-2}$$

substituting F_{t-1} into the equation for F_t

$$F_t = \alpha * A_{t-1} + (1-\alpha) * [\alpha * A_{t-2} + (1-\alpha) * F_{t-2}]$$

substituting F_{t-2} into the equation for F_t

$$F_t = \alpha * A_{t-1} + (1-\alpha) * [\alpha * A_{t-2} + (1-\alpha) * \{\alpha * A_{t-3} + (1-\alpha) * F_{t-3}\}]$$

simplifying

$$F_t = \alpha * A_{t-1} + [(1-\alpha) * \alpha] * A_{t-2} + [(1-\alpha) * (1-\alpha) * \alpha] * A_{t-3} + (1-\alpha)^3 * F_{t-3}$$

3.4.1.3 Weighted Moving Average (3 period)

As opposed to the Simple Moving Average which gives equal weight to each of the preceding values, the 3-period Weighted Moving Average allows you to give a higher or lower weight to each of the three previous periods. The number of periods is fixed at 3, and the sum of the weights must equal 1. If all the weights are equal (for the 3-period 0.33) this is the same as a 3 period moving average. A 2-period, 4-period or n-period weighted moving average would follow the same logic.

3-Period Weighted Moving Average

F_t = Forecast for period t (or the coming period)

A_{t-1} = Actual demand in period t - 1 (or the previous period)

w = Weight

$$F_t = w_1 A_{t-1} + w_2 A_{t-2} + w_3 A_{t-3}$$

$$1 = w_1 + w_2 + w_3$$

3.4.1.4. Trend Adjusted Exponential Smoothing

Single Exponential Smoothing assumes that the data fluctuate around a reasonably stable mean (no trend or consistent pattern of growth or decline). If the data contains a trend, the *Trend Adjusted Exponential Smoothing* model should be used.

Trend Adjusted Exponential Smoothing works much like simple smoothing except that two components must be updated each period: level and trend. The level is a smoothed estimate of the value of the data at the end of each period. The trend is a smoothed estimate of average growth at the end of each period. Again, the weighting or smoothing factors, alpha and delta can never exceed 1 and higher values put more weight on more recent time periods.

$$
\begin{aligned}
&F_t = \text{The exponentially smoothed forecast for period t}\\
&T_t = \text{The exponentially smoothed trend for period t}\\
&FIT_t = \text{The forecast including trend for period t}\\
&FIT_{t-1} = \text{The forecast including trend made for the prior period}\\
&A_{t-1} = \text{The actual demand for the prior period}\\
&\alpha = \text{Smoothing constant alpha}\\
&\delta = \text{Smoothing constant delta}\\
&FIT_t = F_t + T_t\\
&F_t = FIT_{t-1} + \alpha(A_{t-1} - FIT_{t-1})\\
&T_t = T_{t-1} + \delta(F_{t-1} - FIT_{t-1})
\end{aligned}
$$

3.4.1.5 Trend and Seasonal Effects

The *Trend and Seasonal* forecasting model is an extension of the *Trend Adjusted Exponential Smoothing* model. In addition to a trend, the model also adds a smoothed adjustment for seasonality. This template is a quarterly model, where the number of seasons is set to 4. There are three smoothing constants associated with this model. Alpha is the smoothing constant for the basic level, delta smoothes the trend, and gamma smoothes the seasonal index. Again, the weighting or smoothing factors, alpha, delta and gamma can never exceed 1 and higher values put more weight on more recent time periods:

$$
\begin{aligned}
L_t &= \frac{\alpha \cdot A_t}{S_{t-4}} + (1-\alpha)(L_{t-1} + T_{t-1})\\
T_t &= \delta(L_t - L_{t-1}) + (1-\delta) \cdot T_{t-1}\\
S_t &= \gamma \frac{A_t}{L_t} + (1-\gamma) \cdot S_{t-1}\\
F_t &= (L_{t-1} + T_{t-1}) \cdot S_{t-4}
\end{aligned}
$$

Winter's Model with Trend and Seasonal Effects

F_t = Forecast for current period

L_t = Current level value

L_{t-1} = Level value from previous period

T_t = Current trend value

T_{t-1} = Trend value from previous period

S_t = Current seasonal value

S_{t-1} = Seasonal value from previous period

S_{t-4} = Seasonal value from previous season (1 year ago = 4 periods)

A_t = Current demand (time t)

α = Smoothing constant alpha

δ = Smoothing constant delta

γ = Smoothing constant gamma

3.4.1.6. Linear Trend

The *Linear Trend* method can be used if the data contains a trend (consistent pattern of growth or decline). The forecasts are calculated using least squares regression to fit a straight line to the data. This line can be extrapolated into the future to obtain the forecast:

F_t = Forecast for period t

b = Y intercept

m = Slope

t = Time period of interest ($t = 1$ for the first time period)

$$F_t = mt + b$$

To find m and b

A = Actual demand

$\overline{A}$ = Average of all actual demands

t = Time period

$\bar{t}$ = Average of time periods

$$m = \frac{\sum (t - \bar{t})(A - \overline{A})}{\sum (t - \bar{t})^2}$$

$$b = \overline{A} - m\bar{t}$$

3.4.2 Negative Binomial Regression (NBR) Analysis Method

Negative binomial regression (NBR) is similar to regular multiple regression except that the dependent (Y) variable is an observed count that follows the negative binomial distribution. Thus, the possible values of Y are the nonnegative integers: 0, 1, 2, 3, and so on.

Most of the regression models are based on an underlying probability distribution function. Namely, the Poisson regression model has a Poisson probability distribution function, logistic regression model has the binomial probability distribution function and ordinary least square regression model has Gaussian probability distribution function.

Likewise, the negative binomial regression is derived from a Poisson-gamma mixture distribution. The mean and variance of the Poisson probability distribution function are equal. When the mean and variance are not equal, the Poisson probability distribution function is violated and it results under or over- dispersion. Over dispersion is when the variance is greater than the mean (Hilbe, 2011).

Below is a list of some analysis methods you may have encountered. Some of the methods listed are quite reasonable, while others have either fallen out of favor or have limitations.

•Negative binomial regression - Negative binomial regression can be used for over-dispersed count data, that is when the conditional variance exceeds the conditional mean. It can be considered as a generalization of Poisson regression since it has the same mean structure as Poisson regression and it has an extra parameter to model the over-dispersion. If the conditional distribution of the outcome variable is over-dispersed, the confidence intervals for the Negative binomial regression are likely to be narrower as compared to those from a Poisson regression model.

•Poisson regression - Poisson regression is often used for modeling count data. Poisson regression has a number of extensions useful for count models.

•Zero-inflated regression model - Zero-inflated models attempt to account for excess zeros. In other words, two kinds of zeros are thought to exist in the data, "true zeros" and "excess zeros". Zero-inflated models estimate two equations simultaneously, one for the count model and one for the excess zeros.

•OLS regression - Count outcome variables are sometimes log-transformed and analyzed using OLS regression. Many issues arise with this approach, including loss of data due to undefined values generated by taking the log of zero (which is undefined), as well as the lack of capacity to model the dispersion.

Negative binomial regression is a generalization of Poisson regression, which loosens the restrictive assumption that the variance is equal to the mean made by the Poisson model. In the context of this research, it has been decided that the analysis of the data and variables of both telephone models should be analyzed using the "Negative Binomial Regression Model":

This is formulated as:

$$P(Y = y \mid X_1, X_2, X_3) = \frac{e^{-\mu(X)}\left[\mu(X)\right]^y}{y!} \qquad y = 0,1,2,...$$

a) Link Function: g(μ) = log(μ)

b) Systematic Component:

$$g(\mu) = \log(\mu) = \alpha + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3$$
$$\Rightarrow \quad \mu = e^{\alpha + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3}$$

c) The Pearson residuals are obtained by computing:

$$e_i = \frac{Y_i - \hat{\mu}_i}{\sqrt{V(Y_i)}} = \frac{Y_i - \hat{\mu}_i}{\sqrt{\hat{\mu}_i}} = \frac{\text{observed - fitted}}{\sqrt{\text{fitted}}} \qquad X^2 = \sum e_i^2$$

d) Pearson Residuals for this model is obtained below with:

$$e_i = \frac{Y_i - \hat{\mu}_i}{\sqrt{V(Y_i)}} = \frac{Y_i - \hat{\mu}_i}{\sqrt{\hat{\mu}_i + \hat{\mu}_i^2 / \hat{k}}} \qquad X^2 = \sum e_i^2$$

e) Mass Function of the Negative Binomial Model:

$$P(Y = y \mid X_1, X_2, X_3, k) = \frac{\Gamma(y+k)}{\Gamma(k)\Gamma(y+1)}\left(\frac{k}{k+\mu}\right)^k \left(\frac{\mu}{k+\mu}\right)^y \qquad y = 0,1,2,...$$

E(Y) = μ   V(Y) = μ+(μ^2/k)
Link Function: g(μ) = log(μ)

f) Systematic Component:

$$g(\mu) = \log(\mu) = \alpha + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3$$
$$\Rightarrow \quad \mu = e^{\alpha + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3} = e^{x'\beta} \quad \left(x' = \begin{bmatrix} 1 & X_1 & X_2 & X_3 \end{bmatrix}\right)$$

The conditional variance of the negative binomial distribution exceeds the conditional mean. Overdispersion results from neglected unobserved heterogeneity. The negative binomial model with variance function Var model, which is quadratic in the mean, is referred to as the NB2 model. The Poisson distribution is a special case of the negative binomial distribution. A test of the Poisson distribution can be carried out by testing the hypothesis that $\alpha=0$. A Wald test of this hypothesis is used.

The Poisson regression model can be generalized by introducing an unobserved heterogeneity term for observation. Thus, the individuals are assumed to differ randomly in a manner that is not fully accounted for by the observed covariates. SPSS 24.0 program was used in all the analyzes described above and the findings were interpreted by showing them in tabular form.

3.4.3 Machine Learning Analysis Method

Finally, in order to determine the "algorithm" that will make the most effective and accurate estimation in the demand forecasts in the mobile phone industry, analyzes were made using "machine learning method". Using the WEKA program, data from (A) Plus and (B) phones were included in the analyzes.

WEKA [Witten & Frank, 2005], for Waikato Environment for Knowledge Analysis, is a collection of various ML algorithms, implemented in Java, that can be used for data mining problems. Apart from applying ML algorithms on datasets and analyzing the results generated, WEKA also provides options for pre-processing and visualization of the dataset. It can be extended by the user to implement new algorithms.

Firstly, the "pearson linear correlation" analyzes were performed separately for each "algorithm" whether there is a linear dependence between the SIM activation/actual sales quantities of the two phones and the sales figures estimated. Analyzes made within this scope were made separately on sales and SIM activation data collected according to two different periodicals, monthly and weekly, of two different phones.

In order to understand how monthly and weekly sales and activation data of both phones are cluster around the best fit line, “Mean absolute error (MAE)” and “Root mean squared error” (RMSE) are calculated. In this stage, finally the findings are analyzed according to the size and size of the value of each algorithm by looking at the "average of the differences" of the values in MAE and RMSE.

Relative absolute error (RAE) value is calculated separately for each algorithm in the third and last stage of learning machine. Later RAE values were divided into actual values of sim activation separately for both phone models and periods and percentage was taken to determine which algorithm received the smallest RAE value.

Thus, it has been tried to determine which machine learning algorithm will perform best in terms of estimating the SIM activation numbers of both the (A) and the (B) phones for "next week" and "next month":

199.5092 * __Return_to_Service_of_GM_5_Plus_for_previous_week +

511.7818 * _Sales_volume_of_GM_5_Plus_for_previous_month_(GFK) +

723.1105 * _Sales_price_of_Iphone_5S_for_previous_month_(GFK) +

-795.9975 * _Sales_volume_of_Huawei_P9_Lite_for_previous_month_(GFK) +

1525.9855 * _Sales_price_of_Lenovo_Vibe_P1_for_previous_month_(GFK) +

-1562.9012 * _Sales_volume_of_LG_K10_for_previous_month_(GFK) +

-1415.1615 * _Sales_price_of_LG_K10_for_previous_month_(GFK) +

311.112 * _Sales_volume_of_Galaxy_J7_Prime__for_previous_month_(GFK) +

443.182 * _Sales_price_of_Galaxy_J7_Prime_for_previous_month_(GFK) +

-239.0333 * _Sales_price_of_Samsung_A3_2016_for_previous_month_(GFK) +

-525.8212 * _Sales_volume_of_Galaxy_J5_(2016)_for_previous_month_(GFK) +

-818.6847 * _Sales_price_of_Galaxy_J5_(2016)_for_previous_month_(GFK) +

-256.8314 * _Sales_price_of_Galaxy_On7_for_previous_month_(GFK) +

-142.1391 * Special_Days +

1767.5296 * Months_(1-12)=May,April,Jan,June,July,August,December,November,Sept,October +

-1064.9335 * Months_(1-12)=April,Jan,June,July,August,December,November,Sept,October +

1170.8312 * Months_(1-12)=June,July,August,December,November,Sept,October +

-639.4277 * Months_(1-12)=July,August,December,November,Sept,October +

398.4444 * Months_(1-12)=November,Sept,October +

-929.8243 * Months_(1-12)=Sept,October +

1739.478 * Months_(1-12)=October +

-225.8981 * _Sales_volume_of_GM_5_Plus_for_previous_week +

165.3852 * Sim_Act_2_weeks_ago +

217.3296 * Sim_act_this_week +

1880.5468

In all of analyzes described above, the WEKA program was used and the findings were interpreted by showing them in tabular form.

4. FINDINGS

This research has three stages in terms of data analysis. In the first stage, descriptive statistics analyzed. Then, correlation and negative binomial regression (NBR) analyses were conducted. In the second stage, forecasting were conducted by employing machine-learning method. Then the findings were briefly explained with the following headings.

4.1 NEGATIVE BINOMIAL REGRESYON (NBR) ANALYSIS FINDINGS

The NBR model includes two telephone models (dependent variables) that are subject to demand forecasting: the first is the "(A) Phone model" and the second is the "(B) " phone model. The findings of correlations and regression analyzes were evaluated under two different headings because there were two different telephone models (dependent variables) subject to demand forecasting.

4.1.1 Demand Forecast for (A) Phone Model

The findings of the descriptive, correlation and regression analyzes of the "(A)" telephone model (dependent variable), which is the subject of demand forecasting in the NBR model developed within the scope of the research, are evaluated under the headings below.

4.1.1.1 Descriptive Statistics for (A) Phone Model

The "A" phone, the first phone model that is the subject of demand forecasting, and the descriptive values of the research data of competing phones are shown in the table below:

Table 4.2: Descriptive Statistics for the (A) Mobile Phone Model

Variables	min	max	mean	SD
S.V. of (A) Mobile Phone Model for P.W.	1	19536	3781,81	3585,09
Sim Activation of (A) Mobile Phone Model for P.W.	49	5058	3037,63	1059,62
Return to Service of (A) Mobile Phone Model for P.W.	9	2279	1131,65	694,67
Average Weekly Exchange Rate for P. W.	2,8279	3,814	3,3232	0,3241
Firstday of month stock (A) Mobile Phone Model	10	25897	7891,69	7432,31
S.V. of (A) Mobile Phone Model for P. M.	4500	47400	32143,06	10606,17
S.P. of (A) Mobile Phone Model for P. M.	1014,1	1238,7	1145,13	72,13
S.V. of (CB1) Mobile Phone Model P.M.	12300	89200	51113,56	23044,94
S.P. of (CB1) Mobile Phone Model for P.M.	1529	1658	1590,9	38,244
S.V. of (CB2) Mobile Phone Model for P.M.	4000	13900	9534,97	3114,56
S.P. of (CB2) Mobile Phone Model for P.M.	1516	1709	1612,12	79,4
S.V. of (CB3) Mobile Phone Model for P. M.	6000	13600	8921,6	2656,03
S.P. of (CB3) Mobile Phone Model for P. M.	1239	1295	1267,86	24,6
S.V. of (CB4) Mobile Phone Model orP. M.	1000	4000	2642,86	1336,31
S.P. of (CB4) Mobile Phone Model for P. M.	1287	1386	1327,71	45,508
S.V. of (CB5) Mobile Phone Model for P. M.	6000	15800	12707,89	3395,02
S.P. of (CB5) Mobile Phone Model for P. M.	881	975	920,38	31,75
S.V. of (CB6) Mobile Phone Model for P. M.	25100	135200	67730,22	36944,05
S.P. of (CB6) Mobile Phone Model for P. M.	1183,5	1604,9	1344,21	150,86
S.V. of (CB7) Mobile Phone Model for P. M.	6000	142600	88900	42617,28
S.P. of (CB7) Mobile Phone Model for P. M.	1260	1360	1294,79	36,87
S.V. of (CB8) Mobile Phone Model for P. M.	9700	31000	24525,93	6801,31
S.P. of (CB8) Mobile Phone Model for P. M.	1172	1345	1292,6	39,3
S.V. of (CB9) Mobile Phone Model for P. M.	17200	87300	38640,72	24847,42
S.P. of (CB9) Mobile Phone Model for P. M.	993,9	1257,5	1107,86	89,77
S.V. of (CB10) Mobile Phone Model for P. M.	1000	17700	13453,5	5158,4
S.P. of (CB10) Mobile Phone Model for P. M.	1065	1291	1183,59	75,836
S.V. of (CB11) Mobile Phone Model for P. M.	2200	22100	16661,54	6564,21
S.P. of (CB11) Mobile Phone Model for P. M.	915	969	930,65	18,62

**Descriptions: S.V.= Sales volume; S.P.= Sales price; p.m.= Previous month; p.w.= Previous week; (D) = A research company; (A) = Selected mobile phone model in this research (market driven mobile phone model); (B)=Selected mobile phone model in this research (new model to be marketed); (CB)=Competative brand; TL=TRY=Turkish lira.*

As seen in the table above, (A) phone model;

a) The number of SIM activations in the previous week is between 49 and 5.058[1].

b) At least 1 in the previous week; with a maximum of 19,536 sales and a weekly average of 3,781 sales are achieved.

[1] As can be seen, the values of the dependent variable are composed of whole numbers which are not negative. In the literature, such data is called "count data" (A. Colin Cameron and Pravin K. Trivedi (1998), Regression Analysis of Count Data, Econometric Society Monograph No.30, Cambridge University Press, 1998.)

c) The number of weekly technical service return devices is between 9 to 2,279 per week.
d) The average number of devices that return weekly technical service is 1131.
e) First day of month stock is minimum 10; maximum 25.897.
f) Sales volume of previous week changes between 4500 and 47.400.
g) The average number of monthly sales volume is 32.143.
h) The sales price for the previous month is between 1.014 ₺ and 1.238 ₺.
i) The monthly average sales price is 1.145 ₺.

As seen in the table, among the competitor phones for (A) mobile phone model;

a) The Model with the highest monthly average sales price is (CB2) mobile phone model (1.612, 12 ₺). The second phone with the highest sales price with an average sales price of 1.590,9 ₺ is (CB1) mobile phone model.
b) The phone with the lowest monthly average sales price is (CB5) mobile phone model (920 ₺).

Looking at the figures of the "Sales of Competitive Phones" given in the table;

c) The model with the highest sales volume for the previous week is (CB7) mobile phone model (88.900); the second one is (CB6) mobile phone model (67.730) and (CB1) mobile phone model model is the third one in the row (51.113).
d) The phone with the lowest monthly average sales volume is (CB4) mobile phone model (2642).

Finally, for the years 2016 and 2017 covered by the data in this study;

e) Minimum weekly exchange rate is 2,8279 ₺
f) Maximum weekly exchange rate is 3,814 ₺
g) The weekly average rate is 3,3232₺.

Within the scope of the research, "special days" variables were created and included in the analyzes in the opinion that special days might be effective in telephone sales. The variances for the "Special days" variable using the data for sales of the (A) mobile phone model are shown in the following table:

Table 4.3: Descriptive Statistics for (A) Mobile Phone Model

Variable	Value	Frequency	Percent
Special Days	0- NO special day	50	69,4
	0,5-Two weeks Before Special Day	11	15,3
	1-One week Before Special Day	11	15,3
	Total	72	100
MONTHS	January	4	5,6
	February	4	5,6
	March	5	6,9
	April	6	8,3
	May	8	11,1
	June	10	13,9
	July	8	11,1
	August	8	11,1
	September	6	8,3
	November	4	5,6
	October	4	5,6
	December	5	6,9
	Total	72	100,0

As shown in the table, there are 11 weeks that include "special days" in the years 2016 and 2017. In terms of sales, the number of weeks for which there are no "special days" is calculated as 50 weeks.

Finally, it was examined whether the SIM activation numbers of the (A) mobile phone model show a seasonally different distribution. As the table shows, the maximum number of SIM activations occurred in June; the months of least activation are January, February, October and November.

4.1.1.2 Findings of the Correlation Analysis for (A) Mobile Phone Model

The correlation matrix that includes the results of the correlation analysis of al 30 variables is presented:

The correlation analysis between the dependent variable "SIM activation of the (A) mobile phone model and all other variables is presented in the following truncated correlation matrix table.

Table 4.4: Truncated Correlation Matrix for the Dependent Variable Only

			Sim Activation of (A) mobile phone model -p.w.
1	Sim Activation of (A) mobile phone model -p.w.	Pearson r	1
2	Return to Service of (A) mobile phone model -p.w.	Pearson r	-,316**
3	AverageWeekly Exchange Rate-p.w.	Pearson r	-,340**
4	First day of month stock of (A) mobile phone model.	Pearson r	0,118
5	S.V.- (A) mobile phone model -p.m.	Pearson r	,811**
6	S.P.- (A) mobile phone model -p.m.	Pearson r	-,283*
7	S.V. of (CB1) Mobile Phone Model P.M.	Pearson r	,280*
8	S.P. of (CB1) Mobile Phone Model for P.M.	Pearson r	0,148
9	S.V. of (CB2) Mobile Phone Model for P.M.	Pearson r	-0,218
10	S.P. of (CB2) Mobile Phone Model for P.M.	Pearson r	-0,045
11	S.V. of (CB3) Mobile Phone Model for P. M.	Pearson r	0,049
12	S.P. of (CB3) Mobile Phone Model for P. M.	Pearson r	0,147
13	S.V. of (CB4) Mobile Phone Model orP. M.	Pearson r	,303**
14	S.P. of (CB4) Mobile Phone Model for P. M.	Pearson r	,444**
15	S.V. of (CB5) Mobile Phone Model for P. M.	Pearson r	,455**
16	S.P. of (CB5) Mobile Phone Model for P. M.	Pearson r	,476**
17	S.V. of (CB6) Mobile Phone Model for P. M.	Pearson r	0,107
18	S.P. of (CB6) Mobile Phone Model for P. M.	Pearson r	-,370**
19	S.V. of (CB7) Mobile Phone Model for P. M.	Pearson r	-,379**
20	S.P. of (CB7) Mobile Phone Model for P. M.	Pearson r	-0,169
21	S.V. of (CB8) Mobile Phone Model for P. M.	Pearson r	,402**
22	S.P. of (CB8) Mobile Phone Model for P. M.	Pearson r	0,187
23	S.V. of (CB9) Mobile Phone Model for P. M.	Pearson r	0,051
24	S.P. of (CB9) Mobile Phone Model for P. M.	Pearson r	-,382**
25	S.V. of (CB10) Mobile Phone Model for P.M.	Pearson r	-,349**
26	S.P. of (CB10) Mobile Phone Model for P. M.	Pearson r	-0,186
27	S.V. of (CB11) Mobile Phone Model for P. M.	Pearson r	,424**
28	S.P. of (CB11) Mobile Phone Model for P. M.	Pearson r	,558**
29	Special Days	Pearson r	-0,034

30	Months 12 (12 months)[1]	Pearson r	,626**
	* Correlation is significant at the 0.05 level (2-tailed).		
	** Correlation is significant at the 0.01 level (2-tailed).		

**Descriptions: S.V.= Sales volume; S.P.= Sales price; p.m.= Previous month; p.w.= Previous week; (D) = A research company; (A) = Selected mobile phone model in this research (market driven mobile phone model); (B)=Selected mobile phone model in this research (new model to be marketed); (CB)=Competative brand..*

Based on the findings of the correlation analysis, presented in the table above, there is a statistically significant but negative relationship between the dependent variable SIM Activation and return to service numbers of the same phone (r= -0,316). According to this finding, as the number of (A) mobile phone model return to service numbers increase, the number of SIM activations showing the sales figures of the phone is decreasing.

Again, as seen in the table, there is a negative and moderate relationship between the number of SIM activation of the (A) mobile phone model and the weekly average exchange rate (r= -0,340). According to this finding, as the exchange rates increase, the number of "SIM activation" of the phone decreases. Another variable negatively associated with the Sim activation of the (A) mobile phone model is the "selling price" (r= -283). As the selling price of the device increases, the number of SIM activations decreases.

Other variables that are statistically significant but "negative" in relation to the "SIM activation numbers" of the (A) mobile phone model are:

a) Sales Price of (CB6) mobile phone model (r=-0,370),
b) Sales Volume of (CB7) mobile phone model (r=-0,379),
c) Sales Price of (CB9) mobile phone model (r=-0,382)
d) Sales Volume of (CB10) mobile phone model (r=-0,349).

On the other hand, looking at the above table, there is a significant and positive relationship between the SIM activation of (A) mobile phone model and the sales volume of this model (r=0,811)[2]. Naturally, as the sales volumes increase, the number

[1] Each month within a year is included separately in the correlation analysis. The months are numbered 1 to 12 and included in the correlation analysis.
[2] However, it is also understood that there might be a "homoscedasticity problem" between these two variables. Because, as stated in the literature, if a high correlation is calculated between two variables inserted into the correlation analysis, this might indicate that both variables measure the same quantitative

of SIM activation increases, indicating that there is a high correlation coefficient between the two variables. According to this finding, it might be said that the "number of SIM activations in the previous week" and "sales figures in the previous month" of the (A) mobile phone model have the same meaning.

The last variable, which is statistically significant in relation to the Sim activation numbers of the (A) mobile phone model, is the month variable. This relationship is a positive and strong relationship(r=0,626).

Finally, according to findings from the correlation analysis, the other variables that have a statistically significant positive correlation with the "SIM activation figures" of the(A) mobile phone model are:

a) Sales Volume of (CB4) Mobile Phone Model (r=0,303),
b) Sales Price of (CB4) Mobile Phone Model (r=0,444),
c) Sales Volume and Sales Price of (CB5) Mobile Phone Model (r=0,455 and r=0,476 respectively),
d) Sales Volume of (CB8) Mobile Phone Model (r=0,402),
e) Sales Volume and Sales Price of (CB11) Mobile Phone Model (r=0,424 and r=0,558 respectively).

4.1.1.3 Findings of NBR Analysis for (A) Mobile Phone Model

Before going to Negative Binomial Regression (NBR) analysis, it was examined whether the probability distributions of the research variables were within the scope of "Poisson multiple regression analysis model".

This study models the number of “Sim Activation of (A) Mobile Phone Model for previous week” over a two year period. Because the sim activation frequencies are discrete and non-negative integer values, the Poisson regression technique is the first choice for modeling such data. However, The Kolmogorov-Smirnov test yielded that the data has not a Poisson probability distribution function. Then the mean and variance are checked and determined that there is an over dispersion in the data which means a Poisson-gamma mixture distribution. Based on this, negative binomial regression analysis is conducted (Hilbe, 2011).

---

data. Field, A. P. (2009). Discovering statistics using SPSS: (and sex and drugs and rock 'n' roll). Los Angeles [i.e. Thousand Oaks, Calif.: SAGE Publications.

Four different models are created and four NBR analysis are conducted. In the first model, only the variables about (A) Mobile Phone Model are counted in the analysis along with the average weekly exchange rate, special days and months variables. The results of the NBR analysis for the model 1 and 2 are presented in table 3.

Table 4.5: NBR Findings for (A) Mobile Phone – Model 1 and Model 2

	Model 1		Model 2	
	B	p	B	p
S.v. of (A) Mobile Phone for p.w.	,00000	,886		
Return to service of (A) Mobile Phone for p.w.	,00013	,245		
Average Weekly Exchange Rate for p.w.	-,54297	,011		
First day of month stock (A) Mobile Phone	,00002	,000		
S.v. of (A) Mobile Phone for p.m.	,00002	,000		
S.p. of (A) Mobile Phone for p.m.	,00033	,638		
[SpecialDays=,0]	,03901	,530		
[SpecialDays=,5]	-,02244	,774		
[SpecialDays=1,0]	0[a]			
Months 12	,02231	,043		
(Negative binomial)	,03213			
Pearson Chi-Square Value/df= 1,197				
Omnibus Test sig=0,000				
S.V. of (CB1) Mobile Phone Model P.M.			-,000003	,575
S.V. of (CB2) Mobile Phone Model P.M.			-,000026	,022
S.V. of (CB3) Mobile Phone Model P.M.			,000049	,000
S.V. of (CB4) Mobile Phone Model P.M.			-,000096	,006
S.V. of (CB5) Mobile Phone Model P.M.			,000009	,832
S S.V. of (CB6) Mobile Phone Model P.M.			,000031	,000
S.V. of (CB7) Mobile Phone Model P.M.			,000004	,254
S.V. of (CB8) Mobile Phone Model P.M.			,000017	,098
S.V. of (CB9) Mobile Phone Model P.M.			-,000048	,000
S.V. of (CB10) Mobile Phone Model P.M.			-,000046	,144
S.V. of (CB11) Mobile Phone Model P.M.			,000024	,000
(Negative binomial)			,026	
Pearson Chi-Square Value/df= 1,073				
Omnibus Test sig=0,000				
Dependent Variable: Sim Activation of (A) Mobile Phone for previous week				

**Descriptions: S.V.= Sales volume; S.P.= Sales price; p.m.= Previous month; p.w.= Previous week; (D) = A research company; (A) = Selected mobile phone model in this research (market driven mobile phone model); (B)=Selected mobile phone model in this research (new model to be marketed); (CB)=Competative brand.*

As seen in the above table, the analysis results for the "Model-1" created within the scope of the NBR analysis are as follows:

a) The model-1 fits the data well (Pearson Chi-Square Value/df= 1,197) and the model-1 is statistically significant (Omnibus Test sig=0,000).
b) Each unit increase in exchange rates indicates a decrease of 0.5430 units in the expected SIM activation log numbers of the (A) Mobile Phone (B=-0,5430, p=0,011).
c) One unit increase in stock numbers on the first day of the month for (A) Mobile Phone, SIM activation shows an increase of 0.00002 units in log numbers (B=0,00002, p=0,000).
d) Each unit increase in (A) Mobile Phone sales volumes in the previous month indicates an increase of 0.00002 units in the SIM activation log numbers (B=0,00002, p=0,000).
e) In each increment of the units in the month, the SIM activation log increases 0.02231 units (B=0,02231, p=0,043). This result indicates that there is a seasonal effect on SIM card activations.

The analysis results for the "Model-2" created within the scope of the NBR analysis are as follows:

a) The model-2 fits the data well (Pearson Chi-Square Value/df= 1,073) and the model-1 is statistically significant (Omnibus Test sig=0,000).
b) An increase of 1 unit in sales figures of (CB2) Mobile Phone Model for the previous month shows a decrease of 0.000026 units in SIM activation log numbers of (A) Mobile Phone (B=-0,000026, p=0,022).
c) Each 1 unit increase in sales figures for (CB3) Mobile Phone Model in the previous month indicates an increase of 0.000049 units in SIM activation log numbers (B=0,000049, p=0,000).
d) The 1-unit increase in (CB4) Mobile Phone Model sales for the previous month shows a decrease of 0.000096 units in the SIM activation log of the (A) Mobile Phone (B=-0,000096, p=0,006).
e) The 1-unit increase in (CB6) Mobile Phone Model sales for the previous month shows an increase of 0.000031 units in SIM activation log numbers (B=0,000031, p=0,000).

f) 1 unit increase in sales volumes of (CB9) Mobile Phone Model in the previous month, SIM activation log numbers decrease by 0.000031 units (B=-0,000048, p=0,000).

g) The 1-unit increase in (CB11) Mobile Phone Model's sales volumes over the previous month shows an increase of 0.000024 units in SIM activation log numbers (B=0,000024, p=0,000).

The findings of the NBR analysis for "Model-3" and "Model-4" are presented in the following table:

Table 4.6: NBR Findings for (A) Mobile phone- Model 3 and Model 4

	Model 3		**Model 4**	
	B	**p**	**B**	**p**
S.p. of (CB1) Mobile Phone Model P.M.	,000	,097		
S.p. of (CB2) Mobile Phone Model P.M.	,000	,449		
S.p. of (CB3) Mobile Phone Model P.M.	,000	,228		
S.p. of (CB4) Mobile Phone Model P.M.	,008	,000		
S.p. of (CB5) Mobile Phone Model P.M.	-,010	,000		
S.p. of (CB6) Mobile Phone Model P.M.	,005	,000		
S.p. of (CB7) Mobile Phone Model P.M.	-,015	,000		
S.p. of (CB8) Mobile Phone Model P.M.	,000	,282		
S.p. of (CB9) Mobile Phone Model P.M.	-,003	,093		
S.p. of (CB10) Mobile Phone Model P.M.	,009	,004		
S.p. of (CB11) Mobile Phone Model P.M.	,001	,000		
(Negative binomial)	,038			
Pearson Chi-Square Value/df= 1,238				
Omnibus Test sig=0,000				
S.v. of (CB2) Mobile Phone Model P.M.			-,00004	,002
S.v. of (CB3) Mobile Phone Model P.M.			,00001	,270
S.v. of (CB4) Mobile Phone Model P.M.			-,00002	,880
S.v. of (CB6) Mobile Phone Model P.M.			,00000	,636
S.v. of (CB9) Mobile Phone Model P.M.			-,00001	,476
S.v. of (CB11) Mobile Phone Model P.M.			-,00001	,563
S.p. of (CB4) Mobile Phone Model P.M.			,00894	,000
S.p. of (CB5) Mobile Phone Model P.M.			-,01265	,001
S.p. of (CB6) Mobile Phone Model P.M.			,00182	,060
S.p. of (CB7) Mobile Phone Model P.M.			-,01683	,000
S.p. of (CB10) Mobile Phone Model P.M.			,00903	,000
S.p. of (CB11) Mobile Phone Model P.M.			,00028	,024
Average Weekly Exchange Rate for p.w.			-,43172	,214
First day of month stock (A) Mobile phone			,00003	,000

S.v. of (A) Mobile phone for p.m.			,00000	,898
Months 1-12[1]			,04152	,001
(Negative binomial)			,01923	
Pearson Chi-Square Value/df= 1,338				
Omnibus Test sig=0,000				
Dependent Variable: Sim Activation of (A) Mobile phone for previous week				

**Descriptions: S.V.= Sales volume; S.P.= Sales price; p.m.= Previous month; p.w.= Previous week; (D) = A research company; (A) = Selected mobile phone model in this research (market driven mobile phone model); (B)=Selected mobile phone model in this research (new model to be marketed); (CB)=Competative brand*

The analysis results for the "Model-3" created for the NBR analysis shown in the table are as follows:

a) In case of 1-unit increase in sales price of (CB4) Mobile Phone Model in the previous month, SIM activation log numbers of the (A) Mobile Phone Model increases by 0.008 units (B=0,008, p=0,000).

b) In 1-unit increase of sales price of (CB5) Mobile Phone Model the previous month, (A) Mobile Phone Model SIM activation log numbers decrease by 0,010 units (B=-0,010, p=0,000).

c) In 1-unit increase in sales price of (CB6) Mobile Phone Model in the previous month, (A) Mobile Phone Model SIM activation log numbers increase by 0.005 units (B=0,005, p=0,000).

d) When the (CB7) Mobile Phone Model has a 1 unit increase in sales price for the previous month, (A) Mobile Phone Model SIM activation log numbers also decrease of 0.015 units (B=-0,015, p=0,000).

e) When the sales price of (CB9) Mobile Phone Model increase by 1 unit in the previous month, (A) Mobile Phone Model SIM activation log numbers shows an increase of 0.009 units (B=0,009, p=0,004).

f) While the (CB11) Mobile Phone Model previous month's sales price increase 1 unit, the (A) Mobile Phone Model SIM activation log numbers also increase by 0.01 units (B=0,01, p=0,000).

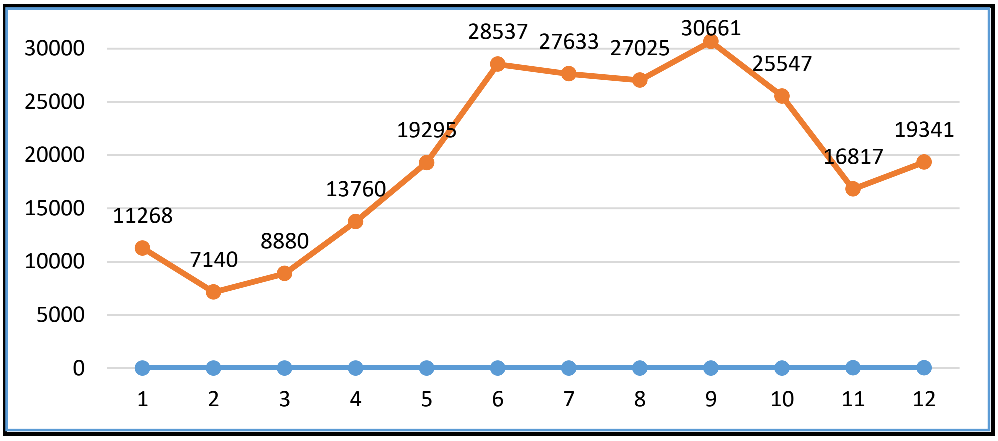
Finally, the analysis results for the "Model 4" created for the NBR analysis shown in the above table are as follows:

[1] Each month within a year is included separately in the correlation analysis. The months are numbered 1 to 12 and included in the correlation analysis.

a) When the (CB2) Mobile Phone Model has an increase of 1 unit in the sales volumes of the previous month, the SIM activation log numbers of the (A) Mobile Phone Model decrease 0,00004 units (B=-0,00004, p=0,002).
b) In 1 unit increase in sales price of (CB4) Mobile Phone Model in the previous month, SIM activation has an increase of 0.00894 units in log numbers (B=0,00894, p=0,000).
c) In 1 unit increase of sales price of (CB5) Mobile Phone Model in the previous month, the number of SIM activation log decreases by 0.011265 units (B=-0,01265, p=0,001).
d) When the (CB6) Mobile Phone Model is increased by 1 unit in the previous month's sales price, SIM activation log numbers has a decrease of 0.01683 units (B=-0,01683, p=0,000).
e) When the (CB7) Mobile Phone Model 's sales price in the previous month is increased by 1 unit, the (A) Mobile Phone Model activation log numbers has an increase of 0.00903 units (B=0,00903, p=0,000).
f) When the sales price in the previous month of (CB11) Mobile Phone Model is increased by 1 unit, (A) Mobile Phone Model SIM activation log numbers increases by 0,00028 units (B=0,00028, p=0,024).
g) When the sales volume of (A) Mobile Phone Model for the previous month increase 1 unit, the SIM activation log numbers of the same model increase 0,00003 units (B=0,00003, p=0,000).
h) With 1-unit increase in the months, (A) Mobile Phone Model SIM activation log numbers has an increase of 0.04152 units (B=0,04152, p=0,001).

The last finding in Model 4 shows that the (A) Mobile Phone Model has a seasonal effect on SIM card activations. According to this finding, the following figure 1 was created to show the seasonal change in SIM activations of the (A) Mobile Phone Model more clearly:

Figure 4.1: Seasonal Change in SIM card activations of (A) Mobile Phone Model



As seen in the figure showing seasonal effect on SIM activations of the (A) Mobile Phone Model, the peak of the SIM activations of the (A) Mobile Phone Model (and therefore the sales) is the peak of September (9). The following is June (6).

According to this, the months in which the most SIM activations of (A) Mobile Phone Model occur are June (6), July (7), August (8) and September (9). On the other hand, the month of lowest SIM activation is February (2).

4.2.2 Demand Forecast for (B) Mobile Phone Model

The findings of the descriptive, correlation and regression analyzes of the "(A)" telephone model (dependent variable), which is the subject of demand forecasting in the NBR model developed within the scope of the research, are evaluated under the headings below.

4.2.2.1 Descriptive Statistics for (B) Mobile Phone Model

The other dependent variable determined in this research is SIM activation numbers of (B) Mobile Phone Model, which is a different model phone.

a) The number of SIM activation is between 1328 and 11656. For this reason, the dependent variable is count data consisting of whole numbers that are not negative. The average number of SIM activations in the previous week was 6004.

b) The minimum sales volume of the (B) Mobile Phone Model for the previous week is 860 and the maximum is 21876. The average sales volume is 5969.

c) The average number of Return to service of the (B) Mobile Phone Model for the previous week is 2133. First day of moth stock numbers are between 7294 and 55300 and the avegare is 25470.

d) The mean sales volume of (B) Mobile Phone Model for the previous month 7485.

e) Sales price of the (B) Mobile Phone Model is between 957₺ and 1004 ₺, and the average price is 992₺.

f) Finally, for the years 2016 and 2017 covered by the data in this study;

g) Minimum weekly exchange rate is 2,8648 ₺

h) Maximum weekly exchange rate is 3,814 ₺

i) The weekly average rate is 3,344₺.

Table 4.7: Descriptive Statistics for (B) Mobile Phone Model

Variables	min	max	mean	SD
Sim Activation of (B) Mobile Phone Model for P. W.	1328	11656	6004,59	2438,81
S.V. of (B) Mobile Phone Model for P. W.	860	21876	5969,2	4593,1
Return to Service of (B) Mobile Phone Model for P. W.	1	4012	2133,09	1209,89
Average Weekly Exchange Rate for P. W.	2,8648	3,814	3,344	0,314
Firstday of month stock (B) Mobile Phone Model	7294	55300	25470,09	14680,09
S.V. of (B) Mobile Phone Model for P. M. GFK	4600	9000	7485,71	1476,31
S.P. of (B) Mobile Phone Model for P.M. GFK	957	1004	992,13	15,23
S.V. of (CB1) Mobile Phone Model P.M.	12300	89200	50567	23538,77
S.P. of (CB1) Mobile Phone Model for P.M.	1529	1658	1590,31	39,45
S.V. of (CB2) Mobile Phone Model for P.M.	4000	13900	9534,97	3114,56
S.P. of (CB2) Mobile Phone Model for P.M.	1516	1709	1612,12	79,4
S.V. of (CB3) Mobile Phone Model for P. M.	6000	13600	8921,6	2656,03
S.P. of (CB3) Mobile Phone Model for P. M.	1239	1295	1267	24,6
S.V. of (CB4) Mobile Phone Model orP. M.	1000	4000	2642,86	1336,31
S.P. of (CB4) Mobile Phone Model for P. M.	1287	1386	1327,71	45,51
S.V. of (CB5) Mobile Phone Model for P. M.	6000	15800	12897,14	3475,08
S.P. of (CB5) Mobile Phone Model for P. M.	881	975	920,02	33,09
S.V. of (CB6) Mobile Phone Model for P. M.	25100	135200	65957,62	36722,71
S.P. of (CB6) Mobile Phone Model for P. M.	1184	1605	1350,29	151,19
S.V. of (CB7) Mobile Phone Model for P. M.	6000	142600	88900	42617,28
S.P. of (CB7) Mobile Phone Model for P. M.	1260	1360	1294,79	36,87
S.V. of (CB8) Mobile Phone Model for P. M.	9700	31000	24280,39	6922,89
S.P. of (CB8) Mobile Phone Model for P. M.	1172	1321	1289,26	38,136
S.V. of (CB9) Mobile Phone Model for P. M.	17200	87300	36907,71	23905,91
S.P. of (CB9) Mobile Phone Model for P. M.	994	1258	1112,37	88,99
S.V. of (CB10) Mobile Phone Model for P. M.	1000	17700	13453,5	5158,4
S.P. of (CB10) Mobile Phone Model for P. M.	1065	1291	1183,59	75,84
S.V. of (CB11) Mobile Phone Model for P. M.	2200	22100	16661,54	6564,21
S.P. of (CB11) Mobile Phone Model for P. M.	915	969	930,65	18,62

**Descriptions: S.V.= Sales volume; S.P.= Sales price; p.m.= Previous month; p.w.= Previous week; (D) = A research company; (A) = Selected mobile phone model in this research (market driven mobile phone model); (B)=Selected mobile phone model in this research (new model to be marketed); (CB)=Competative brand.*

When the sales volumes of the competitors of the (B) Mobile Phone Model for the previous month were analyzed in the;

a) The most selling device is (CB7) Mobile Phone Model with an average sales figure of 88900. The second in the order is (CB6) Mobile Phone Model with 65957 sales. (CB1) Mobile Phone Model is in third place with an average sales figure of 50,567.
b) (CB4) Mobile Phone Model has the lowest sales figure among rival phones with an average of 2642 sales.
c) When the selling prices for the previous month of the rival phones were examined, it is seen that (CB2) Mobile Phone Model is the first place with 1612₺ average selling price. With an average price of 1590₺; (CB1) Mobile Phone Model device is the second most expensive selling model. The (CB6) Mobile Phone Model is also in the third place with an average selling price of 1350₺.
d) Among the rival phones, (CB5) Mobile Phone Model is the lowest priced device with an average price of 920₺.

Table-7 below shows frequency distributions of the special days and months variables that are not related to phone models. There are 10 special weeks including a special day which may affect the cell phone sales and 49 weeks not including a special day.

Table 4.8. Descriptive Statistics for (B) Mobile Phone Model

Variable	Value	Frequency	Percent
Special Days	0- No special day	49	71
	0,5-Two week Before Special Day	10	14,5
	1-One week Before Special Day	10	14,5
Weeks	Total	69	100
	January	4	5,8
	February	4	5,8
	March	5	7,2
	April	4	5,8
	May	7	10,1
	June	10	14,5
	July	8	11,6
	August	8	11,6
Months	September	6	8,7

	November	4	5,8
	October	4	5,8
	December	5	7,2
	Total	69	100,0

In order to analyze whether the SIM activation numbers of the (B) Mobile Phone Model show a seasonally different distribution, 12 months of the year are analyzed as variables. According to the findings, the month with the most activation is June, while the months with the least activation are January (12), February (2), April (4) and October (1), November (11).

4.2.2.2 Findings of Correlation Analysis for (B) Mobile Phone Model

The correlation matrix that includes the results of the correlation analysis of al 30 variables is presented in the appendix-3.

The correlation analysis between the dependent variable “SIM activation of the "(B) Mobile Phone Model” and all other variables is presented in the following truncated correlation matrix table.

a) The number of SIM activations of the (B) Mobile Phone Model for the previous week has a significant positive correlation with the sales volume of the same device in the previous week (r= 0,663).
b) There is a negative and strong relationship between the SIM activation of the (B) Mobile Phone Model and the number of return to service for the same device (r= -0,581). As the number of return to service increases, the number of SIM activation of the phone decreases.
c) There is also a negative and strong relationship between the number of SIM activations of the (B) Mobile Phone Model and the weekly average exchange rate (r= -0,710). As the exchange rates increase, the SIM activation of the phone, that is, the sales figures, is also decreasing.
d) Another positive and statistically significant variable with the SIM activation of (B) Mobile Phone Model is the sales volume of the same model (r = 0,698) and sales prices (r=0,680). As sales figures and sales prices increase, SIM activation numbers also increase.

Variables that are statistically significant and positive correlations between the sales numbers and sales prices of rival phone brands and the SIM activation number of (B) Mobile Phone Model are:

a) Sales volume of (CB1) Mobile Phone Model (r=0,525),
b) Sales Price of (CB1) Mobile Phone Model (r=0,265).
c) Sales volume of (CB5) Mobile Phone Model (r=0,707),
d) Sales Price of (CB5) Mobile Phone Model (r= 0,665).
e) Sales volume of (CB6) Mobile Phone Model (r=0,360),
f) Sales volume of (CB8) Mobile Phone Model (r= 0,568),
g) Sales Price of (CB8) Mobile Phone Model (r= 0,360).
h) Sales volume of (CB9) Mobile Phone Model (r=0,364)
i) Sales Price of (CB9) Mobile Phone Model (r=0,387).

Table 4.9: Correlation Matrix for the Dependent Variable Only

			Sim Activation of (B) Mobile Phone Model -p.w.
1	Sim Activation of (B) Mobile Phone Model -pw	Pearson r	1
2	SV-(B) Mobile Phone Model -pw	Pearson r	,663**
3	Return to Service of (B) Mobile Phone Model -pw	Pearson r	-,581**
4	Average Weekly Exchange Rate-pw	Pearson r	-,710**
5	First day of month stock (B) Mobile Phone Model	Pearson r	,024
6	S.V. of (B) Mobile Phone Model P.M.	Pearson r	,698**
7	S.P. of (B) Mobile Phone Model for P.M.	Pearson r	,680**
8	S.V. of (CB1) Mobile Phone Model P.M.	Pearson r	,525**
9	S.P. of (CB1) Mobile Phone Model for P.M.	Pearson r	,265*
10	S.V. of (CB2) Mobile Phone Model for P.M.	Pearson r	-,493**
11	S.P. of (CB2) Mobile Phone Model for P.M.	Pearson r	-,358**
12	S.V. of (CB3) Mobile Phone Model for P. M.	Pearson r	-,232
13	S.P. of (CB3) Mobile Phone Model for P. M.	Pearson r	-,166
14	S.V. of (CB4) Mobile Phone Model orP. M.	Pearson r	,061
15	S.P. of (CB4) Mobile Phone Model for P. M.	Pearson r	,199
16	S.V. of (CB5) Mobile Phone Model for P. M.	Pearson r	,707**
17	S.P. of (CB5) Mobile Phone Model for P. M.	Pearson r	,665**
18	S.V. of (CB6) Mobile Phone Model for P. M.	Pearson r	,360**
19	S.P. of (CB6) Mobile Phone Model for P. M.	Pearson r	-,539**
20	S.V. of (CB7) Mobile Phone Model for P. M.	Pearson r	-,657**
21	S.P. of (CB7) Mobile Phone Model for P. M.	Pearson r	-,592**
22	S.V. of (CB8) Mobile Phone Model for P. M.	Pearson r	,568**
23	S.P. of (CB8) Mobile Phone Model for P. M.	Pearson r	,360**
24	S.V. of (CB9) Mobile Phone Model for P. M.	Pearson r	,364**
25	S.P. of (CB9) Mobile Phone Model for P. M.	Pearson r	-,603**
26	S.V. of (CB10) Mobile Phone Model for P.M.	Pearson r	-,687**
27	S.P. of (CB10) Mobile Phone Model for P. M.	Pearson r	-,607**

28	S.V. of (CB11) Mobile Phone Model for P. M.	Pearson r	,217
29	S.P. of (CB11) Mobile Phone Model P.M.	Pearson r	,387**
30	Special Days	Pearson r	,056
31	Months1.-12. [1]	Pearson r	,513**
	**. Correlation is significant at the 0.01 level (2-tailed).		
	*. Correlation is significant at the 0.05 level (2-tailed).		

**Descriptions: S.V.= Sales volume; S.P.= Sales price; p.m.= Previous month; p.w.= Previous week; (D) = A research company; (A) = Selected mobile phone model in this research (market driven mobile phone model); (B)=Selected mobile phone model in this research (new model to be marketed); (CB)=Competative brand*

The variables that have statistically significant and negative correlation between sales figures and sales prices of rival phone brands and the SIM activation of (B) Mobile Phone Model phone are as follows:

a) Sales Volume of Casper Via A1 (r= -0,493) and Sales Price (r= -0,358).
b) Sales Price of Galaxy J7 2016 (r=-0,539),
c) Sales Volume of Galaxy J7 Prime (r=-0,657) and Sales Price (r=-0,592).
d) Sales price of Galaxy J5 2016 (r=-0,603),
e) Sales Volume of Galaxy J5 Prime (r= -0,687) and Sales Price (r= -0,607).
f) The last variable, which has a statistically significant relationship with the Sim activation numbers of the (B) Mobile Phone Model, is the month variable. This relationship is a positive and strong relationship (r=0,513).

4.2.2.3 Findings of NBR Analysis for (B) Mobile Phone Model

Since a dataset for the (A) Mobile Phone Model and (B) Mobile Phone Model has a Poisson-Gama mixture distribution, it has been previously described that negative binomial regression analysis should be performed. The findings of Negative Binomial Regression analysis for the (B) Mobile Phone Model phone are presented in the following tables 9 and 10.

NBR analysis was done by creating four models. In the first model, only the variables related to the (B) Mobile Phone Model model and weekly average exchange rate variable, month variable and special day variable are included. In the analysis for Model-1, the model goodness of fit statistics shows a good fit (Pearson Chi-Square Value/df= 1,035) and Model-1 is statistically significant (Omnibus Test sig=0,000).According to the findings in Model-1, 5 variables were statistically significant to estimate the SIM activation probability of (B) Mobile Phone Model.

[1] Each month within a year is included separately in the correlation analysis. The months are numbered 1 to 12 and included in the correlation analysis.

a) In each unit increase in sales figures of the previous week of (B) Mobile Phone Model, the number of SIM activation log increases by 0,00002 units (B=0,00002, p=0,007).

b) As predicted, there is a significant and negative relationship between the weekly average exchange rate and the SIM activation. In each unit increase in exchange rates, the expected SEM activation log numbers show a decrease of 1.38106 units (B=-1,38106, p=0,000). It is an expected result that sales of imported cell phones are dependent on exchange rates.

c) In each unit increase of stock numbers on the first day of the month, the number of SIM activation log increases by 0.00001 units (B=0,00001, p=0,000).

d) In each unit increase in sales figures of (B) Mobile Phone Model for the previous month, the number of SIM activation log increases by 0,00017 units (B=0,00017, p=0,000).

e) In each unit increase in sales prices of (B) Mobile Phone Model in the previous month, the number of SIM activation log decreases by 0.00161 units (B= -0,00161, p=0,001).

Table 4.10: NBR Findings for (B) Mobile Phone: Model 1 and Model 2

	Model 1		**Model 2**	
	B	**p**	**B**	**p**
(Intercept)	12,98113	0,000		
S.v. of (B) Mobile Phone for p.w.	0,00002	,007		
Return to service of (B) Mobile Phone for p.w.	0,00002	,794		
Average Weekly Exchange Rate for p.w.	-1,38106	,000		
First day of month stock (B) Mobile Phone	0,00001	,000		
S.v. of (B) Mobile Phone for p.m.	0,00017	,000		
S.p. of (B) Mobile Phone for p.m.	-0,00161	,001		
Months 12	0,00849	,618		
[Special Days=,0]	-0,02885	,722		
[Special Days=,5]	0,00354	,974		
[Special Days=1,0]	0,00000			
(Negative binomial)	0,05317			
Pearson Chi-Square Value/df= 1,035				
Omnibus Test sig=0,000				
(Intercept)			7,02067	0,000
S.V. of (CB1) Mobile Phone Model P.M.			0,00001	,151

S.V. of (CB2) Mobile Phone Model P.M.			-0,00003	,039
S.V. of (CB3) Mobile Phone Model P.M.			0,00005	,004
S.V. of (CB4) Mobile Phone Model P.M.			-0,00017	,001
S.V. of (CB5) Mobile Phone Model P.M.			0,00004	,509
S S.V. of (CB6) Mobile Phone Model P.M.			0,00005	,000
S.V. of (CB7) Mobile Phone Model P.M.			0,00002	,004
S.V. of (CB8) Mobile Phone Model P.M.			0,00003	,018
S.V. of (CB9) Mobile Phone Model P.M.			-0,00009	,000
S.V. of (CB10) Mobile Phone Model P.M.			-0,00008	,060
S.V. of (CB11) Mobile Phone Model P.M.			0,00001	,113
(Negative binomial)			0,04345	
Pearson Chi-Square Value/df= 1,243				
Omnibus Test sig=0,000				
Dependent Variable: Sim Activation of (B) Mobile Phone Model for previous week				

**Descriptions: S.V.= Sales volume; S.P.= Sales price; p.m.= Previous month; p.w.= Previous week; (D) = A research company; (A) = Selected mobile phone model in this research (market driven mobile phone model); (B)=Selected mobile phone model in this research (new model to be marketed); (CB)=Competative brand*

Variables included in the analysis of the second model for negative binomial regression analysis are sales figures of other phone brands in the market, which are competitors for the (B) Mobile Phone Model.

According to findings of Model 2:

a) In each unit increase of sales volume of (CB2) Mobile Phone Model for the previous month, the number of SIM activation log of (B) Mobile Phone Model shows 0,00003 units decrease (B=-0,00003, p=0,039).
b) In each unit increase of (CB3) Mobile Phone Model's sales figures for the previous month, the (B) Mobile Phone Model SIM activation log numbers increase by 0.00005 units (B=0,000049, p=0,004).
c) In each unit increase of (CB4) Mobile Phone Model sales in the previous month, (B) Mobile Phone Model SIM activation log numbers show a decrease of 0,00017 units (B=-0,00017, p=0,001).
d) In each unit increase of (CB6) Mobile Phone Model sales in the previous month, the (B) Mobile Phone Model SIM activation log numbers increase by 0.00005 units (B=0,00005, p=0,000).

e) In each unit increase of (CB7) Mobile Phone Model's sales figures for the previous month, the (B) Mobile Phone Model SIM activation log numbers increase by 0.00002 units (B=0,00002, p=0,004).
f) In each unit increase of the sales figures of the previous month of the Samsung A3 2016 phone, the (B) Mobile Phone Model SIM activation log numbers increase by 0.00003 units (B=0,00003, p=0,018).
g) In each unit increase of sales of the (CB8) Mobile Phone Model in the previous month, the (B) Mobile Phone Model SIM activation log numbers show a decrease of 0.00009 units (B=-0,00009, p=0,000).

In the analyzes for explaining the variation of the SIM activation log numbers of the (B) Mobile Phone Model, the variables comprising the sales prices of the competitor telephone brands in the previous month were analyzed with a different model (model 3).

The findings of the Model 3 analysis are presented in Table 10 below. According to the findings of Model 3 analysis;

a) One of the variables statistically significant with the SIM activation log numbers of the (B) Mobile Phone Model is the sales price of the (CB4) Mobile Phone Model in the previous month. There is a statistically significant and positive relationship between these two variables. In each unit increase of sale price of (CB4) Mobile Phone Model the previous month, the number of SIM activation log increases by 0.00821 units (B=0,00821, p=0,001).
b) A statistically significant but negative relationship was found between the sales prices of (CB5) Mobile Phone Model the previous month and the SIM activation numbers of (B) Mobile Phone Model. For each unit increase of sales price of (CB5) Mobile Phone Model in the previous month, the number of SIM activation log decreases by 0.01057 units (B=-0,01057, p=0,002).
c) In each unit increase of sales price of Galaxy J7 2016 phone in the previous month, the number of SIM activation log of (B) Mobile Phone Model increases by 0.00497 units (B=0,00497, p=0,001).

d) SIM activation log numbers for the (B) Mobile Phone Model show a decrease of 0.01544 units when the (CB6) Mobile Phone Model 's sales price increase one unit for the previous month (B=-0,01544, p=0,014).

e) The last result, which is significant in Model 3, is the sales prices of (CB11) Mobile Phone Model for previous month. When the selling price of (CB11) Mobile Phone Model increases by one unit for the previous month, the number of (B) Mobile Phone Model SIM activation log increases by 0,00039 units (B=0,00039, p=0,000).

Table 4.11: NBR Findings for (B) Mobile Phone- Model 3 and Model 4

	Model 3		**Model 4**	
	B	**p**	**B**	**p**
(Intercept)	13,56928	,000		
S.p. of (CB1) Mobile Phone Model P.M.	-0,00012	,357		
S.p. of (CB2) Mobile Phone Model P.M.	-0,00003	,781		
S.p. of (CB3) Mobile Phone Model P.M.	0,00004	,753		
S.p. of (CB4) Mobile Phone Model P.M.	0,00821	,001		
S.p. of (CB5) Mobile Phone Model P.M.	-0,01057	,002		
S.p. of (CB6) Mobile Phone Model P.M.	0,00497	,001		
S.p. of (CB7) Mobile Phone Model P.M.	-0,01544	,014		
S.p. of (CB8) Mobile Phone Model P.M.	-0,00019	,195		
S.p. of (CB9) Mobile Phone Model P.M.	-0,00083	,761		
S.p. of (CB10) Mobile Phone Model P.M.	0,00791	,069		
S.p. of (CB11) Mobile Phone Model P.M.	0,00039	,000		
(Negative binomial)	0,06309			
Pearson Chi-Square Value/df= 0,881				
Omnibus Test sig=0,000				
(Intercept)			181,85259	,000
S.v. of (B) Mobile Phone Model for p.w.			0,00002	,001
AverageWeekly Exchange Rate for p.w.			-0,21267	,614
First day of month stock (B) Mobile Phone Model			0,00000	,342
S.v. of (B) Mobile Phone Model for p.m.			0,00156	,000
S.p. of (B) Mobile Phone Model for p.m.			0,00447	,226
S.v. of (CB2) Mobile Phone Model P.M.			0,00024	,000
S.v. of (CB3) Mobile Phone Model P.M.			-0,00019	,000
S.v. of (CB4) Mobile Phone Model P.M.			0,01132	,000
S.v. of (CB6) Mobile Phone Model P.M.			-0,00026	,000
S.v. of (CB7) Mobile Phone Model P.M.			-0,00018	,000
S.v. of (CB8) Mobile Phone Model P.M.			-0,00084	,000
S.v. of (CB9) Mobile Phone Model P.M.			0,00045	,000
S.p. of (CB4) Mobile Phone Model P.M.			0,16524	,000
S.p. of (CB5) Mobile Phone Model P.M.			-0,28188	,000
S.p. of (CB6) Mobile Phone Model P.M.			0,07128	,000
S.p. of (CB7) Mobile Phone Model P.M.			-0,18005	,000
S.p. of (CB11) Mobile Phone Model P.M.			0,00260	,000
(Negative binomial)			0,02725	
Pearson Chi-Square Value/df= 1,370				
Omnibus Test sig=0,000				

Dependent Variable: Sim Activation of (B) Mobile Phone Model for previous week	

**Descriptions: S.V.= Sales volume; S.P.= Sales price; p.m.= Previous month; p.w.= Previous week; (D) = A research company; (A) = Selected mobile phone model in this research (market driven mobile phone model); (B)=Selected mobile phone model in this research (new model to be marketed); (CB)=Competative brand.*

Finally, in the negative binomial regression analysis to explain the variance of the SIM activation log numbers of the (B) Mobile Phone Model the previous week, the variables that were statistically significant in the first three models described above were reassembled and analyzed again in model 4. The findings of the Model 4 analysis are shown in the table above.

According to findings, Most of the variables have protected their statistical significance level in Model 4. The variables that lose statistical significance are the weekly exchange rate, the number of stocks on the first day of the month for the (B) Mobile Phone Model device, and the sales prices for the previous month of the (B) Mobile Phone Model device.

According to the findings of Model 4, statistically significant and positive variables with the number of SIM activation of the (B) Mobile Phone Model are as follows:

a) The sales volume and Sales price of (B) Mobile Phone Model for the previous week,
b) The sales volume of (CB2) Mobile Phone Model, (CB4) Mobile Phone Model and (CB9) Mobile Phone Model.
c) The sales prices of (CB4) Mobile Phone Model, (CB9) Mobile Phone Model and (CB11) Mobile Phone Model.

According to the findings of Model 4, statistically significant but negative variables with the number of SIM activation of (B) Mobile Phone Model are:

a) The sales volume of (CB3) Mobile Phone Model, (CB6) Mobile Phone Model, (CB7) Mobile Phone Model and (CB8) Mobile Phone Model,
b) The sales price of (CB5) Mobile Phone Model and (CB7) Mobile Phone Model.

4.2 TIME SERIES ANALYSIS FINDINGS

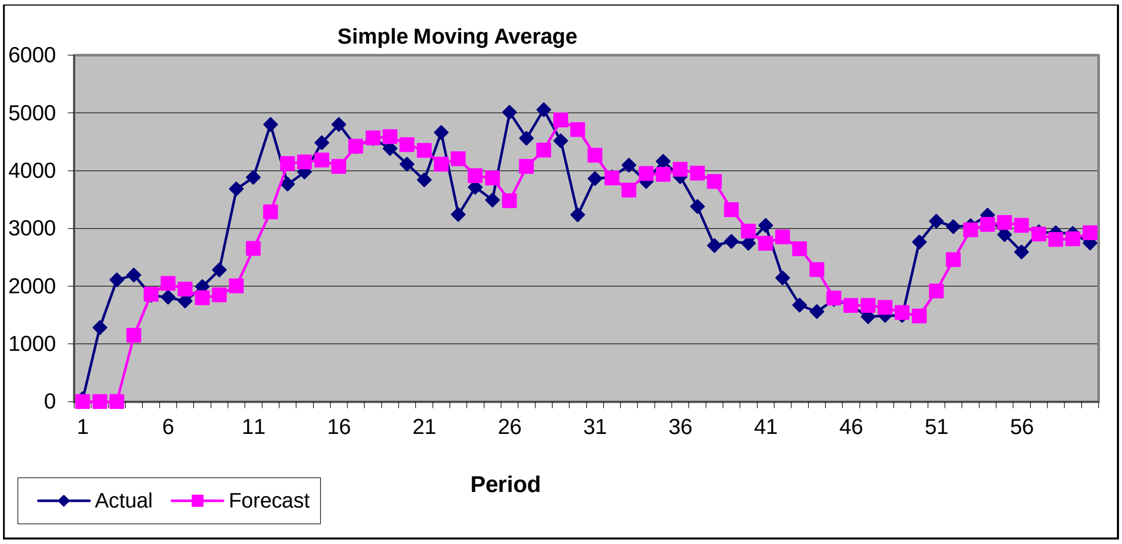
4.2.1 Time Series Forecasting for (A) Mobile Phone Model

The actual and forecasted sales volumes of the (A) Mobile Phone Model are calculated with "simple moving average", "Weighted Moving Average" (3 period), "Single Exponential Smoothing", "Trend Adjusted" "Exponential Smoothing", "Trend and Seasonal Effects" and "Linear Trend" methods of the time series and the findings are explained under the following headings.

4.2.1.1 Simple Moving Average

The figure below shows the actual and forecasted sales volumes of the (A) Mobile Phone Model calculated with simple moving average method. The periods are set to three, which means the forecasted volumes are the average of the last 3 periods. Mean Absolute Deviation-MAD and Mean Square Error-MSE, which shows the precision of the forecasting models are 477 and 43756, respectively.

Figure 4.2: Actual and Forecasted Sales Volume of (A) Mobile Phone Model Simple Moving Average

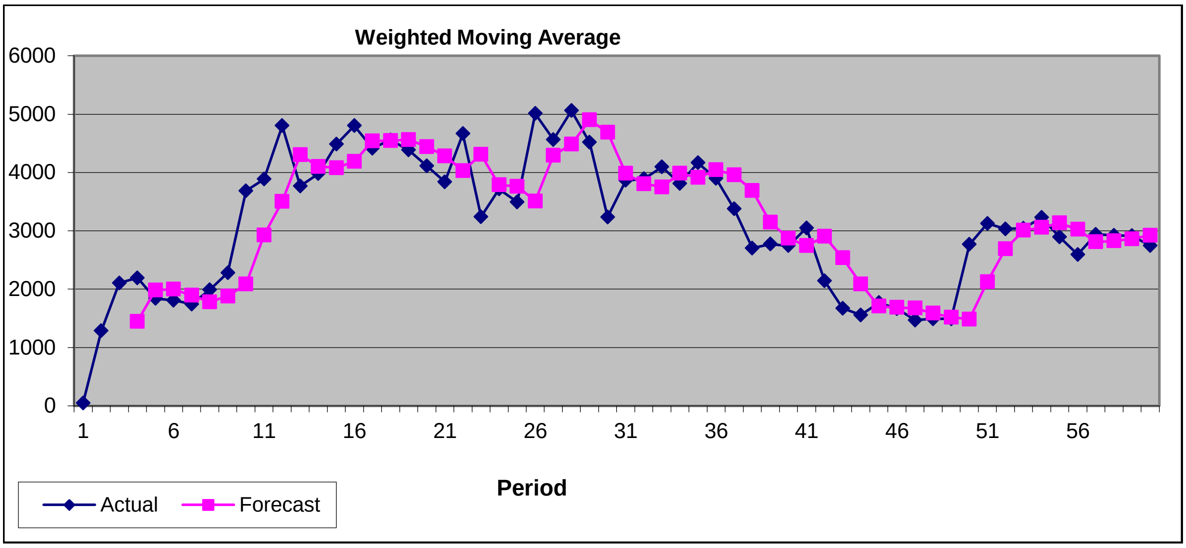


When the figure is examined, it is seen that the actual sales of the (A) Mobile Phone Model was higher at the first 12 period. Then, in the 13th and 14th periods, the actual sales declined under the forecasted volumes. The actual sales volume steadily began to decline in the 36th period until the 50th period. The forecasted volumes during these 14 period was higher than the actual volumes. The actual sales sharply increased in the 50th period from 1490 to 2766 with an error of 1283.

4.2.1.2 Weighted Moving Average (3 period)

The figure below shows the actual and forecasted sales volume of (A) Mobile Phone Model telephone calculated with weighted moving averages. The period is set to three and the weight for the most recent period is 0,5. It is 0,3 for the second period and it is 0,2 for the least recent period. Mean Absolute Deviation-MAD is 434 and Mean Square Error-MSE is 362265.

Figure 4.3: Actual and Forecasted Sales Volume of (A) Mobile Phone Model Weighted Moving Average

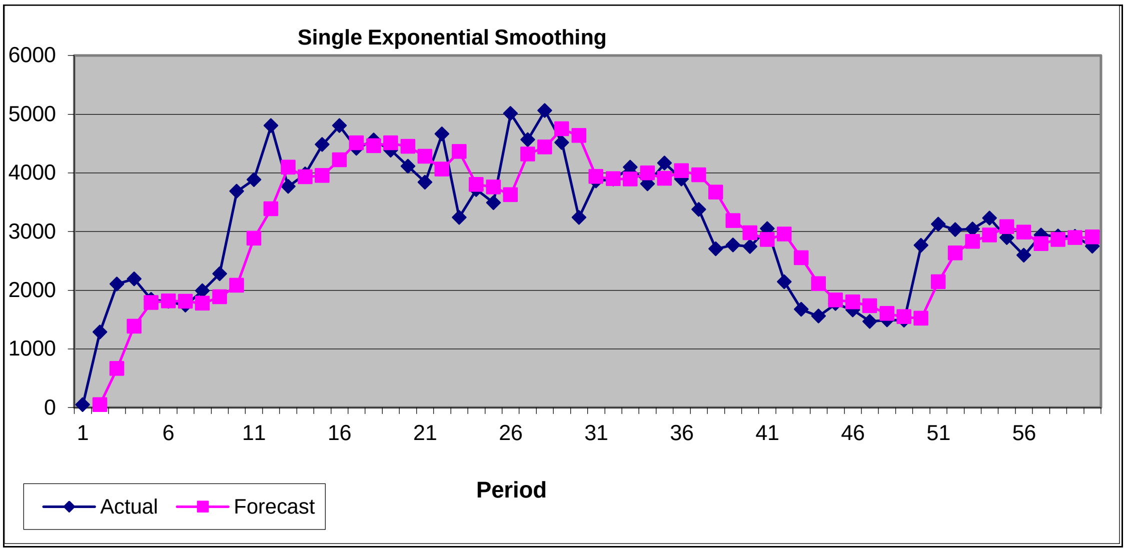


The weighted moving averages of the (A) Mobile Phone Model for the 60 period is similar to its simple moving averages. It is seen in the figure that the actual sales of the (A) Mobile Phone Model was higher at the first 12 period. Then, in the 13th and 14th periods, the actual sales declined under the forecasted volumes. The actual sales volume steadily began to decline in the 36th period until the 50th period. The forecasted volumes during these 14 period was higher than the actual volumes.

4.2.1.3 Single Exponential Smoothing

The smoothing constant α is set as 0,5 for this analysis. The smoothing constant is the weight. The smoothing constant adjust the amount of smoothing. It defines how each component reacts to current conditions. Lower weights give less weight to recent data, which produces a smoother line. Higher weights give more weight to recent data, which produces a less smooth line.

Figure 4.4: Actual and Forecasted Sales Volume of (A) Mobile Phone Model Single Exponential Smoothing

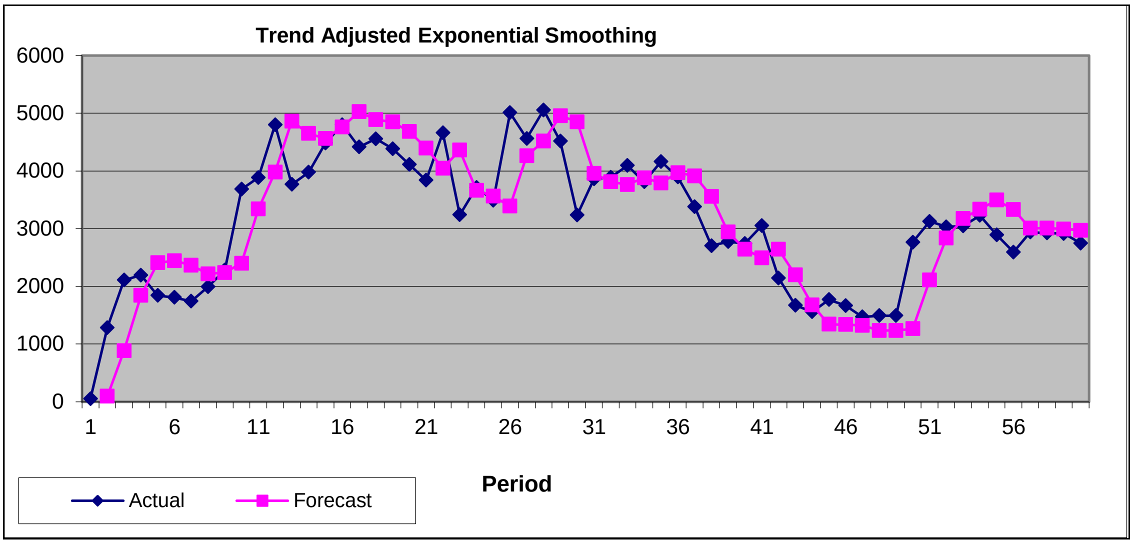


The figure above shows the single exponential smoothing with a constant of 0,5. Mean Absolute Deviation-MAD is 458 and Mean Square Error-MSE is 410013. Single exponential smoothing assumes that the data move wavelike pattern around a stable mean.

4.2.1.4 Trend Adjusted Exponential Smoothing

An added trend adjustment factor or a smoothing constant for trend is the feature of adjusted exponential smoothing. A high smoothing constant for trend reflects trend changes more than a low one. The α for this smoothing is set to 0,5 and the smoothing constant for trend is set to 0,25

Figure 4.5: Actual and Forecasted Sales Volume of (A) Mobile Phone Model Trend Adjusted Exponential Smoothing

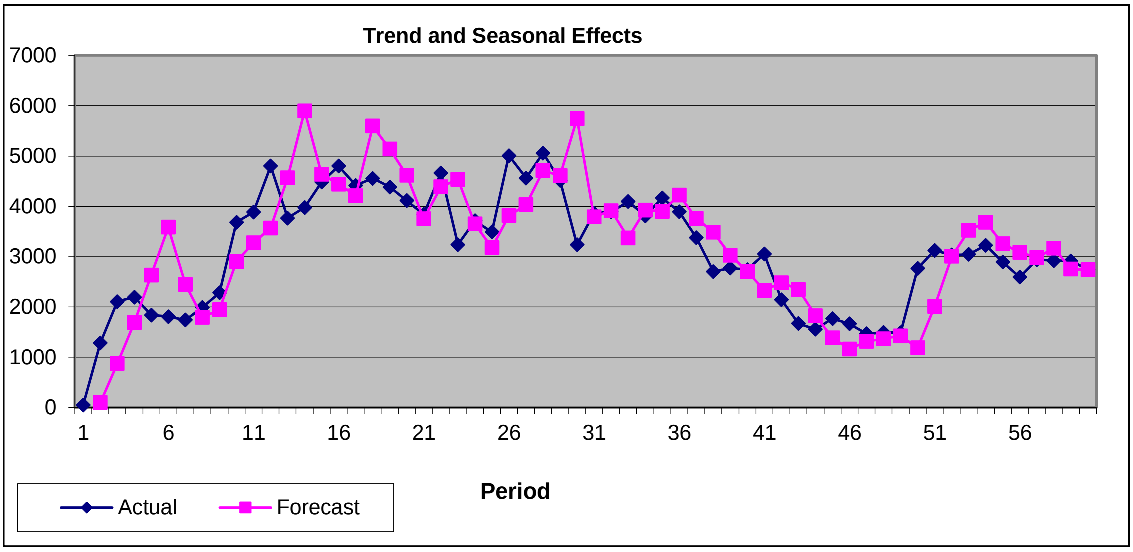


The figure above shows the trend adjusted exponential smoothing. Mean Absolute Deviation-MAD is 489 and Mean Square Error-MSE is 417982. Trend adjusted exponential smoothing is consistently higher than the previous exponentially smoothed forecast. However, in general, the pattern, or degree of smoothing is very similar for both forecasts.

4.2.1.5 Trend and Seasonal Effects

A smoothed adjustment for seasonality is the additional feature of trend and seasonal effects different than the trend adjusted exponential smoothing model. The number of seasons is set to 4 and the smoothing constants associated with this model is three.

Figure 4.6: Actual and Forecasted Sales Volume of (A) Mobile Phone Model Trend and Seasonal Effects



Examining the figure above, we can see clear differences from the other models of forecasting mentioned above. The forecasted sales for periods 5,6 and 7 is higher than the actual sales. Likewise, the forecasted sales in period 13 and 14, 18, 19 and 20 and 30 fluctuates well above the actual sales.

The forecasted sales number for period 30, for example, is 5747, but the actual sales for this period is 3236. The difference in this period is the highest point. The second highest difference is in period 14, where the forecasted sales is 5900, but the actual sales is 3978. The third highest difference between the forecasted and actual sales value is in the 6th period. The forecasted sales number is 3586, but the actual one is 1808.

4.2.2.6 Linear Trend

Linear trend is a causal method of forecasting. When demand displays a clear trend over time, linear trend line can be used to forecast demand.

The following figure shows the linear trend line compared with the actual sales data. The trend line does not appear to reflect closely the actual data, which emphasizes not a “good fit”. Therefore, this model cannot be a good forecast model for this case. The Mean Absolute Deviation-MAD and Mean Square Error-MSE values also reflect this poor fit (MAD=835 and MSE=1041542).

Figure 4.7: Actual and Forecasted Sales Volume of (A) Mobile Phone Model Linear Trend

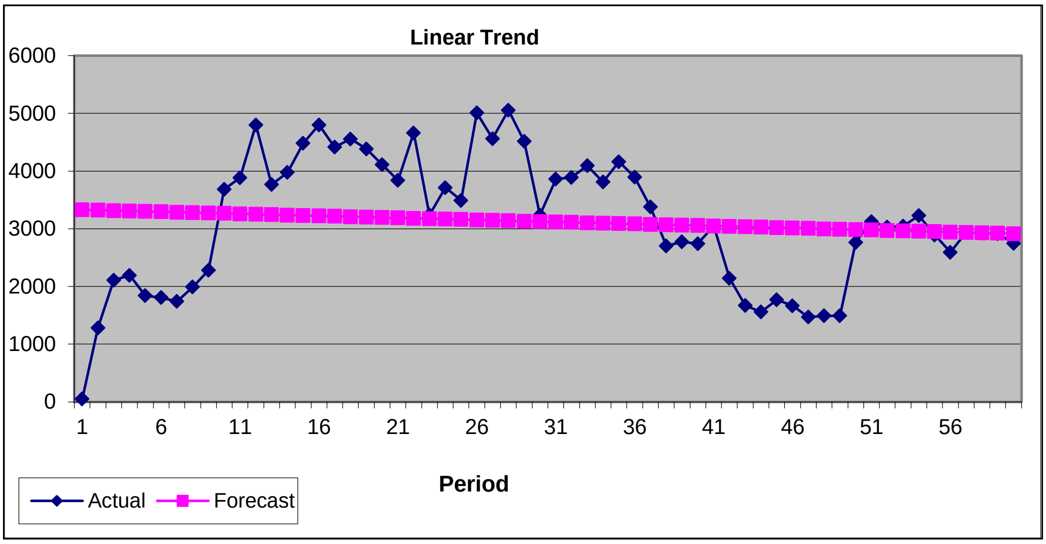


Table 4.12: The Precisions of the Forecasting Models for (A) Mobile Phone Model

(A) Mobile Phone Model (72 Weeks)	Based on the first 60 weeks	
Method	**MAD**	**MSE**
Simple Moving Average	477	434.756
Weighted Moving Average	434	362.265
Single Exponential Smoothing	458	410.013
Trend Adjusted Exp. Smooth	489	417.982
Trend and Seasonal Effects	559	592.704
Linear Trend	835	1.041.542

The table shows the precisions of the forecasting models examined above. Mean Absolute Deviation-MAD and Mean Square Error-MSE are two common measures to evaluate the precision of forecasting systems and these are based on the error or deviation between the forecast and actual values. In general the lower the measures (MAD an MSE) the better the forecasting model. The table shows that the MAD and MSE measures for weighted moving average is relatively well for forecasting among the other models.

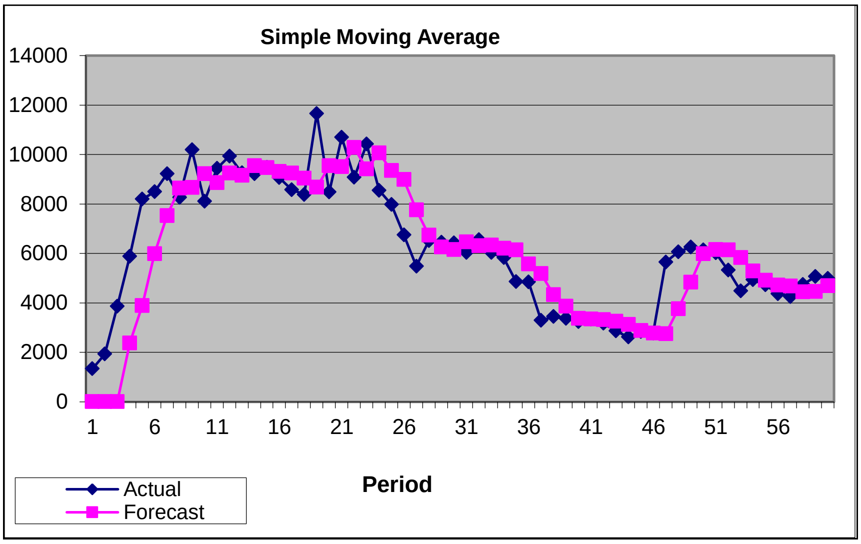
4.2.2 Time Series Forecasting for (B) Mobile Phone Model

The actual and forecasted sales volumes of the (B) Mobile Phone Model are calculated with "simple moving average", "Weighted Moving Average" (3 period), "Single Exponential Smoothing", "Trend Adjusted" "Exponential Smoothing", "Trend and Seasonal Effects" and "Linear Trend" methods of the time series and the findings are explained under the following headings.

4.2.2.1 Simple Moving Average

The figure below shows the actual and forecasted sales volumes of the (B) Mobile Phone Model calculated with simple moving average method. The periods are set to three, which means the forecasted volumes are the average of the last 3 periods. Mean Absolute Deviation-MAD and Mean Square Error-MSE, which shows the precision of the forecasting models are 935 and 1804750, respectively.

Figure 4.8: Simple Moving Average of (B) Mobile Phone Model

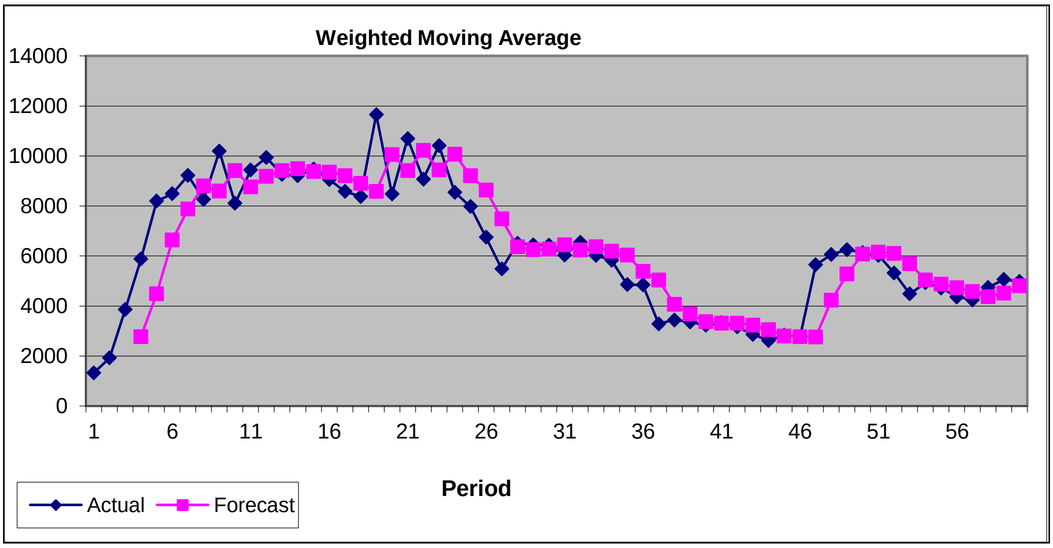


When the figure is examined, it is seen that the actual sales of the (B) Mobile Phone Model was higher than the forecasted ones for the first 8 period. In period 9, 19, 47, 48 and 49 the actual sales highly fluctuates over the forecasted sales. The actual sales and the forecasted sales go over to 8000 phone sales at the period-6. The sales go over this volume until the period 25. The inclination goes down after 25th period steadily until the period 46. Then it increases sharply in the 47th period.

4.2.2.2 Weighted Moving Average (3 period)

The figure below shows the actual and forecasted sales volume of (B) Mobile Phone Model calculated with weighted moving averages. The period is set to three and the weight for the most recent period is 0,5. It is 0,3 for the second period and it is 0,2 for the least recent period. Mean Absolute Deviation-MAD is 860 and Mean Square Error-MSE is 1502637.

Figure 4.9: Weighted Moving Average (3 period) (B) Mobile Phone Model



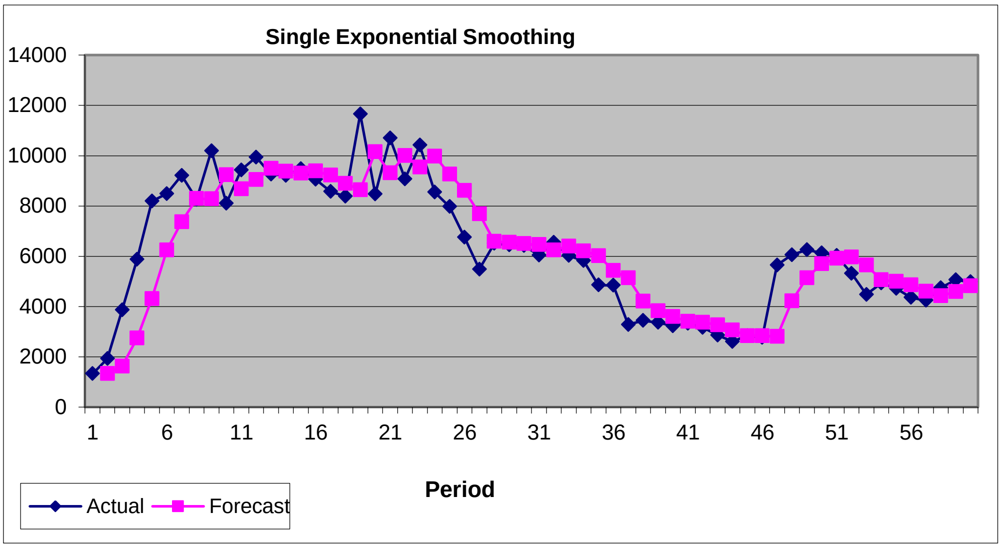
The weighted moving averages of the (B) Mobile Phone Model for the 60 period is similar to its simple moving averages. It is seen in the figure that the actual sales of the (B) Mobile Phone Model were higher at the first 7 periods. The actual sales volume steadily began to decline in the 24th period until the 46th period.

The actual sales in the 19th period is dramatically higher than the forecasted sales. There is another one period which we can see a higher jump for the actual sales, 47th period. The steady decline between 24th and 46th period stops and the actual sales increases from 2777 to 5650 in this 47th period.

4.2.2.3 Single Exponential Smoothing

The smoothing constant α is set as 0,5 for this analysis. The smoothing constant is the weight. The smoothing constant adjust the amount of smoothing. It defines how each component reacts to current conditions. Lower weights give less weight to recent data, which produces a smoother line. Higher weights give more weight to recent data, which produces a less smooth line.

Figure 4.10: Single Exponential Smoothing of (B) Mobile Phone Model

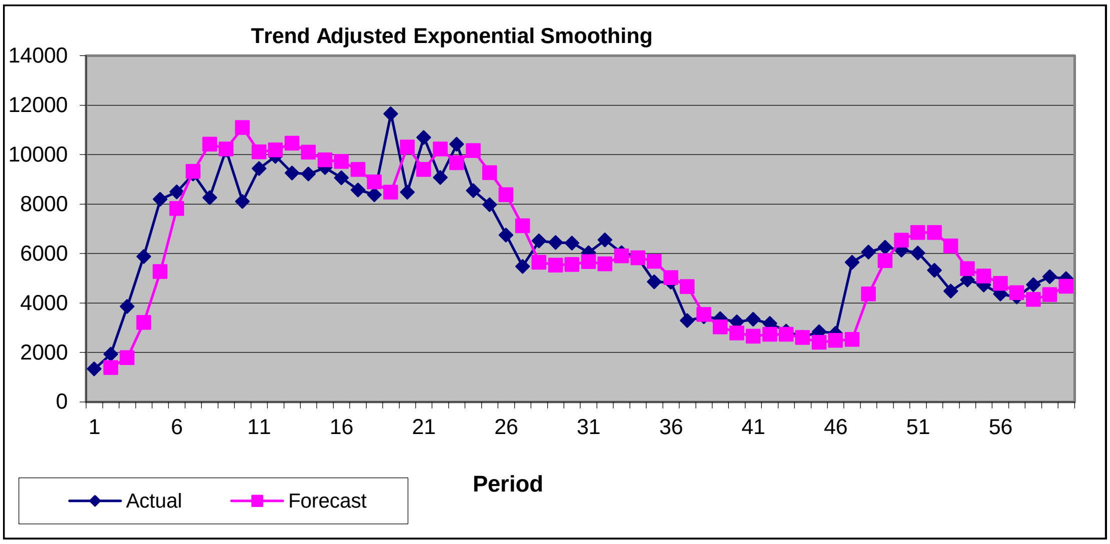


The figure above shows the single exponential smoothing with a constant of 0,5. Mean Absolute Deviation-MAD is 914 and Mean Square Error-MSE is 1654274.

4.2.2.4 Trend Adjusted Exponential Smoothing

An added trend adjustment factor or a smoothing constant for trend is the feature of adjusted exponential smoothing. A high smoothing constant for trend reflects trend changes more than a low one. The α for this smoothing is set to 0,5 and the smoothing constant for trend is set to 0,25

Figure 4.11: Trend Adjusted Exponential Smoothing of (B) Mobile Phone Model

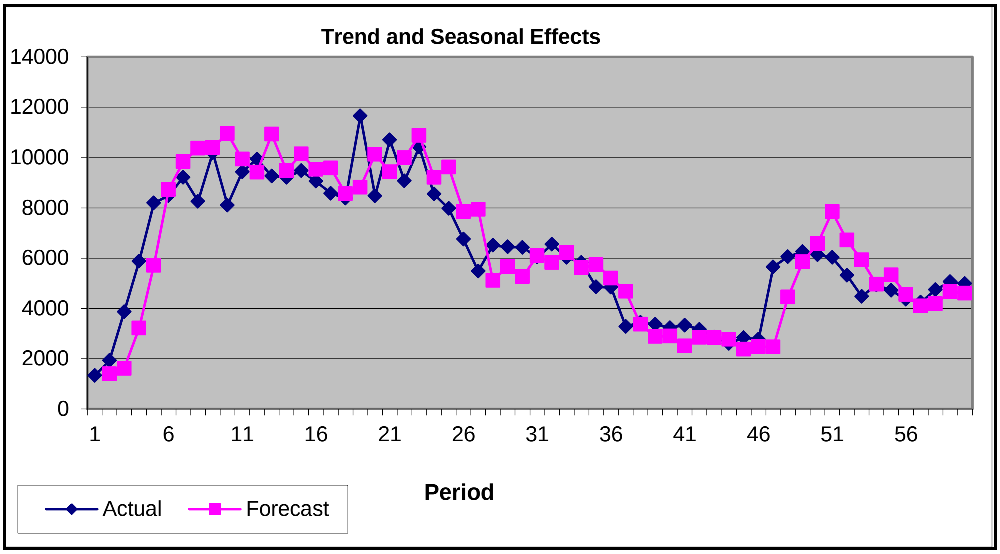


The figure above shows the trend adjusted exponential smoothing. Mean Absolute Deviation-MAD is 954 and Mean Square Error-MSE is 1613029. Trend adjusted exponential smoothing is consistently higher than the previous exponentially smoothed forecast. However, in general, the pattern, or degree of smoothing is very similar for both forecasts.

4.2.2.5 Trend and Seasonal Effects

A smoothed adjustment for seasonality is the additional feature of trend and seasonal effects different than the trend adjusted exponential smoothing model. The number of seasons is set to 4 and the smoothing constants associated with this model is three.

Figure 4.12: Trend and Seasonal Effects of (B) Mobile Phone Model



Examining the figure above, we can see clear differences from the other models of forecasting mentioned above. However, we can see again the clear increase of the actual sales for period 19. This is the peak of the actual sales for (B) Mobile Phone Model. The actual sales volume in the 18th period is 8383. With a 2834 difference, the highest sales volume of the model is 11656 for the period 19. Interestingly the sales go down at the 20th period to 8475.

4.2.2.6 Linear Trend

Linear trend is a causal method of forecasting. When demand displays a clear trend over time, linear trend line can be used to forecast demand. The following figure shows the linear trend line compared with the actual sales data. The trend line does not appear to reflect closely the actual data, which emphasizes not a "good fit".

Therefore, this model cannot be a good forecast model for this case. The Mean Absolute Deviation-MAD and Mean Square Error-MSE values also reflect this poor fit (MAD=1353 and MSE=2971093).

Figure 4.13: Linear Trend of (B) Mobile Phone Model

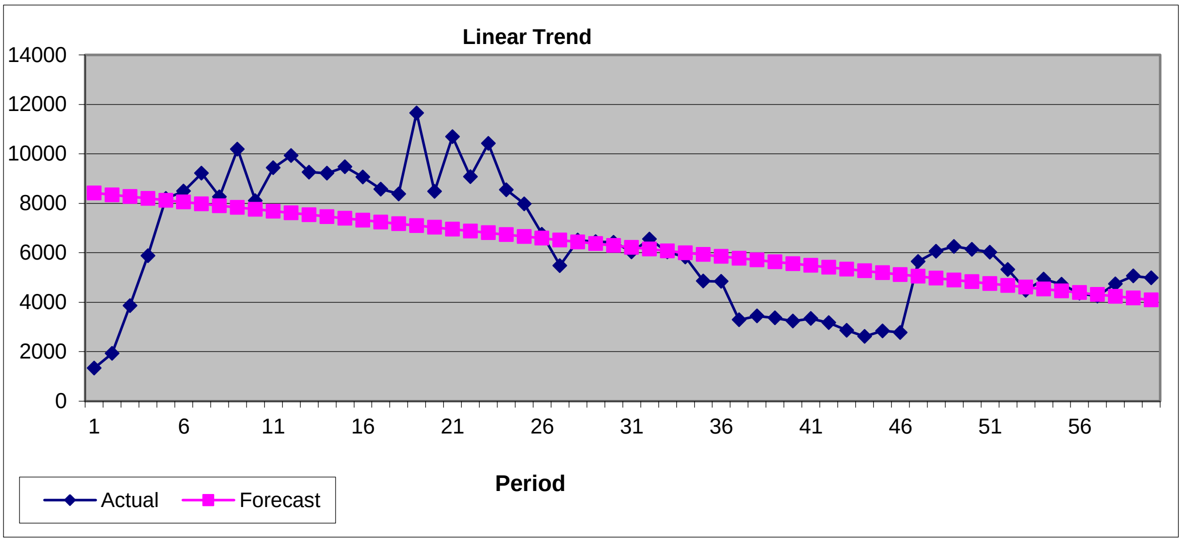


Table 4.13: The precisions of the forecasting models for (B) Mobile Phone Model

***(A) Mobile Phone Model* (69 Weeks)**	Based on the first 60 weeks	
Method	**MAD**	**MSE**
Simple Moving Average	935	1.804.750
Weighted Moving Average	860	1.502.637
Single Exponential Smoothing	914	1.654.274
Trend Adjusted Exp. Smooth	954	1.613.029
Trend and Seasonal Effects	931	1.564.579
Linear Trend	1.353	2.971.093

The table shows the precisions of the forecasting models examined above. Mean Absolute Deviation-MAD and Mean Square Error-MSE are two common measures to evaluate the precision of forecasting systems and these are based on the error or deviation between the forecast and actual values. In general the lower the measures (MAD an MSE) the better the forecasting model. The table shows that the MAD and MSE measures for weighted moving average is relatively well for forecasting among the other models.

4.3 MACHINE LEARNING ANALYSIS FINDINGS

The table below shows the results of different algorithms for (A) Mobile Phone Model Sim Activation Prediction for next week.

Table 4.14: (A) Mobile Phone Model Sim Activation Prediction/ Next Week- 10-fold cross validation (predicted_ver2_NEXT_WEEK)

ALGORITHM	CORRELATION COEFFICIENT	MEAN ABSOLUTE ERROR	ROOT MEAN SQUARED ERROR	RELATIVE ABSOLUTE ERROR (percent)
SMO reg.- RBF c=2, g=0.09	0.8112	462.6124	592.01	54.5359 percent
SMO reg – Poly c=1, e=2	0.7752	550.9144	684.3967	64.9455 percent
MLP, hidden layers=1	0.794	525.0661	657.4542	61.8983 percent
Linear Regression	0.2006	1734.6131	6915.0884	204.4879 percent
k-NN, k=3	0.6876	532.0619	751.3737	62.7231 percent
Random Forest	0.8478	412.9693	534.6837	48.6836 percent

Pearson correlation coefficient is a measure of linear correlation. So a value close to 1 or -1 shows only that there is a linear dependence between the actual values of SIM activation of (A) Mobile Phone Model and the prediction of SIM activation of (A) Mobile Phone Model. Based on this, the higher the correlation coefficient the higher the fit of the linear relation. Among the Algorithms in the table, the higher correlation belongs to the random forest algorithm (r= 08478).

Mean absolute error (MAE) is a measure of difference between two continuous variables. Root mean squared error (RMSE) is a measure of how spread out these residuals are. In other words, how concentrated the data is around the line of best fit. It is a frequently used measure of the differences between values predicted by a model.

In MAE and RMSE, we look at the average difference between those two values. Therefore, the smaller MAE and RMSE is desirable. Looking at the table above, we see that the smallest MAE is 412,9693 and the smallest RMSE is 534,6837 which belongs to the random forest algorithm.

In Relative absolute error (percent) (RAE), we divide those differences by the variation of actual values of SIM activation of (A) Mobile Phone Model and multiply this value by 100 to get a percentage.

Therefore, these values tell us how much actual values of SIM activation of (A) Mobile Phone Model differs from itself. Based on these explanations, the smallest RAE is 48,6836 percent and it belongs to random forest model.

Based on these results (A) Mobile Phone Model Sim Activation Prediction for next week, Random Forest has better performance than the other algorithms.

The table below shows the results of different algorithms for (A) Mobile Phone Model Sim Activation Prediction for next month:

Table 4.15: (A) Mobile Phone Model Sim Activation Prediction / Next Month 10-Fold cross validation (_NEXT_MONTH_ver1)

Algorithm	Correlation coefficient	Mean absolute error	Root mean squared error	Relative absolute error (percent)
SMOreg – RBF c=2, g=0.09	0.855	387.4174	512.9187	45.9493 percent
SMOreg – Poly c=1, e=2	0.7483	551.8095	696.8041	65.4468 percent
MLP, hidden layers=1	0.5651	680.4007	880.5101	80.6982 percent
Linear Regression	0.6491	572.4848	867.7671	67.899 percent
k-NN, k=3	0.7422	481.4951	673.5434	57.1072 percent
Random Forest	0.8987	340.49	444.7739	40.3835 percent

Pearson correlation coefficient is a measure of linear correlation. So a value close to 1 or -1 shows only that there is a linear dependence between the actual values of SIM activation of (A) Mobile Phone Model and the prediction of SIM activation of (A) Mobile Phone Model.

Based on this, the higher the correlation coefficient the higher the fit of the linear relation. Among the Algorithms in the table, the higher correlation belongs to the random forest algorithm (r= 08987).

Mean absolute error (MAE) is a measure of difference between two continuous variables. Root mean squared error (RMSE) is a measure of how spread out these residuals are. In other words, how concentrated the data is around the line of best fit. It is a frequently used measure of the differences between values predicted by a model. In MAE and RMSE, we look at the average difference between those two values.

Therefore, the smaller MAE and RMSE is desirable. Looking at the table above, we see that the smallest MAE is 340,49 and the smallest RMSE is 444,7739 which belongs to the random forest algorithm.

In Relative absolute error (percent) (RAE), we divide those differences by the variation of actual values of SIM activation of (A) Mobile Phone Model and multiply this value by 100 to get a percentage.

Therefore, these values tell us how much actual values of SIM activation of (A) Mobile Phone Model differs from itself. Based on these explanations, the smallest RAE is 40,3835 percent and it belongs to random forest model.

Based on these results (A) Mobile Phone Model Sim Activation Prediction for next month, Random Forest has better performance than the other algorithms.

Table 4.16: (A) Mobile Phone Model Sim Activation Prediction / Next Month fold cross validation (_NEXT_MONTH_ver2)

Algorithm	Correlation coefficient	Mean absolute error	Root mean squared error	Relative absolute error (%)
SMOreg – RBF c=2, g=0.09	0.9373	890.0178	1281.6525	28.0048%
SMOreg – Poly c=1, e=2	0.937	957.5583	1300.4064	30.13%
MLP, hidden layers=1	0.8859	1296.6139	1735.9732	40.7986%
Linear Regression	0.307	1896.5019	7093.3108	59.6743%
k-NN, k=3	0.8215	1549.5354	2175.1122	48.7569%
Random Forest	0.9413	900.1748	1284.2122	35.0006%

Based on the explanations above, the higher the correlation coefficient the higher the fit of the linear relation. Among the Algorithms in the table, the higher correlation belongs to the random forest algorithm (r= 0.9413).

As explained above the smaller MAE and RMSE is desirable. Looking at the table above, we see that the smallest MAE is 890.0178 and the smallest RMSE is 1281.6525, which belongs to the SVM with RBF Kernel.

The values of Relative absolute error (percent) (RAE) tells us how much actual values of SIM activation of (A) Mobile Phone Model differs from itself. Based on these explanations, the smallest RAE is 28.0048 percent and it belongs to SVM with RBF Kernel.

Based on these results (A) Mobile Phone Model Sim Activation Prediction for next month, SVM with RBF Kernel has better performance than the other algorithms.

5. DISCUSSION

The estimation analyzes carried out within the scope of the research were carried out in three stages. In the first stage, research data were analyzed within the NBR model; in the second stage, "demand forecasts" were made in six different ways according to the "time series analysis" method. In the third and final stages of the analysis, the "machine learning" method was used to determine the demand estimates for the telephones and to determine which algorithm should be used in case of using the algorithm.

In this part of the research, we will try to evaluate the findings that are obtained as the result of three different demand forecasting analysis methods on the (A) Mobile Phone Model and the (B) Mobile Phone Model. In this sense, it is appropriate briefly to summarize the findings of Negative Binomial Regression Analysis (NBR) multiple regression analysis.

In this context, the correlation analysis before the NBR analyzes were conducted to examine whether there are statistically significant relationships between the dependent varibles and the independent variables. Namely, SIM activation (dependent variables) of the (A) Mobile Phone Model and (B) Mobile Phone Model phone models and the sales figures of the same model, the number of return to service phones, the exchange rates, sales prices and sales volume of other competing brands in the sector, special sales days in the month, and seasonal effect of 12 months within a year. As a result of the Pearson correlation analysis performed in this context, the SIM activation numbers of both phones show an increase and decrease according to the counted variables; it has been found that there are positive and negative interactions between variables.

These findings are in parallel with the researches in the literature: For example, the findings are similar to the results of following research, Kehoe and Boughton (2001), Gunasekaran et al. (2001) and (2004), Gunesekaran and Kobu (2007) Deshpande (2012), Rexhausen et al. (2012). The findings also resemble the results of studies suggesting demand forecasting through models known as "probable stock models" (Axsater, 1993; Chen, 1999; Hariga, 2010; Yang et al., 2011).

On the other hand, as a result of the analyzes conducted for both phones through the models created within the scope of the Negative Binomial Regression (NBR), some findings that both validated the correlation analysis and enable demand forecasting have been found. To summarize these findings briefly; sales of both phone models in the week and month are affected by exchange rates, inventory numbers, sales volumes, and by a certain increase or decrease in one unit of the number and amount of sales of the competitors.

However, the findings of the NBR analysis for the (A) Mobile Phone Model phone showed that some of the findings were different from those of the (A) Mobile Phone Model. Especially the weekly exchange rate, the number of stocks on the first day of the month of the (A) Mobile Phone Model and the sales prices of the (B) Mobile Phone Model for the previous month were found to be losing statistical significance in terms of SIM activations of this phone. For this reason, it is possible to say that demand forecasting with NBR for this phone model, newly introduced to the market, has lost effectiveness and functionality.

As a matter of fact, the findings of the NBR analyzes for the months of sales for both phones are only foreseen by the (A) Mobile Phone Model product, which already exists in the market. In contrast, it is understood that the NBR analysis method is insufficient to make these estimates for the (B) Mobile Phone Model, which has just been introduced to the market.

Findings in this context indicate that the (A) Mobile Phone Model has a seasonal effect on SIM card activations. It is estimated that the highest season for this phone's SIM activations (and therefore the greatest increase in sales) will be the month of September and the second highest sales will be in June. In contrast, it is estimated that the (A) Mobile Phone Model will have the lowest SIM activation, so the lowest mobile sales will be in February.

In the second stage of the study, demand forecasts of (A) Mobile Phone Model and (B) Mobile Phone Model telephones were tried to be calculated. For this purpose, time series analysis is used in demand forecasting. Some findings have been reached as a result of the time series analysis. "Simple moving average", "Weighted Moving Average" (3 periods), "Single Exponential Smoothing", "Trend Adjusted", "Exponential Smoothing", "Trend and Seasonal Effects" and "Linear Trend " methods were employed.

The findings among the time series analysis model yielded that the most effective and better predictive power for both the (A) Mobile Phone Model and the (B) Mobile Phone Model, is the "WEIGHTED MOVING AVERAGE" model. The findings reached at the end of these analyzes showed that long-term demand forecasts are related to a product that already exists in the market, so estimated sales figures are more than actual sales figures. This leads to continuous inventory and inventory overhead and extra cost to the business.

Looking at the demand forecasts by this method, (A) Mobile Phone Model's actual sales in the first 12, 13 and 14 weeks period fell below forecasts; it has been understood that the actual sales figures are in a constant downward trend between 36 weeks and 50 weeks. To determine the time span between the actual sales figures and the estimated sales figures of the newly introduced (B) Mobile Phone Model phone, the "weighted moving average" of the phone was calculated over the 60-week period measured.

According to findings, actual sales figures are higher than estimated figures in the first 7-week period. Actual sales figures have declined since the 24th period and declined until the 46th period. In particular, the actual sales figures for the 19th Period are obviously higher than predicted and the 60th Period is the highest peak. This finding suggests that the demand forecast for (B) Mobile Phone Model, a newly introduced to market, is well above the actual sales. This indicates two facts:

First, the traditional demand forecasting methods such as Regression and Time Series analysis are losing the efficiency when conducted for new products in the market; thus, causing increasing inventory and storage costs for the businesses. As a matter of fact, when we look at the literature, it is seen that many researches reached similar findings (Lynn et al., 1999, Bass et al., 2001, Kahn, 2002, Bhattacharya, 1997, Kotler, Wong, Saunders and Armstrong, 2005, Reiner et al., 2009).

If so, it can be said that if a product is new to the market and it is a "high-tech products" and "short-lived" mobile phones, the demand forecasting in the context of sales, order, production, SCM and inventory management employing the "time series analysis" method may not be a precise option.

Another common finding is that short-term demand forecasts such as weekly and daily are not statistically meaningful with these two methods. Actually, this finding is compatible with the findings of many studies using time series analysis in the literature. For example, Kirby (1996) failed to find significant results in monthly forecasting and Zhou et al., (2002) failed to find significant results in hourly and daily forecasting of water supply demand. Baker and Fitzpatrick (1986) found no meaningful conclusion in the weekly and daily forecasting of the estimates of daily emergency medical care and routine health care claims for the four counties of South Carolina. Schultz (1987) found no statistically significant results in the weekly forecast of a product claim that was irregular in a business operating in the healthcare sector.

Because demand forecasts are predicted more successfully over a long period in all of the listed studies, they do not represent meaningful results in the short term. However, when there are abundant historical data that are constantly separate on the market, both methods make it easier and quicker to save the day.

In addition, the findings of the studies in the literature confirm this finding. For example, Bhattacharya (1974) was able to predict potential phone subscription sales and order quantities on a quarterly and yearly basis only as a result of his research on estimating telephone claims in Australia. For this reason, it can be said that time series and regression analysis models are inadequate especially in the estimation of weekly demand and, in the long run, giving misleading predictions is compatible with the results of the studies in the literature such as: Mahajan et al. (2000), Mead and Islam, (2006), Ching et al. (2010), Qian'e (2012), Ivanov (2009), Graefe and Armstrong (2011), Berbain, Bourbonnais, Vallin (2011), Semco Jahanbin Paul Goodwin and Sheik Meeran (2013) Hsi-Tse Wang and Ta-Chung Wang (2016), and finally Chen, Tzu and Liang (2017).

These findings, which are found in the result of the research and are in accordance with the literature, show that satisfying findings about the demand forecasting by using both methods which are rooted in the literature as traditional quantitative methods are very difficult especially in terms of new and high-tech products. From this point on, the third phase of analysis, which is used in the research, has been started.

In this context, demand forecasting has been tried by using various algorithms with machine learning method. Analyzes made in the context of machine learning are in three stages, so they will be evaluated in four stages in the findings. In the first phase of these analyzes using the WEKA program, the data for the (A) Mobile Phone Model were checked primarily for "pearson linear correlation" analysis to determine whether there was a linear dependence between the SIM activation / actual sales quantities of the two phones and the estimated sales figures.

Findings have shown that the machine learning algorithm will perform well in terms of estimating the "next week" and "next month" sim activation numbers / sales figures for both (A) Mobile Phone Model and (B) Mobile Phone Model. In addition, it is revealed that employing random forest algorithm for a new mobile phone offered for sale to the national and global markets will provide precise and clear findings to determine the optimum amount of stocking and potential sales on a weekly and monthly basis. According to these findings.

6. CONCLUSION AND SUGGESTIONS

It has always been more important to gain sustainable competitive advantage by succeeding to survive in the new economic order in which businesses experience rapid changes and transformations in their internal and external environment.

Especially in terms of the enterprises operating in the mobile phone sector mentioned in this thesis, in general, in the production, marketing and SCM processes; in particular the "demand forecast" under the scope of inventory and order management has become quite critical to the success.

Today, mobile phone sector is an extremely dynamic and innovative sector both in the world and in Turkey where demand is changing every day according to new models and competition is experienced. All businesses that want to survive in this sector have to make "demand forecasts" very accurately within SCM, inventory, sales and order management.

Qualitative and quantitative research methods have been used in this research in order to determine the effective demand forecasting method to provide full time optimization of the SCM and inventory management processes of the enterprises in the mobile telephone sector. It is possible to conclude the findings obtained as a result of the research and to make some suggestions comparing with the findings in the literature.

First of all, it is understood from the research result that the estimations of the sales numbers of the (A) Mobile Phone Model and the (B) Mobile Phone Model, which are subject to demand forecasting within the scope of the research, are changed in the positive or negative sense according to the following variables. These variables are; number of return to service, exchange rates, stock numbers of these phones in the first days of the month, sales prices and sales volumes of other competing brands in the sector, special days in the month, and month variables.

Especially in this sense, it is found that the sales of both phone models subject to demand forecast in the week and month; affected by a certain increase or decrease in one unit of the number and amount of sales of the competitors’ sales volume and sales price and exchange rates.

However, the study concluded that the number of stocks on the first day of the month of the (B) Mobile Phone Model device that was recently introduced to the market and the variables of the previous month's sales prices and the weekly exchange rate variables are variables that are statistically insignificant in terms of sim activations of this phone. These results are interpreted as demand forecasting with both regression analysis and time series analysis for a phone newly introduced in the mobile phone sector, resulting in loss of effectiveness and functionality.

Thus, research has shown that using more reliable, realistic, and quantitative methods such as time series or regression analysis to gain the ability to make demand forecasts based on short periods (daily and weekly) are insufficient for businesses in the mobile phone sector.

However, in this research, it has been determined that the quantitative demand forecasting method, which allows to estimate the demands with higher precision and accuracy level, is the "machine learning" method. According to this result of the research, it can be said that it is possible to use the "random forest algorithm" to find demand forecasts related to sales of a new mobile phone product offered for sale to national and global markets.

In addition, research has concluded that demand forecasts based on precise and clear dates in this sector can be reached by means of the machine learning method. Machine learning produces solutions according to the "rule of association" in order to predict and forecast where and how to sell a new mobile phone to be marketed in the mobile phone sector. In the light of these results, it is possible to make some recommendation for the future researches. In this context, it should first be said that the algorithm of "machine learning" method based on artificial intelligence is now a very effective way of solving problems that have not been written yet.

However, the number of studies that have been widely used in this country, especially within the country, is rather limited. However, running the WEKA program, which is similar to SPSS, AMOS and EVIEWS, it is easy to use the machine learning method to solve research problems in different disciplines and contents.

Finally, for future researchers, in addition to demand forecasting for two telephone models, one of which is old and the other one is old, demand forecasting for the more telephone models and models included in the business stocks can be estimated.

Thus, competing products in the sector will be able to make a more comprehensive evaluation in terms of seeing the sales value and number of products offered for sale by each competitor product sales or sim activation realized in Turkey and global markets. Thus, product storage costs can be reduced in this regard.

REFERENCES

Books

Acar, Z., Köseoğlu, A. M. (2014), *Lojistik yaklaşımıyla tedarik zinciri yönetimi,* Ankara: Nobel Akademik Yayıncılık.

Alpaydın, E., (2011). *Yapay öğrenme.* İstanbul:Boğaziçi Yayınları.

Bowersox, D.J., Closs, D.J., Cooper, M.B., (2002). *Supply chain logistics management*. NY: McGraw-Hill.

Cameron A. Colin and Pravin K. Trivedi (1998), *Regression analysis of count data, econometric society monograph.* No.30, UK: Cambridge University Press.

Collier, Paul M. (2009), *Fundamentals of risk management for accountants and managers*, Burlington: Butterworth-Heinemann Reed Educational And Professional Publishing Ltd.

Cristianni, N.,Shawe-Taylor, J. (2000). *An introduction to support vector machines and other kernel-based learning methods,* UK: Cambridge UniversityPress.

Demir, Hulusi., GÜMÜŞOĞLU, Şevkinaz. (2003). Üretim Yönetimi-İşlemler Yönetimi. Beta Basım Yayım, 6. Baskı: İstanbul.

Dunham, M. (2003). *Data mining ıntroductory and advanced topics,* NY:Prentice Hall Pearson Education Inc.

Eroğlu, A. (2002*). Deterministik envanter modelleri*, Isparta:Fakülte Kitabevi.

Field, A. P. (2009). *Discovering statistics using SPSS:* (and sex and drugs and rock 'n' roll). Los Angeles: SAGE Publications.

Fitzgerald, L., Johnston, R., Brignall, S., Silvestro, R., Voss, C., (1991). *Performance measurement in service business.* London: CIMA.

Frees, Edward W. (1996). *Data analysis using regression models*: New Jersey: The Business Perspective. Prentice-Hall.

Habibi, Y., Sheisi, G. H., Abdi, H. (2015). *Voltage Instability Detection in Power SystemUsing Support Vector Machine* (SVM).

Hilbe, J. M. (2011). *Negative Binomial Regression.* (2nd ed.). Cambridge: Cambridge University Press.

Kamauff, J., (2009). *Manager's guide to operations management,* Newyork:Mc Graw Hill Ltd.

Kobu, B. (2006). *Üretim Yönetimi.* 13. Baskı, İstanbul: Beta Yayınevi.

Koçel, T. (2007), *İşletme Yöneticiliği*, İstanbul:Arıkan Basım Yayın.

Krajewski, L.J., Ritzman, L.P, Malhotra, M.K., (2013). *Operations Management-Process and Supply Chains*. 9th Edition, (Çeviri: Semra Birgün. Ankara: Nobel Akademik Yayıncılık.

Kress, George J., Snyder, John. (1994). *Forecasting and Market Analysis Techniques: A Practical Approach.* USA: Quorum Books:

Kumar, S. A., Suresh, N. (2008). *Production and Operations Management*. 2. Baskı, 271 s., Yeni Delhi, Hindistan: New-Age International Publishers.

Leenders, M. L., Fearon, H. E., Flynn, A. E., Johnson, P. F., (2002). *Purchasing & Supply Management.* NY: McGraw-Hill.

Mangan, J., Lalwoni, C., Butcher, T. (2008), *Global Logistics and Supply Chain Management*, UK: John Wiley and Sons.

Monks, J. G. (1996). *Operation Managements. Schaum's Outlines*, 2nd Edition, USA:Mc-Graw Hill.

Monks, Joseph G. (1987). *Operations Management*. Third Ed. Singapore: McGraw-Hill International.

Nahmias, S. (2009). *Production and Operation Analysis*. 6. Baskı, NY: Mc-Graw Hill,

Nebol, E., Uslu, T., Uzel E. (2014). *Tedarik Zinciri ve Lojistik Yönetimi*, İstanbul: Beta Yayınları.

Render, Barry, STAIR, Ralph M. (2000). *Quantitative Analysis for Management*. Seventh Ed: USA: Prentice- Hall Inc.,

Sağbaş, E.A. ve Ballı, S., (2015). *Transportation mode detection by using smartphone sensors and machine learning*" Muğla: Muğla Sıtkı Koçman Üniversitesi Yayınları.

Schroeder, R.G. (1989). *Operations Management: Decision Making in the OperationsFunction.* Third Ed.: Singapore: McGraw-Hill Book Co.

Stevenson, W.J., (2012). *Operations Management*. 18th Edition, NY: McGraw-Hill.

Tek, B.,. (1999). *Pazarlama İlkeleri: Global Yönetimsel Yaklaşım Türkiye Uygulamaları.* 8. Baskı, İstanbul:Beta Basım Yayım,.

Tengilimoğlu, D. Ve Yiğit, V. (2013), *Sağlık İşletmelerinde Tedarik Zinciri ve Malzeme Yönetimi,* Ankara: Nobel Yayıncılık.

Tersine, R. J. (1994). *Principles of Inventory and Materials Management*. 4th Edition, NY: Printice Hall.

Tütek, Hülya., Gümüşoğlu, Şevkinaz. (2000). *İşletme İstatistiği.* İzmir: Barış Yayınları.

Ülgen, Hayri ve Mirze, S. Kadri (2007). *İşletmelerde Stratejik Yönetim*, İstanbul: Arıkan Basım Yayım Dağıtım Ltd.

Yenersoy, G., (2011). *Üretim Planlama ve Kontrol*. İstanbul: Papatya Yayınları.

Yüksel, H. (2010). *Üretim/İşlemlerYönetimi Temel Kavramlar*. 2. Baskı, Ankara: Nobel Yayın Dağıtım.

Periodicals

Alon, I., QI, Min., Sadowski, Robert J. (2001). Forecasting Aggregate Retail Sales: A Comparison of Artificial Neural Networks and Traditional Methods, *Journal of Retailing and Consumer Services,* 8(3).

Amos, B. H. Turner and J. White, (2013)"Applying machine learning classifiers to dynamic Android malware detection at scale," *9th International Wireless Communications and Mobile Computing Conference (IWCMC),* Sardinia, pp. 1666-1671.

Aghezzaf, E.H., (2006). “Production planning and warehouse management in supply networks with inter- facility mold transfers”. *European Journal of Operational Research*, 182, 1122-1139.

Alazab, A. M. Hobbs, J. Abawajy ve M. Alazab, (2012). Using Feature Selection for Intrusion Detection System. International Symposium on Communications and Information Technologies (ISCIT). Indian.

Amasyalı, m. F., Bilgin, M., (2015), Comparison of Machine Learning Methods for the Sequence Labelling Applications. Sage pub.

Axsater, S. (1993). Continuous review policies for mul- ti-level inventory systems with stochastic demand. In: Graves, S.C. (Ed.), *Handbooks in Operations Research and Management Science,* vol. 4. North Holland, Amsterdam, The Netherlands.

Aytekin, Sinan (2009), “Tam Zamanlı Stok Yönetimi Felsefesinin Hastane İşletmelerine Uygulanabilirliği Ve Bir Üniversite Hastanesi Örneği”, *Balıkesir Üniversitesi Sosyal Bilimler Enstitüsü Dergisi,* Cilt 12 Sayı 21, Haziran, s.102-115.

Bace R. ve P.Mell, 2011. NIST Special Publication on Intrusion Detection Systems. *Publications of National Institute of Standards and Technology*, pp. 1-53,.

Bagchi, P.K., (1996). “Role of benchmarking as a competitive strategy: the logistics experience”. *International Journal of Physical Distribution and Logistics*, 26, 4–22.

Bahrololum, M. E. Salahi ve M. Khalegni, 2009. Machine Learning Techniques for feature Reduction in Intrusion Detection Systems: A Comparison. *Fourth International Conference on Computer Sciences and Convergence Information Technology,* Indian.

Baker,J.R., Fitzpatrick, K.E. (1986).Determination of an Optimal Forecast Model for Ambulance Demand Using Goal Programming, *Journal of Operational Research Society,* 37(11).

Balkhi T. Z., Benkherouf L. (2004). On an inventory model for deteriorating items with stock depen- dent and time varying demand rates. *Computers and Operations Research* 31, 223-240.

Bayındır, Z. P., Birbil, Ş. İ., Frenk, J. B. G. (2006). The joint replenishment problem with variable production costs. *European Journal of Operational Research,* 175, 622-640.

Bayındır, Z. P., Birbil, Ş. İ., Frenk, J. B. G. (2007). A deterministic inventory/production model with general inventory cost rate function and piecewise linear concave production costs. *European Journal of Operational Research,* 179, 114-123.

Beamon, B.M., (1998), "Supply chain design and analysis: models and methods". *International Journal of Production Economics*, 55, 281-294.

Beamon, B.M., (1999). "Measuring supply chain performance". *International Journal of Operations&Production Management,* 19, 275-292.

Ben-Daya, M., Darwish, M., Ertogral, K. (2008). Joint economic lot sizing problem; A review and extensi- ons. *European Journal of Operational Research,* vol. 185/2, 726-742.

Bitter, C. D. A. Elizondo ve T. Watson, Application of Artificial Neural Networks and Related Techniques to Intrusion Detection, IJCNN, 2010.

Burger, C.J.S.C., Dohnal, M., Kathrada, M., LAW, R. (2001). A Practitioners Guide to Time-Series Methods for Tourism Demand Forecasting – A Case Study of Durban, South Africa, *Tourism Management*, 22(4).

Businger, Mark P., Read, Robert, R. (1999). Identification of Demand Patterns for Selective Processing: A Case Study, Omega, *International Journal of Management Science*, 27(2).

Çalış, K. O. Gazdağı ve O. Yıldız, (2013). Reklam İçerikli Epostaların Metin Madenciliği Yöntemleri ile Otomatik Tespiti,» *Bilişim Teknolojileri Dergisi*, cilt 6, no. 1.

Cárdenas, J. J., Romeral, L., Garcia, A., & Andrade, F. (2012). Load forecasting framework of electricity consumptions for an Intelligent Energy Management System in the user-side. *Expert Systems with Applications*, 39(5), 5557-5565

Carlson, RL and Umble, M (1980). Statistical demand functions for automobiles and their use for forecasting in an energy crisis. *The Journal of Business*, 53,2-10.

Chen Z. ve G. Zhang, Forecasting tourism demand based on empirical mode decomposition and neural network. Knowledge-Based Systems, 26, 281-287.

Ching,S. W., Wang, S.-L., Chiu, Y.-S.P. (2010). Determining the optimal run time for EPQ model with scrap, rework, and stochastic breakdowns. *European Journal of Operational Research,* 180(2), 664- 676.

Chu, Ching-Wu., ZHANG, Guoqiang Peter. (2003). A Comparative Study of Linear and Nonlinear Models for Aggregate Retail Sales Forecasting, *International Journal of Production Economics,* 86(3).

Chui, Y.S. P., Cao H. D., (2011). Mathematical Modeling for Solving Manufacturing Run Time Problem with Defective Rate and Random Machine Breakdown. Computers and Industrial Engineering, 60, 576-584.

Croxton, K.L., Lambert, D.M., Garcia-Dastugue, S.J., Rogers, D.S., (2002). "The demand management process". *International Journal of Logistics Management*, 13, 51-66.

Darwish, M. (2008). EPQ model with varying setup cost. *International Journal of Production Economics*, 113, 297-306.

Dem H., Singh S.R., Kumar J. (2014). An EPQ model with trapezoidal demand and under volume flexibility, *International Journal of Industrial Engineering Computations*. 5, 127-138.

Deshpande, A., (2012), "Supply Chain Management Dimensions, Supply Chain Performance and Organizational Performance: An Integrated Framework". *International Journal of Business and Management*, 7, 1-19.

Dünder, E., Cengiz, M. A., Koç, H., Savaş, N. (2013). Bayesci ağlarda risk analizi: Bankacılık sektörü üzerine bir uygulama. *Erzincan üniversitesi sosyal Bilimler Enstitüsü Dergisi*, 6(1), 1-14.

Ertogral, K. (2011). A Vendor-buyer lot sizing problem with stochastic demand: An exact procedure under service level approach. *European Journal of Industrial Engineerin*g, 5/1, 101-110.

Farid D. ve M. Rahman, 2010. Anomaly Network Intrusion Detection Based on Improved Self Adaptive Bayesian Algorithm, *Journal of computers*, cilt 5, no. 1, pp. 23-31.

Feng, Y., D'amours, S., Beauregard, R., (2008), "The value of sales and operations planning in oriented strand board industry with make-to-order manufacturing system: cross functional integration under deterministic demand and spot market recourse". *International Journal of Production Economics*, 115,189–209.

Fildes, R., Kumar, F. (2002), The forecasting journals and their contribution to forecasting research: Citation analysis and expert opinion, *International Journal of Forecasting*, 22(3):415– 432.

Fildes, Robert., Hastings, Robert. (1994). The Organization and Improvement of Market Forecasting, *Journal of the Operational Research Society*, 45(1).

Gavcar, E., Şen, S., Aytekin, A. (1999), "Prediction Forecasting of the Papers used in Turkey". *Turkish Journal of Agriculture and Forestry*, 3 (2), 203-211.

Gong X. ve X. Guan, «Intrusion Detection Model Based on the Improved Neural Network and Expert System,» IEEE Symposium on Electrical & Electronics Engineering (EEESYM), 2012.

Goodwin, P. (2012). Correct or combine? Mechanically Integra- ting Judgmental Forecasts With Statistical Methods, *International Journal of Forecasting,* 16: 261-275.

Guinness, Robert E., (2015) Beyond Where to How: A Machine Learning Approach for Sensing Mobility Contexts Using Smartphone Sensors, 2015, pp.9962—9985

Gunasekaran, A. ve KOBU, B., (2007), "Performance measures and metrics in logistics and supply chain management: a review of recent literature (1995-2004) for research and applications". *International Journal of Production Research,* 45, 2819-2840.

Gunasekaran, A., Patel, C. and Tirtiroglu, E., (2001), "Performance measurement and metrics in a supply chain environment". *International Journal of Operations & Production Management,* 21, 71–87.

Gunasekaran, A., Patel, C., Mcgaughey, R.E., (2004), "A framework for supply chain performance measurement". *International Journal of Production Economics,* 87, 333-347.

Hariga, M.A. (2010). A single-item continuous revi- ew inventory problem with space restriction. *International Journal of Production Economics*, 128, 153–158

Hayek, P. A., Salameh, M. K. (2001). Production lot si- zing with the reworking of imperfect quality items produced. *Production Planning and Control*, 12(6), 584-590.

Huss, William R. (1985). Comparative Analysis of Company Forecasts and Advanced Time Series Techniques Using Annual Electric Utility Energy Sales Data, *International Journal of Forecasting,* 1(3).

Jaber, M., Y., Goyal, S. K., Imran, M. (2008). Economic production quantity model for items with imper- fect quality subject to learning effects. *International Journal of Production Economics,* 115, 143-150.

Jemili, F. M. Zaghdoud ve M. Ben Ahmed, 2007. A Framework for an Adaptive Intrusion Detection System using Bayesian Network, *IEEE Intelligent and Security Informatics*.

Kamenetzky, Ricardo D., Shuman, Larry J., Wolfe, Harvey. (1982). Estimating Need and Demand for Prehospital Care, *Operations Research*, 30(6).

Kehoe, D.F., Boughton, N.J., (2001), "New paradigms in planning and control across manufacturing supply chains: the utilization of internet technologies". *International Journal of Operations & Production Management*, 21, 582–593.

Kendall, K. Database of Computer Attacks for the Evaluation of Intrusion Detection Systems, *MIT Department of Electrical Engineering and Computer Science*, 1999.

Kirby, Robert M. (1966). A comparison of short and medium range statistical forecasting methods, Management Science, 13(4).

Klassen, Robert D., Flores, Benito E. (2001).Forecasting Practices of Canadian Firms: Survey Results and Comparisons, *International Journal of Production Economics*, 70(2).

Koc, L. T. Mazzuchi ve S. Sarkani, 2013. A Network Intrusion Detection System Based on a Hidden Naïve Bayes Multiclass Classifier. *Expert Systems with Applications*, cilt 39, pp. 13492-13500,.

Lambert, D.M., Cooper, M.C., (2000), "Issues in supply chain management". *Industrial Marketing Management,* 29, 65–84.

Lapide, L., (2007), "Sales and operations planning (S&OP) mindsets". *Journal of Business Forecasting*, 26, 21-31.

Lapide, L., (2008), "Segment strategically". *Supply Chain Management Review, 1*2, 8-9.

Law, R., & Au, N. (1999). A neural network model to forecast Japanese demand for travel to Hong Kong. *Tourism Management,* 20(1), 89-97.

Lee, C. H. (2015). A gradient approach for value weighted classification learning in naiveBayes. *Knowledge-Based Systems*.

Liao, J. J. (2007). On an EPQ model for deteriorating items under permissible delay in payments. *Applied Mathematical Modelling*, 31, 393-403.

Liu, G. Z. Yi ve S. Yang, «A Hierarchical Intrusion Detection Model Based on the PCA Neural Networks,» Neurocomputing, cilt 70, pp. 1561-1568, 2007.

Lockamy, I, A., Mccormack, K., (2004), "Linking SCOR planning practices to supply chain performance: an exploratory study". *International Journal of Operations&Production Management,* 24, 1192– 1218.

Mahata, G. C. (2012). An EPQ-based inventory model for exponentially deteriorating items under retailer partial trade credit policy in supply chain. *Expert Systems with Applications,* 39, 3537–3550.

Majumder P., Bera, U.K. (2013). An EPQ-based inven- tory model for deteriorationg items under stock- dependent demand with immediate part payment, *Journal of Applied Mathematics and Physics*, 1, 25- 30.

Malik, Mazhar Ali Khan., Ahmad, Iqbal. (1981). Forecasting Demand for Food in Libya- Using Confidence Limits, *Long Range Planning*, 14(59.

Michie, D. D. Spiegelhalter ve C. Taylor, (1994). Machine Learning Neural and Statistical Classification, New York: Ellis Horwood Limited.

Mu, Q. Y. Chen ve Y. Zhang, 2012. Incremental SVM Algorithm to Intrusion Detection Base on Boundary Areas,» *International Conference on Systems and Informatics*,.

Nguyen T. ve G. Armitage, 2008. Survey of Techniques for Internet Traffic Classification Using Machine Learning, *IEEE Communications Surveys and Tutorials,* cilt 10, no. 4, pp. 56-76.

Pentico, D. W., Matthew, J. D., Toews, C. (2009). The deterministic EPQ with partial backordering: a new approach. Omega, 37, 624-636.

Rexhausen, D., Pibernick, R., KAİSER, G., (2012), “Customer-facing supply chain practices: The impact of demand and distribution management on supply chain success”. *Journal of Operations Management,* 30, 269-281.

Sana S. S. (2008). An EOQ model with a varying de- mand followed by advertising expenditure and sel- ling price under permissible delay in payments: for a retailer, *International Journal of Modelling, Identification and Control,* 5 (2), 166-172.

Sanders, Nada R., Manrodt, Karl B. (2003).The Efficacy of Using Judgmental versus Quantitative Forecasting Methods in Practice, *International Journal of Management Science,* 31(6).

Sani, B., Kingsman, B.G. (1997). Selecting theBest Periodic Inventory Control and Demand Forecasting Methods for Low Demand Items, *The Journal of Operational Research Society,* 48(7).

Sarkar B., Sana S. S., Chaudhuri K. (2011). An imper- fect production process for time varying demand with inflation and time value of Money – An EMQ model. *Expert System with Applications*, 38 (11), 13543-13548.

Scarfone K. ve P. Mell, Guide to Intrusion Detection and Prevention Systems (IDPS), *NIST Special Publication*, 2007, pp. 80-94.

Schultz, Carl R. (1987). Forecasting and Inventory Control for Sporadic Demand under Periodic Review, The Journal of the Operational Research Society, 38(5).

Sebastiani, F. «Machine Learning in Automated Text Categorization,» *ACM Computing Surveys (CSUR),* cilt 34, no. 1, pp. 1-47, 2002.

Semco Jahanbin Paul Goodwin and Sheik Meeran “New Product Sales Forecasting in the Mobile Phone Industry: an evaluation of current methods” ,Supply Chain Forum An International Journal, pp.36

Shin, H., Collier, D.A., Wilson, D.D., (2000), “Supply management orientation and supplier/buyer performance”. *Journal of Operations Management,* 18, 317-333.

Singh C., Singh S.R. (2011). Imperfect production pro- cess with exponantial demand rate, Weibull dete- rioration under inflation. *International Journal of Operational Research,* 12 (4), 430-445.

Sorias, S. (2014). Psikiyatrik Tanıda Betimsel ve Kategorik Yaklaşımların Kısıtlılıklarını Aşmak: Bayes Ağlarına Dayalı Bir Öneri.

Stewart, G., (1995), “Supply chain performance benchmarking study reveals keys to supply chain excellence”. *Logistics Information Management*, 8, 38-44.

Teng J.T., Chang C.T. (2005). Economic production quantity models for deteriorating iitems with price and stock dependent demand. *Computer and Operations Research* 32, 297-308.

Teng J.T., Ouyang L.Y., Chang C.T. (2005). Determi- nistic economic production quantity models with time-varying demand and cost. *Applied Mathematical Modelling* 29, 987-1003.

Teng, J. T., Chang, C. T. (2009). Optimal Manufacturer's Replenishment Policies in the EPQ Model under Two Levels of Trade Credit Policy. *European Journal of Operational Research,* 195, 358-363.

Ungan, M. C. (2011), "En İyi Tedarik Zinciri Uygulamaları ve Bir Saha Çalışması", *Süleyman Demirel Üniversitesi İktisadi ve İdari Bilimler Dergisi*, 16 (2), 307-322.

Uzun, A., Karataş, E. (2012), "Tedarikçi-Müşteri İlişkilerinin Stoklar Açısından Tedarik Zinciri Performansına Etkisi", *Atatürk Üniversitesi İktisadi ve İdari Bilimler Dergisi*, 26, 257-272.

Vonderembse, M.A., Uppal, M., Huan, S.H., Dismukes, J.P., (2006), "Designing supply chains:towards theory development". *International Journal of Production Economics*, 100, 223-238.

Vural Y. ve Ş. Sağıroğlu, «Kurumsal Bilgi Güvenliğinde Güvenlik Testleri ve Öneriler,»Gazi Üniv. Müh. Mim. Fak. Der., cilt 26, no. 1, pp. 89-103, 2011.

Willemain, Thomas R., SMART, Charles N., SCHWARZ, Henry F. (2004). A New Approach toForecasting Intermittent Demand for Service Parts Inventories, *International Journal of Forecasting,* 20(3).

Wu S. ve W. Hung (2014) «The Use of Computational Intelligence in Intrusion Detection Systems:A Review,» *Applied Soft Computing,* cilt 10, no. 1, pp. 1-35..

Xiang, C. P. Yong ve L. Meng, 2008.«Design of multiple-level hybrid classifier for intrusion detection system using Bayesian clustering and decision trees,» *Pattern Recognition Letters,* cilt 29, pp. 918-924,

Yang, L., Yang, J., Gang, Y., Zhang, H. (2011). Near- optimal (r,Q) Policies for a Two-stage Serial Inven- tory System with Poisson Demand. *International Journal of Production Economics,*133, 728-735.

Zhang Y. ve Y. Zhu, 2010. Application of Improved Support Vector Machines in Intrusion Detection,» percent 1 içinde *2nd International Conference on e-Business and Information System Security*.

Zhou, S.L., Mcmahon, T.A., Walton, A.,Lewis, J. (2002). Forecasting Operational Demand for an Urban Water Supply Zone, *Journal of Hydrology,* 259(1-4).

Zotteri, G., Kalchschmidt, Matteo.,Caniato, Federico. (2005). The Impact of Aggregation Level on Forecasting Performance, *International Journal of Production Economics*, 93- 94.

Other Publishing

Bhattacharya, Sutanuka.(1997). “AComparative Study of Different Methods of Predicting Time Series”, Unpublised thesis, Concordia University, Canada.

Boese, M. (2015) “Forecasting demand for groups of items, such as mobile phones”, 2017.

Chen, Tzu-Liang, (2017) Hareketli Cihazların Zaman Serileri ve Gri Teorisini Kullanarak Tahmini Taşıyıcı Hacminin Araştırılması , National Central University, 2017.

ICT, (2017). Statistics Home Page» [online] http://http://www.itu.int/en/ITU-D/Statistics/Documents/facts/ICTFactsFigures2013-e.pdf. [accessed 29 November 2017].

Schuh, G. (2006). Produktionsmanagements I, WZL/ FIR, Aachen Universitat.

Tilford, M. B., (2009), “Developing for Demand- An Analysis of Demand SegmentationMethods and Real Estate Development”. Master Thesis: Gonzaga University, Boston University School of Management, Massachusetts Institute of Technology.

Zhang, X. L. Jia, H. Shi, Z. Tang ve X. Wang, (2012). The Application of Machine Learning Methods to Intrusion Detection.