

DOKUZ EYLÜL UNIVERSITY
GRADUATE SCHOOL OF NATURAL AND APPLIED SCIENCES

**UNCERTAINTY THEORY IN AIRLINE
INDUSTRY**

by
Cansu MURAL

August, 2016
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UNCERTAINTY THEORY IN AIRLINE INDUSTRY

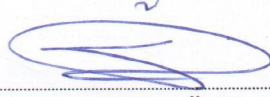
**A Thesis Submitted to the
Graduate School of Natural and Applied Sciences of Dokuz Eylül University
In Partial Fulfillment of the Requirements for the Degree of Master of Science in
Industrial Engineering, Industrial Engineering Program**

**by
Cansu MURAL**

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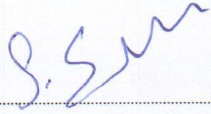
M.Sc THESIS EXAMINATION RESULT FORM

We have read the thesis entitled “**UNCERTAINTY THEORY IN AIRLINE INDUSTRY**” completed by **CANSU MURAL** under supervision of **ASST. PROF. DR. SEREN ÖZMEHMET TAŞAN** and we certify that in our opinion it is fully adequate, in scope and in quality, as a thesis for the degree of Master of Science.



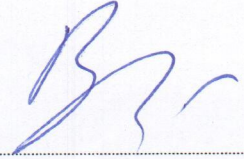
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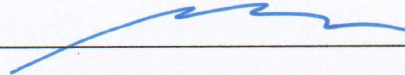
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Cansu MURAL

UNCERTAINTY THEORY IN AIRLINE INDUSTRY

ABSTRACT

In this study, implementation of uncertainty theory, which gives more reasonable solutions to the problems that classic methods are insufficient because of uncertainties, is shown. Airline industry is chosen for the study because it faces unexpected events like weather conditions, natural disasters, economic fluctuations, crude oil and fuel prices, terror attacks more than others. Effects of these uncertainties on airline passenger fluctuations are considered and passenger demand forecasting process is chosen to exemplify the implementation of the theory. In the related study, passenger traffic data between the years 2006 and 2014 of Turkish Airlines, which is the leading airline company in Turkey, are used to forecast the passenger demand of domestic lines, international lines and total for the first quarter of 2015. Besides the combined method, times series methods moving average, simple exponential smoothing, Holt's two parameter and Holt-Winters method are used in certain environment and following these methods grey theory forecasting method is applied in uncertain environment

This thesis presents a hybrid forecasting technique by combining a time series method exponential smoothing and uncertainty theory techniques, expert's experimental data and empirical uncertainty distribution. All solutions that are obtained in certain and uncertain environments are compared within each other by using error analyses techniques. It is found that hybrid method gives more reasonable solutions against the classic methods with its quantitative and qualitative features.

Keywords: Uncertainty theory, demand forecasting, airline industry

HAVAYOLU ENDÜSTRİSİNDE BELİRSİZLİK TEORİSİ

ÖZ

Bu çalışmada, problem çözümlerinde ortam koşullarının belirsiz olması sebebiyle klasik yöntemlerin yetersiz kaldığı durumlar için daha anlamlı sonuçlar veren belirsizlik teorisinin uygulaması gösterilmiştir. Hava koşulları, doğal afetler, ekonomik dalgalanmalar, ham petrol ve yakıt fiyatları, terör olayları vb. gibi beklenmedik olaylara fazlaca maruz kalması sebebiyle havayolu sektörü çalışma için uygun görülmüştür. Bu belirsizliklerin havayolu yolcu talebi değişimine olan etkisini de hesaba katarak, yolcu talebinin tahminlenmesi üzerinden belirsizlik teorisinin uygulaması örneklenmiştir. İlgili çalışmada Türkiye'nin önde gelen havayolu şirketlerinden Türk Havayolları firmasının 2006-2014 yılları arasındaki verileri kullanılarak 2015 yılının ilk çeyreği için iç hat, dış hat ve toplam yolcu talebinin tahminlenmesi yapılmıştır. Öncelikle belirli koşullar altında klasik zaman serisi teknikleri olan hareketli ortalama, üstel düzeltim, Holt'un iki parametrelili tekniği ve Holt-Winters tekniğinin yanı sıra kombine metodu, ardından da belirsizlik altında gri teori tahminleme yöntemi kullanılmıştır.

Bu tezde uygulanan belirsizlik teorisi için bir zaman serisi tekniği olan üstel düzeltim ile belirsizlik teorisine ait uzman verisi ve deneysel belirsizlik dağılımı teknikleri birleştirilerek tahminleme için hibrit bir yöntem sunulmuştur. Belirli ve belirsiz ortamda elde edilen tüm sonuçlar, hem kendi aralarında hem de birbirleri ile hata analiz teknikleri ile karşılaştırılıp kalitatif ve kantitatif özelliğe sahip hibrit modelin ürettiği sonuçların klasik yöntemlere göre daha anlamlı olduğu sonucuna ulaşılmıştır.

Anahtar kelimeler: Belirsizlik teorisi, talep tahminlemesi, havayolu endüstrisi

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CHAPTER ONE

INTRODUCTION

1.1 Introduction to Thesis

Uncertainty is an inseparable part of the world. People have faced with uncertainties in their daily lives and they have coped with these uncertainties without noticing. Sudden and unexpected events happen in the world, and they affect the way of dealing with problems in every aspect of life. Echos of the term uncertainty has been seen in research areas and it has become a crucial issue as time goes by. It has been realized that so many parameters that are considered in an optimization mechanism have been affected by its environment. Thought of uncertainty consideration for obtaining more reasonable solutions in studies has become widespread. Under these circumstances, the questions which come to mind are about the realizing and modelling of the uncertainty. These questions encouraged the researchers to develop new methods that include uncertainty.

Probability theory, fuzzy theory, grey theory and uncertainty theory are the common methods for dealing with uncertain conditions in different problems. When it is hard to estimate an event's consequences beforehand, the problem can be modeled and solved by using probability theory (Kolmogorov, 1933) or uncertainty theory (Liu, 2007; 2015). Possible values' range and random variable's probability can be defined by the probability distribution. Probability theory presents the statistics which helps gathering and commentating the historical data related with the system, to designate the probability distribution (Wang & Peng, 2014). Probability distribution needs so many historical data to give reasonable solutions and in some cases having enough historical data can not be possible (Memon, Lee, & Mari, 2015). In this kind of situation probability theory loses its usability and power.

Another theory that models imprecise data by using membership function is fuzzy theory (Zadeh, 1965). Fuzzy is widely used in so many areas, but the weakness of this theory is hardness of membership function's constitution. While designing the

membership function, the related subject must be deeply known. It is not possible to have strong knowledge for any subject all the time and so fuzzy implementations are restricted (Memon et al., 2015).

Grey theory (Deng, 1989) is another popular theory that deals with uncertainties in the systems. The grey theory can be applied even if the sample data is very few, at least four data. Another point is that strong information is not needed about the related subject in some cases. Although theory's these characteristics, its restrictions can be found when it is thought. For solutions of some problems, grey theory steps require data in a range. These ranges are gathered from experts but the confusing question is how much they can be reliable. In a decision making process by using grey theory, importance of the variables or parameters can be given in a range but they are just assumptions. It can not be identified how sure the experts are while they are giving these ranges. Furthermore, in a problem with so many data grey theory can not give reasonable results, that's because its nature is suitable for studying with a few data. It may give similar or close results with a traditional method and may lose its success dealing with uncertainties. Finally, grey theory uses laws of reality and it is good at dealing with recognitive uncertainties. Unfortunately, to handle the stochastic uncertainties when it is needed, grey theory will be insufficient.

The last method concerns with uncertainty is Uncertainty Theory defined by Liu (Liu, 2007) in 2007. According to Liu for defining any case as uncertainty, uncertainty theory's axioms must be satisfied by those cases. Uncertainty theory considers both qualitative and quantitative values. It is applicable to many different areas like uncertain finance, uncertain statistics, uncertain risk analysis, uncertain goal programming, etc.. It gains the power from its most important feature; degree of belief, because uncertainties can be identified and modeled reasonably when they are based on degree of belief.

Degree of belief is measured by the first main notion of the theory; uncertain measure. Uncertain variable is the second main notion of the theory. Quantities with indecisive knowledge is defined with uncertain variable. Answer of "how many

customers are there in The Bank A” is an example of uncertain variable. Suppose that number of customers is imprecise but known that between 10 and 12. Number of customers are defined with eight different cases. These eight cases are,

$$\emptyset, \{10\}, \{11\}, \{12\}, \{10, 11\}, \{10, 12\}, \{11, 12\}, \{10, 11, 12\}.$$

Each number that changes between 0 and 1 represents every case’s degree of belief, for instance,

$$\begin{aligned}\mathcal{M}\{10\} &= 0.8, & \mathcal{M}\{11\} &= 0.5, & \mathcal{M}\{12\} &= 0.9 \\ \mathcal{M}\{10, 11\} &= 0.4, & \mathcal{M}\{11, 12\} &= 0.8, & \mathcal{M}\{10, 12\} &= 0.6 \\ \mathcal{M}\{\emptyset\} &= 0, & \mathcal{M}\{10, 11, 12\} &= 1.\end{aligned}$$

Those eight cases that range between 0 and 1 identify a set function $\mathcal{M}$ or in other words uncertain measure set and this corresponds the uncertainty theory’s axioms. As a result, “number of customers” can be called uncertain variable. Uncertain variable must be defined with theory’s third notion uncertainty distribution (Liu, 2012; Memon et al., 2015).

Among different branches of uncertainty theory, uncertain statistics assumes presenting techniques for determining uncertainty distribution. Expert experimental data technique gathers data and data’s interpretation is done with the help of different uncertainty distribution techniques like empirical uncertainty distribution, principle of least squares, method of moments, multiple domain experts and Delphi method. These techniques are the basic concepts of uncertain statistics. Expert’s experimental data and empirical uncertainty distribution are chosen for this dissertation to clarify the uncertainty theory’s utility because they are thought to help understanding variables and distributions of the theory. These two techniques will be mentioned in detail, in section 7 and its subsections.

This dissertation aims to propose a novel hybrid method by using uncertainty theory from the point of exemplifying the theory’s usage. Determining which method will be

combined with uncertainty theory is an important step. Under the consideration of chosen uncertainty techniques' statistical nature, forecasting process and its methods are thought to be proper for combination.

Forecasting is an important process and has been in the focus of various research topics for many years. Completing the needed forecasting studies before and after optimization problems can help researchers to see the solution's utility. It can be said that having the optimum forecasting results for future periods constitutes a vital part of so many optimization problems because it help managers to take the rightest strategic decisions. Demand forecasting is one of the important branches of different forecasting areas. Predicting the fluctuations in demand data provides the ability to respond to changes or any unexpected situations quickly so that managers can be ready to increasing or diminishing demand.

There is no forecast result without error also it must be known by predictors that there is always a limit what to forecast. It means forecast results only make a reflection to actual data regardless of which technique or formula is used (Chase, 2013). Yet still, determining the optimal forecasting method according to studied data is also an important step.

There are so many different qualitative and quantitative forecasting methods in the literature. Traditional quantitative forecasting methods are preferred in demand forecasting mostly, because they do not require subjective judgment. They give clearer solutions and also they are more successful in long term forecast. The success of obtained forecasting results enables the company managers to be more efficient in their strategies.

Consideration of all the parameters that effects the forecasting process is another substantial point. So many times it is not so easy to predict the future behaviors of customers even if the historical data was modelled with the optimal forecasting method. There can be unexpected events that change the behaviors of customers or services of companies. Ignorance of these unpredictable events and conditions can

affect the results and related decisions. In case of demand forecasting process, any miscalculation may lead the companies to lose a huge amount of money. Idea of forecasting process is open and vulnerable to uncertainties headed the thesis to present a hybrid forecasting method by using uncertainty theory. Next step is choosing a study area to apply the proposed method.

Besides choosing a popular research area, considering its uncertain environment is very important. Transportation, logistics and supply chain are some of the popular areas of recent days. Choosing the way of transportation is an important matter for the passengers and includes different criterias. Speed and time advantages of the chosen transportation sector are preferred to affordability by the passengers. Most people do not want to spend their time by travelling long hours because it is thought that time is the most valuable thing in today's rapid world. Although airline industry was accepted a luxury transportation formerly, the increasing importance of the factors like time, speed and comfort lead the passengers to choose airline transportation.

Demand of airline passengers have been gaining dynamism and airline transportation has become the vital part of the transportation sector with its speed and time advantages. In the past, there was a few airline transportation companies and ticket prices were under these leading companies' control. Expensive labor cost, aircraft cost, fuel cost etc. makes handling fee of airline transportation more expensive than the other transportation options. In spite of its price disadvantage, the passengers' numbers that choose airline industry have increased as a result of mentioned facts above and the market has realized the mobility in this sector. New companies' entrance to the sector brought competency and managers developed different policies about service and price with the purpose of attracting new passengers or not to lose existing ones in line with their strategic targets. Combination of discounts, promotions and lots of other campaigns with speed and time advantages made airline transportation attractive for the passengers.

Taking the right strategic decisions can make a company market leader, otherwise it may cause the bankruptcy of the company and this unfolds the impact of determined

strategy. In this context, it is crucial to forecast the change and fluctuations in demand for the purpose of taking the rightest and optimum strategic decisions about number of airline fleet, crew requirement, pricing policies, optimal scheduling, network optimization, etc., which are the company managers's major targets. Economic fluctuations, weather conditions, terror attacks, fuel prices, epidemics, natural catastrophes etc. are unexpected events that the airline industry has experienced. All of these cases can suddenly change airline demand or flight conditions and there is no way to estimate them beforehand. It makes clear that airline industry has an uncertain environment and demand forecasting which is vitally important for airline industry to take the strategic decision is made under these uncertainties.

The aim of this study is to present a hybrid forecasting technique that is exemplified in airline industry to emphasize the importance of uncertainty theory. Turkish Airlines (THY) was chosen as the company that hybrid method will be carried out. Domestic lines, international lines and total passenger traffic data of THY between the years 2006 and 2014 were tackled on a quarterly basis and passenger traffic demand for the first quarter of 2015 was tried to be forecasted. Forecasting process is run for different conditions to compare different method's results under different environments. First of all, by using traditional quantitative forecasting techniques in certain environments, secondly by using grey theory in uncertain environments and finally by using uncertain hybrid method in uncertain environments.

This study emphasizes the importance of uncertainty theory and with consideration of uncertainties how the results are changed. Thesis wants to bring light to new researches by showing uncertainty theory's benefits. Uncertainty theory is hoped to help decision makers for taking the rightest and optimal strategic decisions in the uncertain world.

1.2 Justification of the Study

The new uncertain hybrid forecasting method is the strongest component of this thesis under the consideration of emphasizing uncertainty theory's importance. The most important terms on the way of uncertainty theory is understanding degree of

belief, uncertain measure, uncertain variable and uncertain distribution. That's why, thesis explains and combines the theory's techniques from these points. While combining uncertainty theory methods to propose a novel method, forecasting process was chosen as a tool. Forecasting is a statistical process and uncertainty distribution is one of the subtitles of uncertain statistics. For this reason, it is thought that combining a forecasting technique with an uncertain distribution technique will make sense. Besides, the forecasting process is very suitable to the uncertain environment consideration. Some researches that take place in the literature corroborate this assumption.

Tsaur (2003) combined fuzzy with double exponential smoothing and created a new forecasting method. Exponential smoothing is one of the basic forecasting methods and it gives reasonable results for short term forecastings. Identifying the smoothing constant of this method is the most important part of the process. Method's power comes from its optimal smoothing constant because results change according to this constant. The idea of forecasting environment is uncertain, is accepted widely so forecasting techniques are preferable for the combination of uncertainty methods. Tsaur used fuzzy to assign double exponential smoothing's constant because there is no way to assign this constant for the reason of limited data. He also exemplified his hybrid method's usage on the data of Taiwan's internet users. He not only proved his hybrid forecasting model's success but also showed that fuzzy double exponential method is better than GM(1, 1) and single exponential smoothing model by comparing them according to result's mean square error value (Tsaur, 2003).

Another example is about grey theory combination with exponential smoothing. Ying-ying, Yi-cheng, Jun and Lei (2010) used grey exponentially smoothing method on death rate in safety accidents. Security system and death rate have imprecise and dynamic nature. Everything can change suddenly by the effects of many complex components, so this environment seems proper for uncertain term. They used grey forecasting method because there were not enough data to use other methods and after that, exponential smoothing helped to revise the forecasting's residual errors. At the end of exponential smoothing process, forecast results were obtained more accurately.

This combined method has the advantages of both grey forecasting and exponential smoothing method. With the help of grey forecasting there is no need to have a big amount of historical data. They proved that grey exponentially smoothing model gave more accurate results than GM (1, 1) model (Ying-ying et al., 2010).

These two cases show that forecasting is an important tool to exemplify uncertainty methods because forecasting reflects the effects of uncertainties well. Exponential smoothing is also another key tool to hybrid the methods especially identifying its smoothing constant prompts to combination. From this point of view, uncertainty theory was combined with exponential smoothing method in this thesis. Similar to Tsaur's study (Tsaur, 2003), exponential smoothing constant was assigned by using uncertainty theory. Namely, expert's experimental data technique gathered data from an expert by applying a questionnaire study to identify a smoothing constant. These candidate data were stated with degree of beliefs. Empirical uncertainty distribution assigned smoothing constant by using the list of experimental data with degree of beliefs. When the constant was determined, the rest of the process was conducted just like in the exponential smoothing method. Details about the hybrid model will be given in section 7.6. Thesis also compares this hybrid method with other two types of exponential smoothing methods whose smoothing constants are assigned by optimal ARIMA method and trial and error method, with this comparison step thesis aims to highlight uncertainty theory's success in finding the optimum and reasonable constant. All the calculations in the thesis are repeated for three kinds of passenger traffic data.

Another point that is mentioned in the above literature is the harmony of the case study environment to the model. If there are uncertainties in the problem environment, traditional methods will not give the accurate results. In a certain environment, a traditional technique can give similar results with an uncertain system technique, in that case uncertainty does not matter for the decision maker because results will not be expected to change suddenly and uncertainty techniques lose their meanings and power. For a problem in an uncertain environment, results that include uncertainties make more sense to decision makers or managers. Even if a traditional method gives the similar accuracy with an uncertainty method, there is no doubt that uncertainty

technique is chosen for the study. Uncertainty methods consider the uncertainties and this encourages the decision makers to take strategic decisions according to the results.

Airline industry is chosen under the consideration of its uncertain environment with the purpose of performing the hybrid forecasting method and showing the importance of uncertainty theory. The Airline industry has uncertain features, even some uncertainties come from its nature and affect its demand and strategies.

There are many factors that affect airline demand. Uncertain weather conditions, fluctuations on oil prices, epidemics, terror attacks, natural disasters, economics, wars, can affect airline companies and its demand. Companies can take their precautions for these cases, otherwise they can lose lots of money, even any of them can cause bankruptcy of an airline company.

One of the biggest decline on airline demand was seen in 2001. On September 11, 2001, a terror attack took place in New York and Washington. Two Boeings were crashed on the Twin Towers in New York and one Boeing crashed into Pentagon by the terrorists. Lots of flights were cancelled and many airline companies were affected by this attack. For five days, North American airspace was closed to all airplanes. Eight days after the attacks, Chief Executive Officer of the Lufthansa Jurgen Weber explained that;

... the losses incurred due to the closure of US and Canadian airspace, flight diversions, cancellations and drop in demand have made it necessary for companies to revise their profit forecast and capacity supply. The forecasting was dependent on an economy upswing in the last quarter of the year, which was no longer anticipated in the wake of the 11th September event. The aviation industry has been hit badly by the consequences of the terrorist attacks. Lufthansa Airlines stated that it would require immense efforts on the part of Lufthansa staff if they were to avoid an operating loss that year (www.lufthansa.com).

This statement shows these kinds of attacks' effect on airline companies clearly. Also importance of forecast was highlighted. Airline companies had to revise their capacity assignments, and lots of companies decreased seat capacity because of declining demand due to the the security conditions, in the 2001's fourth quarter.

Another unexpected crisis was an epidemic called severe acute respiratory syndrome (SARS) that affected the airline demand in February 2003. SARS spreaded from Asia to more than twenty countries. Many people got sick around the World and many of them died. The disease was spread by the people who traveled from Asia to Europe. It was recommended not to travel, and it brought the sudden declining in the air transportation demand. One more time, so many airline companies decreased their capacity and changed their routes. Royal Dutch Airlines KLM made a statement on its web site, after SARS crisis, that "... the capacity adjustments particularly on routes to Asia and North America are made in response to declining demand resulting from developments surrounding the SARS virus. All schedule adjustments are temporary..." (Cento, 2009)

Volcanic eruption in Iceland in 2010 is also an example of airline demand decreases. Eyjafjallajökull volcano started to erupt nearly 200 years after the last eruption. This crisis affected economy and so many sectors, mostly the airline industry. Iceland forbid passing of planes over the country. Lots of flight cancelations revealed after the spread of ash clouds. Air traffic in Europe was terribly affected. 17 countries closed their air space completely or almost all of it. Turkish Airlines cancelled the flights to 14 countries mutually (Hürriyet, 2010). It is estimated that the volcano caused \$200 million economic loss per day. Business life was crucially affected. Eurocontrol which controls the flights of 38 countries in Europe declared that 17,000 flights had been cancelled and on the following days this number reached 22,000, that's because most of the passengers had to choose the highway. According to authorities, volcanic eruption caused airline crisis worse than what happened in September 11 in 2001. Emirates Airlines which has an extended flight network to Europe, revealed that the loss of four days was \$1 million. After London, Frankfurt and Paris, the fourth biggest airport in Europe Amsterdam Schiphol Airport declared the loss of being closed for four days was nearly £10 million. Considering the ash

clouds damage to aircraft engines and signals, lots of airline companies canceled their flights by bearing a loss of £200 million (Turkishny, 2010).

As it is mentioned above, these kinds of unexpected crisis' effects are crucial. Unfortunately, it is impossible to know before they happen. While making demand forecasting, so many techniques do not consider these unexpected situations. And it is hard to think bad scenarios and to get ready for them.

There are other methods for uncertain environments such as grey theory or fuzzy logic and also probability theory for some imprecise cases. Remember from the introduction part that, probability theory needs a large amount of data to give clear results. Fuzzy, on the other hand, needs strong knowledge about the related subject to constitute membership functions. Grey and fuzzy theory or their hybrid versions give the solutions still in a sharp context. The researchers have to evaluate solutions in the given conditions or range. In daily life, people use terms like "large size", "very young" and "nearly 500 km". When someone is asked about the distance in İzmir and İstanbul, the answer is "nearly 500 km". If this is accepted as a fuzzy notion, the distance between these two cities is accepted "exactly 500 km" with degree of belief 1 by the membership function. Everyone knows that no one can be sure about the true distance between İzmir and İstanbul being "exactly 500 km". This means zero is the "exactly 500 km" term's real degree of belief. Thinking just the opposite, belief degrees of "exactly 500 km" and "not 500 km" are same and they are equally likely according to possibility measure. This shows that these kind of uncertain terms are not represented by fuzziness or vagueness and uncertainty theory is the only theory that quantifies them (Wang & Peng, 2014).

Membership functions of so many fuzzy sets are the same and this is accepted as the main reason of debates about fuzzy. Some assumptions regard that unsharp concepts can be modeled by fuzzy sets. To demonstrate its contrary, the concept of "old" will be examined. Suppose that "old" has a trapezoidal membership function (50, 60, 70, 80),

$$\mu(x) = \begin{cases} 0, & \text{if } x \leq 50 \\ (x - 60)/10, & \text{if } 50 \leq x \leq 60 \\ 1, & \text{if } 60 \leq x \leq 70 \\ (80 - x)/10, & \text{if } 70 \leq x \leq 80 \\ 0, & \text{if } x \geq 80. \end{cases} \quad (1.1)$$

According to fuzzy theory, two suggestions are obtained:

- “old” involves [60, 70] with possibility measure 1,
- “old” is exactly [60, 70] with possibility measure 1.

First one seems reasonable but the second does not, because it is not possible that ages from 60 to 70 correspond to “old”. This clearly means that “old” can not be accepted as a fuzzy set theory (Liu, 2012).

It is clear that uncertainty theory is more reasonable to model the uncertainties. It gives the flexibility of belief degree and does not restrict the model. Fuzzy is misguided about belief degrees, too. Without considering if two cases are dependent or not, fuzzy accepts union cases’ belief degrees as the individual cases’ maximum degree of belief (Liu, 2015). Uncertainty theory emphasizes the power of expert’s experiment with degree of belief, combines the qualitative and quantitative quantities in its processes. If it is thought deeply, people use degree of belief and uncertainty theory without noticing in their daily lives. It is the implementation of this every day experience to scientific areas.

With all these things, it is tried to give an insight about the reason of why uncertainty theory was chosen for this thesis. Proposed uncertain hybrid forecasting method will show theory’s logic with its implementation to a real life case. Different forecasting methods will show the importance of the chosen technique. Besides, thesis makes the forecast calculations of THY for international and domestic lines and total passengers on a quarterly basis rather than forecastings of two or three cities as a reason of giving chance to companies for planing their capacities, investment, crew or fleet decisions. In the case of two or three cities consideration, there will be no chance to

take any strategic decisions, even if it is taken, it will be too risky because of hardness of aggregating them. Forecast results that will be obtained from this thesis will be suitable to disaggregate demand and to develop new strategies for investments, corporations, crew and fleet increment, etc..

This thesis aims to show uncertainty theory and its advantages by proposing a novel hybrid forecasting method. Theory or its hybrids with traditional methods or other uncertainty methods fill the deficiency of handling with uncertainties in cases better than the others. THY case's solutions will unroll the clearness of uncertainty theory. It is hoped that, it will light the way for new researchs and its implementations to various areas will be seen in the near future.

1.3 Organization of the Thesis

Until now, an introduction to thesis and justification of it were clearly mentioned. Chapter two introduces the airline industry and its characteristics with strong and weak sides of the industry to inform the readers about research area. The industry is analysed in global extent for a worldwide reflection and industry's analyse continues with Turkey. In the last subsection of the chapter, drivers of airline demand are explained. Chapter three is about forecasting and its subsections are about what the forecast is, qualitative and quantitative forecasting methods and information about their specific techniques. Literature research about forecasting in airline industry and forecasting under uncertainty are mentioned in chapter three. Chapter four gives information about the company that the study is carried out. It defines the problem and methodology, and displays the passenger traffic data which is used. While chapter five shows forecasting solutions and evaluations of five different traditional quantitative techniques under certain conditions, chapter six studies same data with grey forecasting to exemplify uncertain environment consideration. Uncertainty theory and its features are told in chapter seven. Novel hybrid forecasting method which is the strongest part of the thesis, is the subsection of this chapter. Hybrid method's solutions are shown and compared with other two types of exponential smoothing method in this chapter, too. General comparison of hybrid method with all the methods used in

the thesis take place separately in chapter eight. Finally, chapter nine includes general conclusion of thesis and emphasizes the importance of uncertainty theory.



CHAPTER TWO

AIRLINE INDUSTRY

2.1 Introduction to Airline Industry

Airplane is one of the most remarkable inventions that effects and changes people's lives. Government assistance has been made to the airplanes by means of technological development of their manufacturing throughout World War I and II. Europe is the first place that commercial plane lines were set up. As time goes by, air transportation's importance has increased. People have begun travelling by airplane as if they were using air transportation for many years. It has shortened time that is spent for travel. It can be said that airline transportation makes life easier and builds bridges between people or countries, as passengers change their distance perception and begin to travel abroad for tourism, visiting or conducting business in a global extent (Investopedia, 2015).

Airline industry has very crucial economic, cultural and social benefits to countries and humanity. There is no doubt that, it increases globalization with this feature. It is subject to the tightest regulations for many years, but it has been seen that economic regulations are deregulated and competency conditions are changed dramatically in recent years. Correspondingly, airline companies change their strategies. With the result of these developments, airline sector takes a place in a more complicated, dynamic and uncertain environment (Gerede, 2015).

In the following subsections, its characteristics and existing situation are introduced in a global and territorial extent.

2.2 Airline Industry Characteristics

Airline transportation developed with technology and existing environment became competitive with increasing number of airline companies. Demand fluctuation is also inconsistent. Airline industry's characteristics' can be called active, diverse and surprising. For any airline company, getting help from operations research makes a

difference from the other companies because it helps managers to find optimal planning, routing, scheduling, market positioning, etc.. It is clear that optimization approach shapes airline industry by bringing rational and optimal solutions to the problems (Jacobs et al., 2012).

The United States (U.S.) Department of Transportation (DOT) separates airline transportation into four parts:

- **International:** Planes in this part have 130 and more seats and transport passengers all around the world. Firms in this part have income about more than \$1 billion.
- **National:** The airline companies' income is between \$100 million and \$1 billion and have a plane capacity of 100-150 passengers.
- **Regional:** This part includes short-haul flights and companies that have income less than \$100 million.
- **Cargo:** As the name suggests, companies in this part make the transportation of goods (Investopedia, 2015).

In 1980, Michael E. Porter defined and explained the five forces that help industries to identify their pros and cons in his book "Competitive Strategy: Techniques for Analyzing Industries and Competitors" (Investopedia, 2014). These five forces have adjusted to different industries, since then. They strengthen companies by showing them sector's characteristics and competitive environment. Companies get a chance to assess themselves and develop strategies according to requirement of the related sector. For the purpose of having much more information about the airline industry and its environment, here is the analysis of airline industry on the focus of Porter's five forces:

Threat of New Entrants: It can be said that airline companies are placed in a saturated market. Entering the market is a hard decision because this industry needs high capital investment. Aircraft, labor, fuel and other customer services' costs are the main cost fraction. New entrants are not important threats when it is thought it is not easy for entrepreneurs to take the risk of failure. Another important factor that make companies hesitate entering is taking attention of customers because it is not easy to change people's habits. Usually passengers do not want to change the airline company that they feel confident with and use for transportation (StudyMode, 2010).

Threat of Substitutes: Despite the fact that there are other transportation options for passengers, its risk level is still medium. Even if airline transportation is thought to be more expensive than others, transportation by airline is the fastest of all and under the consideration of time is the most important cost; customers of this transportation way are increasing.

Power of Buyers: There are two buyer groups in airline industry. First group includes individual passengers. They choose airline transportation with the purpose of business travel, tourism or any personal reason and they buy their tickets through the airline firms. When they choose buying their tickets through an intermediary like agencies or online ticket, this buyer group is called second group. They play a part between passengers and airline companies. They are also in contact with several airline companies so that they help passengers to find optimal flights with optimal price.

Power of Suppliers: Airports, plane manufacturers and fuel firms are the main suppliers of airline industry. There is not a competition between these suppliers because of their limited numbers in the sector. Boeing and Airbus are accepted as the main manufacturers. There are certain rules to be in service in this sector. The manufacturers do not make a difference in planes except some improvements regarding being green-friendly.

Plane manufacturing and other requirements of airline industry need high capital, so firms want to make their supply agreements for a long time. This makes it hard to

alter suppliers for the airline companies. Long term agreements also create an environment of trust between the companies and suppliers and it ends with more credit for the companies (Google, n.d.).

Degree of Rivalry: Number of airline companies both in the local and international market is increasing. This means challenge by means of ticket price, comfort, in-flight services, etc. for the companies to attract customers (StudyMode, 2010). Another important point is that companies cannot easily leave the sector because their entrance to sector with high capital makes it hard to break their agreement and leave the industry (Google, n.d.).

2.3 Airline Industry in Global Extent

In the last century, civil aviation has become one of the most important sectors of economic and social development. For the last five years, airline companies of advanced markets have been struggling with recession and crises. Old fleet, high labor cost and high tariff cost are the biggest difficulty for the European and American based airline companies. Airline companies in the European Market have faced with the difficulties that they never had faced so far over the last five years (Turkish Airlines, 2015).

In spite of this, in 2013, with a rising of 5% against 2012, there has been 3.1 billion of passenger transportation occurred all around the World. Number of aircraft departures have reached 33 million by the increment over 1 billion compared to 2012. In the condition of sustainability of increments, it is thought to reach 6 billion passengers by the year 2030. In 2013, aircraft traffic occurred between 35,000 points with 28,000 aircrafts and had a contribution of 2.2 trillion USA dollars to the World economy. Civil aviation industry has made the World economy gain 540 billion USA dollars by employing 57 million people totally. While passenger based total scheduled international and domestic passenger traffic had gained 7.29% between the years 1960 and 1999, this increment was 4.9% between the years 2000 and 2013 (Türkiye Odalar ve Borsalar Birliği [TOBB], 2014).

According to International Air Transport Association (IATA)'s August-September 2014 Report, airline industry sustained the growth and USA based airline companies took the leadership. As a result of economic constriction and the ebola virus, a 4% fall has been observed in the share price of airline, while 11% increment has still existed worldwide. Jet fuel prices decreased as a result of crude oil price decline. Lots of the regions lost its passenger revenue on the contrary of USA based companies. Passenger volume has grown worldwide with the help of economic development in USA and Asian countries (EcoTripSos, 2014). Following Figure 2.1 shows total passenger market growth by region for November and December 2014.

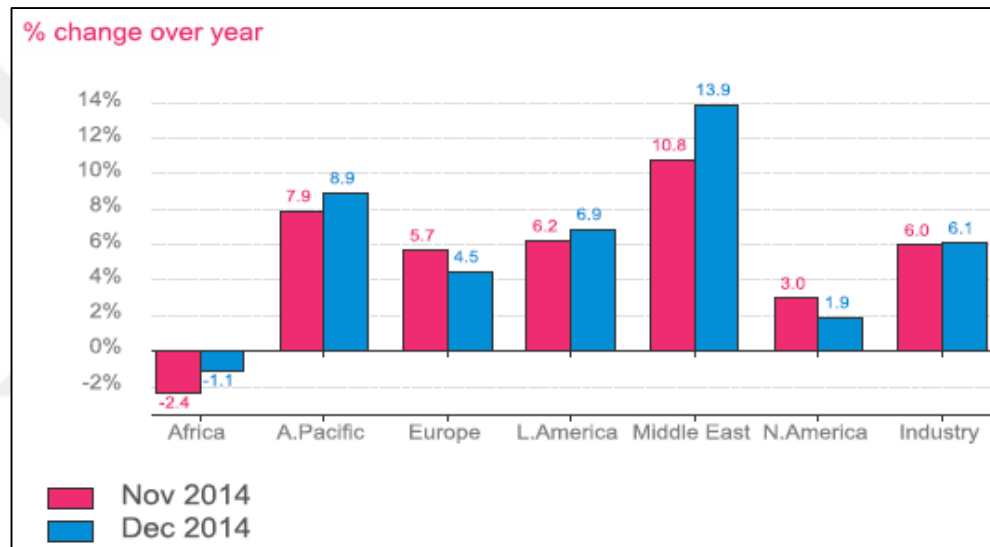


Figure 2.1 Regionally passenger growth for total (IATA)

2.4 Airline Industry in Turkey

1912 was the year that civil aviation studies had started in Turkey and it accelerated with the establishment of State Airports Authority in 1956. Civil aviation industry was developed by Civil Aviation Act that came into force in 1983. Civil Aviation Act enhanced the quality and the credibility of the industry with the development of airports. After the 90s, new companies entered the sector and consequently a cutthroat competition has started in the private sector. In 2003, regional aviation policy showed up and the sector has caught up a growing trend (Öncü, Çömlekçi, & Coşkun, 2010).

Airline industry has an important place in the transportation industry because it is fast, confidential, safe and at the same time economic. Considering our country's economic and social development and integration to the World, a special importance has been given to this transportation industry. Turkey has not only become an exemplary country in the World but also a leader in its region since 2003, with the developments in civil aviation industry. Regulations and adopted politics has airline industry grown incrementally and Turkish Civil Aviation shows an unpredictable improvement. In all airline companies, plane numbers have increased 160%, seat capacity has increased 176%, cargo capacity has 346% and also domestic and international flight points have reached 290 (Sivil Havacilik Genel Müdürlüğü[SHGM], 2014).

Republic of Turkey, Ministry of Transport, Maritime Affairs and Communication, Aviation and Space Technologies Report shows that the number of active airports has increased to 53 in 2014 while it was 26 in 2003. Number of passengers on domestic lines has reached 76.1 million in 2013 and total passenger numbers has reached 166 million in 2014. As of 2014, number of airplanes are 422, seat capacity is 75,700 and cargo capacity is 1,393,632 (Ulastirma Bakanligi, 2014).

Besides the more comfortable, more confidential and faster transportation that is provided by aircraft technology, discounts in ticket prices have increased the share of airline industry in other transportation modes. International organizations and major aircraft manufacturers' medium and long-term forecasting studies show that existing growth will continue until the year 2030s. In Turkey, there has been a crucial increment for passenger and cargo transportation in 2014, comparing with world averages (SHGM, 2014). In the last 12 years, aviation has increased average of 5% in the World while this number is 14.5% in Turkey (Ulastirma Bakanligi, 2014). In 2014, aircraft traffic reached 1,677,350 by increment of 11.45% and total cargo traffic reached 2,886,192 tons by increment of 11.21%. Following Figure 2.2 summarises the airline industry growth in Turkey with the numbers reached by the end of 2014.

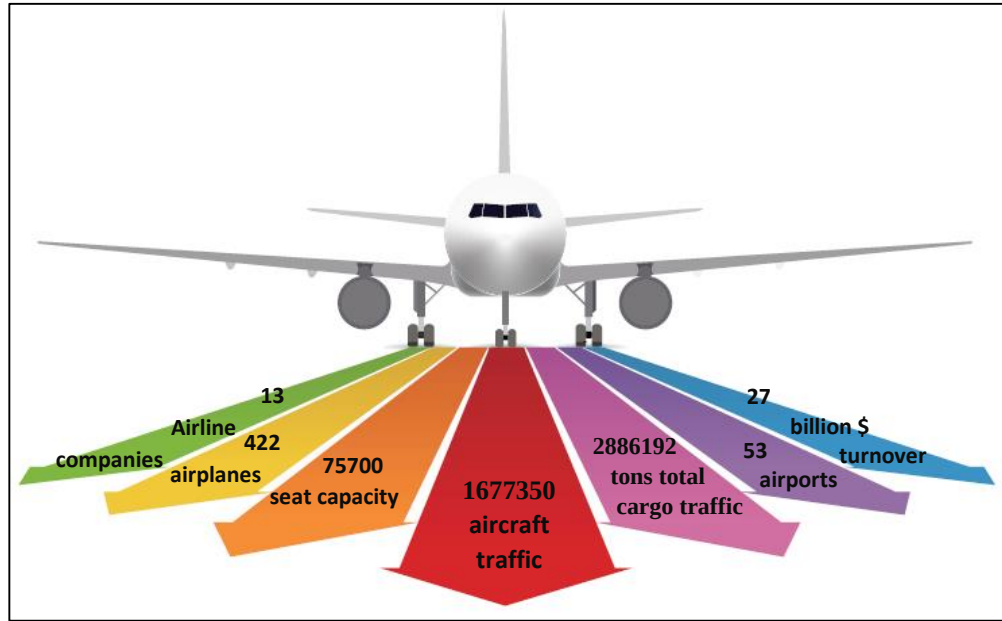


Figure 2.2 Airline industry growth in Turkey by the end of 2014

Even during the economic crisis that effects economy and aviation sector negatively in many countries in 2008, Turkey sustained its success in airline industry. Passenger traffic reached 166 million with 11% increment by the end of 2014. According to the Directorate General of Civil Aviation Activity Report, there are 13 airline companies, 50 air taxi transportation companies, 65 general aviation companies, 25 air balloon companies, 104 maintenance and instruction companies and 80 ground handling companies in Turkey.

Moreover, airline sector makes a contribution to employment. Directorate General of Civil Aviation revealed that employee numbers that were around 65,000 in 2003 have exceeded to 180,000 by the end of 2013. As a result of this, sector's turnover reached 23.8 billion dollars from 2.2 billion dollars, in the last 11 years. And it is expected to reach 27 billion dollars by the end of 2014. Aviation infrastructure and aviation technology developed parallel to the growth in this sector, also a breakthrough has been achieved in aircraft maintenance, replacement part production and modification. As a result, Turkey has peeked to design and produce aircraft. It is clear that, improvements in civil aviation have strategic importance not only for aviation sector but also on the overall development of Turkey, considering the aviation

developments' contribution to the trading volume, national economy, tourism and logistics (SHGM, 2014).

Being located in the middle of the world continents brings Turkey the advantage that it has strategic importance in air transportation. Turkey emphasizes its importance in air transportation competency by increased air traffic every day. At the end of 2013, it ranks 11th following India in world ranking and 5th following Spain in Europe, according to airport passenger traffic. New projects and developments have increased Turkey's passenger share so this rate has become 2.4% in the World and 8.7% in Europe.

Republic of Turkey Ministry of Transport, Maritime Affairs and Communications made airline operations marketization and opened it to the private sector because of air transportation's crucial importance for the future of countries. In the context of developed policies according to regulations in the area of Civil Aviation, reduction in travel costs, improvement of airports' physical conditions and construction of new airports' at a level to compete with rivals in the world gave the sector an acceleration. "Liberalization of the Aviation Project" that started in 2003, enlivened the cross flights and this resulted in increment of carried passenger numbers and flight numbers (Ulastirma Bakanligi, 2014).

2.5 Drivers of Airline Demand

According to The Global Passenger Forecast Report, there exists three factors that drive airline passenger demand. These factors are named with the titles; population and demographics, standard of living, price and availability.

Population and demographics: Besides giving an insight about the changes in the population, these factors also enlighten about the ratio of young and old age population in the future. According to results that have been gained from these factors; population is thought to be decreased substantially in Ukraine, Japan and Russia while the situation is expected to happen just the opposite in African countries. It is accepted

that growing populations mean younger people are increasing. Young people mostly use air transportation in comparison with older ones. The reason is younger people are generally working and they use air transportation for business trip, also they travel a lot more than older people. So that, by considering population and demographics, there can be constituted a foresight about air transportation demand.

Standard of Living: It is known that life standards and income of people shape their choices about everything. Way of transportation is one of them. People with high income usually choose to travel by air. It is seen that number of people who use air transportation are increasing in the situation of per capita income is \$20,000. This means air transportation choice is directly proportional with income value.

Price and Availability: This factor tries to estimate future conditions of air transportation's price and air network. In the last ten years, although oil prices have increased, air transportation unit cost have decreased. In the next 20 years round, it is thought that the air transportation cost reduction will continue by around 1-1.5% per year. Airline companies extend their transportation network by adding new long-distance middle size airplanes on their fleet. It is expected that air transportation will grow by more than 1% per year, considering the much more liberalization of air transportation marketplace (IATA, 2014).

CHAPTER THREE

FORECASTING IN AIRLINE INDUSTRY

3.1 Forecasting

Forecasting is a tool for the future estimation. It uses historical data for the prediction or it uses experimental data in case of not having a history. According to its basic concept, there exists two forecasting techniques; qualitative and quantitative.

When the forecaster's data has no history or comparison can not be possible for the data, qualitative forecasting methods are preferred. Expert opinion approach, management assumptions, market research or surveys that help predictors having information from people in the related areas, are some of the qualitative forecasting techniques. Forecasting results sometimes can be an average of agreement; furthermore, estimations can be constituted from a distribution. Distributed estimation points can be the inputs of a simulation and estimated points which behave like custom distribution are simulated.

Input data for the quantitative forecasting methods are three categories. First one is, data can be time series. To give an example, this kind of data includes time factor for instance sales figures at different months, market share, gross interest and so on. Second kind of data which is not dependent to time called cross-sectional for example number of fizzy drinks purchased per month. Mixed panel is the last one that not only includes time series but also panel data. Predictions are based on time element also external factors such as educational level takes place in modelling forecasting data (Mun, 2010). As it is mentioned before historical data is used in quantitative forecasting techniques. Also cyclic, trend, random or seasonal patterns are seen in the data. So it is very important to consider that forecasting results change when these patterns in the data change.

When the patterns of data change and after all quantitative methods are not satisfactory in consideration of results, predictors can prefer qualitative methods. Qualitative methods include subjective judgment so realizing the changes in the

forecasting environment is very important. Catching up the recent changes and with the help of it interpreting and embedding these changes to forecasting model in a fast way is the power of qualitative methods against quantitative methods. The disadvantage of qualitative methods is that they are not good at realizing trend, cyclic or seasonal patterns in the existing data. However, managers, forecasters or individuals commonly use qualitative forecasting methods for the purpose of collecting different decisions or opinions in forecasting process. Even the major companies chose using quantitative forecasting methods rarely; they integrated judgment into identifying the inputs of forecasting process. Here are the qualitative methods' major advantages:

- Improving costs are not high
- Forecastings are resulted very quickly
- Managers have a strict realization of wide-ranging elements and their effects to sales demand.

It can be said that major companies with numerous products usually prefer quantitative methods because it is thought using qualitative methods in such a wide range of forecasting process leads to confusion (Chase, 2013). In the following two sections brief explanations will be given about qualitative and quantitative methods.

3.2 Qualitative Forecasting Methods

There are so many different qualitative forecasting methods. These methods help making a forecasting considering foresight, subjective opinion and experience. So many times it can be accepted easy to implement but it can not be said about implementing the decided forecasting result. Organizational politics can hinder to operationalize the decions taken at the end of the forecasting process. In fact, they are still used in so many forecasting processes. In the following, a few of them will be introduced.

Jury of Executive Opinion: Managers or experts who have information about what to forecast make the predictions. Forecasting process is carried out in a hierarchial

way. It means that the top level executive in the forecasting process makes the prediction first, after that, predictions are made hierarchically. It can be said that, this method has a top-down process. Also, with a purpose of corroborating the judgments, an empirical analysis can be done.

Sales Force Composite: This technique is just the opposite of the previous method “Jury of Executive Opinion”. Predictions are made from bottom level to top. This method is named “Sales Force Composite” because to see the big picture it means forecast of the market, first of all salesmen are asked for forecasting. After getting their predictions, process continues through the higher levels. In this technique, salesmen predictions are impetus for constituting the forecast of the total market.

Scenario Analysis: Forecasting process is resulted with numeric solutions in Jury of Executive Opinion and Sales Force Composite methods. Just the opposite of them, this technique gives a portrait of the forecasted situation. In other words, this technique has a narrative characteristic (Kahn, 2006).

Delphi Method: Several experts from different specialites make a questionnarrie. This process involves various stages. Experts reveal their opinions and judgments according to their experience to make a forecast about related state. The method is effective in predicting the market dynamism. Also, implementing this technique before putting a new product on the market helps estimating potentials of the marketplace (Kuada, 2008).

Assumptions-Based Modelling: Initially, this technique divides the market into personal constituents. After that it tries to understand and model the market actions. Inputs from these constituents are detected and they are accepted as drivers of the market, so forecasts are formed according to their feedback. This technique is also called “Chain Models” or “Market Breakdown Models” in the literature (Kahn, 2006).

3.3 Quantitative Forecasting Methods

Quantitative forecasting techniques can be collected under two headings. Time Series and Casual Methods. Quantitative forecasting techniques will be analyzed under their specialities.

3.3.1 Time Series Methods

The methods under this heading make forecasts based on historical pattern(s) of past behaviours of what to forecast. Quantitative forecasting methods in this category first investigate if historical data show trend, seasonal or cyclic patterns or not, and then forecast by using these patterns as if they will have the same patterns in the future. There are a variety of time series techniques, and some of them will be investigated in the following.

Naive or Random Walk: This is the basic or simplest of time series methods. It forecasts future behaviors as if they will be the same as the past year's. Another name for it is no-change method. If predictors are really informed about the behaviours of the market, it can be accepted that future behavior will be the same with previous actual value (Chase, 2013). This method is usually used in forecasts about financial areas (Christou, 2012).

Moving Average (MA): This method is very popular in the area of demand forecasting. With the purpose of finding the next period's forecasting result, decided number of latest periods is summed and the sum is divided to that number. It is easier than averaging the whole time series. The advantage of this method is, it gives forecasting results that are closer to recent values because, latest periods' data are included to averaging process (Christou, 2012).

Exponential Smoothing (ES): It is very important to take into consideration the last performance of forecast process. If not so, improvement of future forecast results cannot be done and system performance cannot be evaluated. There is a feedback

mechanism in this method that, single ES considers error in the last forecast value for the next period' forecast. It can be said that actual value and last forecast value are combined and forecast of next period is constituted (Christou, 2012).

Holt's Two-Parameter: This technique forecasts the data with trend by using two smoothing constant α and β and two equations. Firstly, it makes trend adjustment by using first equation after the difference between last two smoothed values is updated (Chase, 2013).

Holt-Winters Method: It includes not only trend but also seasonal factors and three smoothing constants. There are two kinds of Winters' method, first multiplicative and second additive Winters' method. The only difference between them is mathematical operation they use for seasonal factors. Past actual values have exponentially decreasing weights and they change the parameters (Sas, n.d.).

Decomposition: Time series patterns effects sales according to assumption of this technique. Equally weighting for whole sales periods is done by using center MA (Chase, 2013). This technique makes predictions and forecasts with the help of time series patterns. After that, it composes these patterns by using additive or multiplicative model to get the last forecast result. In additive decomposition technique, all time series components in the equations are defined in the same unit and first of all trend and cycle constituents are predicted with centered MA. The process for the multiplicative method is nearly same with the additive method. In multiplicative method, constituents of time series models except trend are expressed as numbers without any unit, while trend is expressed in the same unit with actual data (Christou, 2012).

Auto Regressive Integrated MA (ARIMA): This technique joins regression models and MA. Auto correlation coefficient defines the relationship of a variable's statement at two different periods. This technique is good at forecasting but it is not preferred because of its implementation complexity (Chase, 2013).

3.3.2 Casual Methods

These kinds of methods assume that there are different variables which must be considered in the forecasting process. These variables are strongly related with forecasting subject. If changes in related variables exist, forecasting result will be changed according to variables' latest statement. For instance, demand can change according to discounts, seasonality, promotions, etc.. So it is very important to identify the effects of these relationships with the purpose of having optimal forecasting results.

Simple regression: In this technique, regression is between one variable which is called dependent variable Y and independent variable X. Considering X and Y's linear relationship, equations are constituted as in the following:

$$\hat{Y} = \alpha + b X \quad (3.1)$$

In the equation 3.1, while, α represents the intercept, b represents the slope of a line. This equation models the historical data. Equation aims to constitute a best fit linear line considering the minimization of total distance between the historical data points and predicted points (Chase, 2013).

Multiple Linear Regression: Simple regression is enhanced by adding more independent variables and the name multiple linear regression is given. It has the same purpose with simple regression that it forecasts the dependent variable's manner by using the dependent and independent variables' relation. Although calculations are better to be done by computers because of their complexity; relationships between independent variables may cause to comment the results harder (Freund, Wilson, & Sa, 2006).

ARIMAX: It is the extended version of ARIMA, and extension is made by the addition of explanatory variables. Reducing the variance does not mean that the model is more successful in forecasting, so, it should not be forgotten that whole forecasting process must be improved for the success of forecasting results. Chosing the number

of explanatory variables is very important because it can influence the forecasting process in a negative way. So, for the purpose of deciding how many explanatory variables will be used; statistical tests can be implemented (Chase, 2013).

Unobserved Components Models (UCM): The aim of this technique is minimizing the unexplained variance. It can be said that UCM is the extension of decomposition techniques (Chase, 2013). It separates a time series into its components like trend, cyclical, etc.. UCM can be preferred instead of ARIMA techniques (Stata, 2015).

3.4 Literature Review on Forecasting in Airline Industry

In this section, different studies will be investigated. First of all, forecasting researches in airline industry will be mentioned. Following three forecasting studies use traditional methods. They ignore uncertainty or give a little importance. Here are the details belonging to them.

Singh and Das (2010) studied four forecasting methods; MA, ES, Holt's two parameter and Holt-Winters model to forecast the demand of future period in airline industry. Historical passenger demand data between October, 2006 and August, 2008 was taken from Lufthansa Airlines. Monthly demand data was turned into quarterly data to simplify the calculation. Solutions were calculated by using each of four period one by one and study not only aimed to compare these methods by using their solutions but also aimed to see the forecasting errors of these methods through absolute error (AE), mean squared error (MSE), mean absolute deviation (MAD) and mean absolute percentage error (MAPE). According to the results, it was seen that Holt-Winters model gives more reasonable predictions and its solutions are more similar to pattern of historical data than the other methods. With this study, they tried to help the management by offering and improving new strategies for varying demand (Singh & Das, 2010).

Scarpel (2013) used the mixture of local experts model (MLEM) to cope with the rapidly changing conditions. By using this method, he tried to forecast the monthly domestic passenger numbers at Sao Paulo International Airport in Brazil. Data was taken between January, 1990 and December, 2010, also he tested the accuracy of the model by making the passenger numbers of January 2011 to February 2012 out- of sample data. He compared the proposed method and multiplicative Holt-Winters model for the actual data in those years. The MLEM is built up from a mathematical programming formulation and it contains fuzzy clustering technique for decision variables. The model also uses Gross Domestic Product (GDP) as indicator because of realising demand changes according to economic activities. It can give rapid solutions to demand changes in unexpected conditions because of the divide and conquer approach of MLEM. For this reason, its solutions are closer to real data than Holt-Winters's (Scarpel, 2013).

Tsui, Balli, Gilbey and Gow (2014) aimed to forecast the passenger traffic flow of Hong Kong International Airport (HKIA). They used Seasonal ARIMA (SARIMA) and ARIMAX models to predict the growth of demand to 2015. The data between January 1993 and August 2011 were taken from Airport Authority Hong Kong. HKIA was divided to 11 principal origins and SARIMA was used to forecast each origin. ADF and KPSS unit root tests, and the HEGY seasonal unit root test showed that time series had trend and seasonal stability, also ACF and PACF correlograms tests denoted that time series had seasonal AR an MA processes. Because of taking into consideration the endogenous or exogenous variables and different unexpected events's effects ARIMAX method was used, but only for the data between January 2001 and November 2010. According to forecasting results HKIA's future passengers will have a growing trend until December 2015. Dividing HKIA into different origins helped to obtain which origins's air passenger number will decrease or increase. Finally, with the help of three scenario analyses, the factors that effect changes in the passenger growth tried to be determined (Tsui et al, 2014).

3.5 Literature Review on Forecasting Under Uncertainty

Next studies are about forecasting under uncertainty. In these studies, researchers made forecasting searches in different areas. Their common point is, all of them have uncertain environments. Uncertain conditions make hard to forecast the target point. Forecasting environment has so many rapidly changing conditions that effect the forecasting results. So that, forecasting techniques under uncertainty such as grey models, fuzzy forecasting their hybrid models with each other or other methods like genetic algorithms will be exemplified.

Wang and Hsu (2008) developed a forecasting method by combining genetic algorithms (GAs) and grey model (GM) in forecasting. They tried to predict output and trends of high technology industry in Taiwan, so data were taken from Taiwan's integrated circuit industry. It was possible to make only a few observations because of this industries' characteristics (like, rapid changes in technology, societies requirements). Within this context, traditional methods (simple regression, time series) were insufficient and they used Grey Forecasting Theory. To make the results more accurate, due to GAs known to help solve complex problems, they defined the parameters of grey forecasting model by using GAs. MAPE was used to minimize the forecasting error. The grey forecasting model's equation, that satisfied the objective function of MAPE, was implemented by the steps of GAs. And the model was named Genetic Algorithms Grey Model (GAGM). They used data from 1990-2001 and tried to predict the output of 2002-2005. Results were found by using original GM (1,1), Bayesian GM (1,1), and GAGM. As conclusion GAGM had the least MAPE of all, and could be said that this model gave more reasonable and accurate solutions (Wang & Hsu, 2008).

Tsaur (2008) brought a new perspective to forecasting using the grey model. Because the grey model was insufficient for solving problems with vague and fuzzy-input values, he proposed a new hybrid fuzzy-grey regression model. He worked on two cases, one with crisp-input data and one with fuzzy-input data, for LCD TV demand forecasting between years 2001-2004. He defined two models for fuzzy-grey

regression with crisp-input and with fuzzy-input. For the case with crisp-input, he implemented the model, also he found results with GM (1,1), Watada's fuzzy regression and linear regression and he estimated the error with MAPE. For the case with fuzzy-input, he found the results by using fuzzy grey regression and Watada's fuzzy regression because GM (1,1) and linear regression cannot be studied with fuzzy input. In both cases, the new model gave the most accurate solutions in a reasonable interval, also the new model helped the decision makers to see the best and worst possible scenarios (Tsaur, 2008).

Pi, Liu and Qin (2010) presented an improved grey forecasting model which exemplifies on the two case studies. The basic GM(1,1) based forecasting model has lack of ability of precision when the data has random fluctuation. Remnant GM(1,1) model that is the modification of GM(1,1) defines the differences between real values and the model predicted values as residual series. Considering hardness of gathering residual signs when the historical data is very little, the paper introduced a new GM(1,1) plus 3-points average technique for forecasting. This method has also an advantage of comprising other two GM(1,1) and residual GM(1,1) model. This model improved the background model formula and defined the number of data for initial modeling. Three methods are applied to forecast the electricity demand and energy production in China. Data between the years 1985-1989 are used for modelling and for testing the results data between the years 1990-2006 are analysed. For the two cases, when comparing three grey forecasting model, improved method gave the best results with smaller error. Finally, the model was applied to forecast 2007-2015 energy production of China. It may help policy and decision makers to constitute their strategies (Pi, Liu, & Qin, 2010).

Kayacan, Ulutas and Kaynak (2010) analysed different grey models like GM (1,1), Grey Verhulst Model, modified grey models using Fourier series. They used US dolar to euro parity between 2005-2007 as data, to compare the models' performances for model fitting and forecasting. They explained the models briefly.

They also made some modifications on models, because of the difficulties in time series prediction in financial area. As a modification of GM (1,1), Fourier series were used for error residuals and in time, when three years' data were examined, it could be seen that they were nonlinear and nonstationary. For smoothing the primitive data, MA filter (MAF) with different window sizes were used. According to simulation results, one can say that GM (1,1) gives more accurate predictions for forecasting of the monotonous type of process; also it is clear that modified grey models have higher performance both for model fitting and forecasting. Modified GM (1,1) using Fourier series in time is the best in model fitting and forecasting (Kayacan et al., 2010).

Jing and Zhi-Hong (2012) were focused on grey relational analysis and multiple linear regression in their study. They applied these models on water supply industry in China and pipeline leakage problem. There are many factors that cause pipeline leakage and they are hardly collected and the data's accuracy is poor. So they used grey relational analysis to identify the pipeline leakage factors to handle the uncertainties. The data were collected between the years 2000-2006. While total number of leakage in a year was taken as reference sequence, data of different attributes were taken as comparability sequence. For the nondimensionalization, they studied mean processing model. After they constituted the sequences, they calculated grey relational grades of them. According to the results, they sorted the factors that influenced pipeline leakage. With these factors, they used multiple linear regression to forecast the initial pipeline leakage time after the networks came into use. According to the value of the regression model, considering error, they showed that this model could meet the Macro-management of water supply network's requirements (Jing & Zhi-Hong, 2012).

Ziser, Dong and Wong (2012) aimed to forecast demand of electricity considering weather uncertainty factor because maximum demand forecast helps electricity supply industries to decide changes in investment process for new generation or transmission. Besides other factors that effect forecast accuracy, weather is analyzed specially because of its inherent uncertainty. They propose a new methodology to get the improved market signals. They combine daily demand forecasting with synthetic

weather scenarios and constitute alternative daily maximum demands to reach the long-term growth. To create synthetic weather scenarios, they combine surrogate data techniques and use Wavelet Transform-Iterative Amplitude Adjusted Fourier Transform Technique (WT- IAAFT). Extreme Learning Machine that is an advanced regression technique models daily maximum demand. These inputs help electricity market simulator to predict market prices, levels of unmet load and network congestion. A case study is applied to Australian National Electricity Market (NEM). They also compare other surrogate data techniques with WT- IAAFT which gives the best results of all to create synthetic weather scenarios. Results show that forecasting demand by considering weather uncertainty is more accurate than the industry estimation (Ziser et al., 2012) .

Alvisi and Franchini (2014) focused on the Model Conditional Processor (MCP) which is used for estimating the predictive uncertainty that is the probability distribution of real value of the predictand. MCP is a Bayesian method and it uses Normal Quantile Transform (NQT) for the purpose of transforming the monitored data and their forecasted values to the normal space. Two deterministic forecasting methods help MCP to operate the forecasts. The study applies the MCP model to the water distribution system of Castelfranco Emilia for forecasting hourly demands for 24 hours. In this example, one of the deterministic forecasting model is the Patt_for demand forecasting model and it forecasts the hourly water demand from 1 to 24 hours. The second model is the ANN_for (based on artificial neural network) and used for predicting the 24 hours water demand. The MCP is compared with those models by using Nash-Sutcliffe (NS) and root mean square error (RMSE) and results show that MCP provides more accurate forecasts. MCP also helps reducing the uncertainty by combining information those two forecasting models gave. Finally, it must be known that to get a more accurate predictive uncertainty, the MCP must be parameterized using the dataset of individual forecasting models that are used outside the calibration (Alvisi & Franchini, 2014).

Chen (2014) aimed to assert a novel high-order fuzzy time series model. He used data from Taiwan Stock Exchange Capitalization Weighted Stock Index (TAIEX). The

stock market had a complex environment he used high-order fuzzy time series and applied it to predict stock prices. He analyzed the enrollment records of The University of Alabama for showing the reliability of the model and he applied the model to historical data. Besides these, Chen compared his results with the previous studies done by conventional fuzzy time series.

First of all, according to data from TAIEX, he defined the universe of discourse (U) for the historical data. Next he defined seven linguistic intervals with four iteration and fuzzy sets. As novelty, he defined the linguistic intervals with entropy-based partitioning, with the help of it, high order model could give reasonable linguistic values and overcome the problems resulting from an excess of linguistic values. Chen established the Fuzzy Logical Relationship with artificial neural network after creating the model and he applied this for second and third order fuzzy time series. By using neural network's forecast results, defuzzification was done. Finally, considering the future changes, the model predicts the stock price including the error factor. In conclusion, he repeated iterations of the steps that were used in this model to optimize the linguistic variables so forecasting results were better than conventional ones. As a result of comparing forecasting results of the historical data's enrollment records from Alabama University, one can see that this model performs better than their results (Chen, 2014).

In the following studies traditional forecasting methods and uncertain condition forecasting methods are hybridized. In all studies, it is aimed to show stronger points of new methods; it is clear that in all studies grey or fuzzy forecasting methods that belong to uncertain environment, results are better than traditional ones. On the other side, the best forecasting results are reached with the combination between them..

Benitez, Paredes, Lodewijks and Nabais (2013) tried to forecast growth of the passenger demand in the airline industry, for long lead time. They proposed a new model of GM (1,1) by adding a damping trend parameter to modify the trend component in the GM model. They wanted to compare the results of GM for long lead times, with and without damping trend parameter. This parameter is based on the

assumption that routes pax flows and passenger's demand are inversely correlated, in other words, pax flows growth in a slower rate than in previous years. GM calculations increase exponential as time increases so damping trend parameter, that wants to minimize exponential increase of the GM, decreases the calculations as distance increases. An error modification of GM based on Fourier series is added to the study with the purpose of doing more accurate predictions. They analysed the Airline Fares Consumer Report and used passenger number of travelling between cities from 2005 to 2008. The aim was forecasting the number of passengers 2009-2050. They studied 9 cases and showed simulation results. The results with damping trend parameter were more realistic, considering the plane capacity and reasonable travelling passenger number. They showed that when data were very few (min 4), GM with damping trend parameter was useful to make better predictions (Benitez et al., 2013).

Eğrioğlu, Aladağ, Yolcu, Başaran and Uslu (2009) proposes a new hybrid approach which is the combination of SARIMA and fuzzy time series model with the purpose of analyzing seasonal fuzzy time series. Beside the other time series that are AR structured, this fuzzy series includes MA structure. This hybrid method is based on partial high order bivariate fuzzy time series forecasting model. SARIMA model is applied by using Box-Jenkins and inputs of it help to define the order and the parameters of hybrid fuzzy model. Creating fuzzy relationship with feed forward neural network is another step of the model. Output data of feed forward neural network constitutes inputs for fuzzy forecasting. For final step, centroid method defuzzifies each fuzzy forecast as a reason of getting the results. For showing the usage of hybrid method, it is applied to two real seasonal time series, one consists of measures of sulfur dioxide in the air of Ankara and the second time series consists of the natural logarithms of monthly passenger totals in international air travel between 1949 and 1960. Besides the hybrid method, FO (Chen's first order fuzzy time series model), HO (Chen's high order fuzzy time series model) and FOS (Song's first order seasonal time series model) also applied to case series to compare the results. And the results show that hybrid method gives the more accurate forecasts considering RMSE and MAPE criteria (Eğrioğlu et al., 2009).

Liu (2007) defined uncertainty theory to model uncertainties and he presented belief degree for dealing uncertainty in an event. Disadvantages of probability, fuzzy and grey theory and why fuzzy is failed to model uncertainties can be summarized as follow:

- Probability theory needs a large amount of historical data to give rational results.
- Fuzzy theory needs strong information about related subject to constitute membership function.
- Fuzzy theory is not successful in modeling unsharp events because some events are not possible to be composed of just in the given limited range.
- Fuzzy theory are not suitable to define belief degree because of its exact and limited borders.
- Grey theory studies small sample size and it deals with recognitive uncertainties.

Table 3.1 compares uncertainty theory with probability, fuzzy and grey theory.

Table 3.1 Comparison of uncertainty theory, grey theory, probability theory and fuzzy theory (Memon et al. 2015)

Object	Uncertainty Theory	Grey Theory	Probability Theory	Fuzzy Theory
Research objects	Cognitive uncertainty	Small sample uncertainty	Large sample uncertainty	Cognitive uncertainty
Foundation	Uncertainty distribution	Information coverage	Probability distribution	Fuzzy sets
Requirement	Experience	Few data points	Large number of data points	Experts knowledge
Data requirement	Uncertainty distribution	Any distribution	Probability distribution	Known membership
Objective	Laws of uncertainty	Laws of reality	Laws of statistics	Cognitive expression

Uncertainty theory adapts problems to its methods by using degree of belief, uncertain measure, uncertain variable and uncertainty distribution. Theory has lots of applications to many areas like uncertain statistics, uncertain programming, uncertain risk analysis, uncertain finance, uncertain reliability analysis, uncertain renewal process, etc.. Its uncertainty consideration and modelling success help to obtain more reliable and accurate solutions.

CHAPTER FOUR

CASE STUDY IN TURKISH AIRLINES

This chapter gives information about THY's history, core business, flight points and countries, success and aims. Knowing the company that the study will occur helps gaining information about the case study's environment. Problem will be defined generally in the following. Data type, time interval and techniques that will be used in this thesis will be mentioned in subsections of the chapter.

4.1 Information About the Company

THY which is the national airline company of Turkey was established with a name "State Airlines Administration" under the visitation of Ministry of National Defence in 1933 (Turkish Airlines, 2013). Company's core business is domestic and international passenger and cargo transportation. In 1938, the company continued its activities under the supervision of Ministry of Transport. The company made its first international flight on Ankara-Istanbul-Atina line in 1947. It gave importance to advertisement and promotions to increase the passenger numbers. Even if it was changed for a few times, it had its existing name "Turkish Airlines" in 1955. 1956 was the year THY became a member of IATA which was established with a purpose of ensuring a corporation in areas of trade, technic, and economy between its members and preventing unfair competition.

In the company's 50th year, 30,000 ton cargo and 2.5 million passengers were transported with 30 airplane 4037 seating capacity in 3 continents. SunExpress Airlines was established by THY and Lufthansa with fifty-fifty partnership in 1989. Registered capital reached 50 billion by the year 1996. Same year, Airbus company awarded THY with "airline company that aviates A-340 in the most efficient way in the world". THY's pilots were charged as instructor pilots in Airbus Company.

In 2000, private airline passenger programme "Miles&Smiles" commenced. According to annual audit report of Federal Aviation Administration, there was zero

error in so many plants and units of THY, in 2005. As a conclusion of increasing purchased aircraft numbers, 100th airplane was joined to fleet in 2006. 2008 was the year which THY participated global airline alliance “Star Alliance”. In 2010, it was chosen as the number one in economy class catering by Skytrax which carry out researches about airline industry without commercial concern and evaluates airline companies with passenger votes about airport, cabin crew, catering and other categories (Turkish Airlines, 2013).

According to 2014 Skytrax evaluation, besides being chosen “The Best Airline Company of Europe” for the 4th time in row, THY was chosen “The Best Airline Company of South Europe” for the 6th time in a row. In addition to these, “The Best Business Class Catering Delivery Service in the World” and “The Best Business Class Private Passenger Lounge Catering” awards were given to THY. With these awards, the company registered its success about being preferred by the passengers.

THY serves with 265 passengers and cargo planes to 260 different points of 108 countries in 2015. The company takes its place among the worldwide airline companies with its sustainable success. The company grew its fleet extremely by making an agreement about purchasing planes as a result of its strategical decisions. According to this agreement, total cargo and passenger planes in their fleet are thought to reach 421 by the year 2020, with the purchases starting in 2015 (Turkish Airlines, 2014).

THY sustains its success with the fast and consistent increment of its passengers, although the world wide airline companies have been affected by the economic crisis and recession for the last ten years. The passenger numbers were 10.4 million by the year 2003, this number increased more than two times in 2010 and exceeded 50 million by the end of 2014 (Turkish Airlines, 2016). Following Figure 4.1 shows the network development of THY from the year 2004 to 2014. Figure also includes expected passenger and destination numbers of 2015.

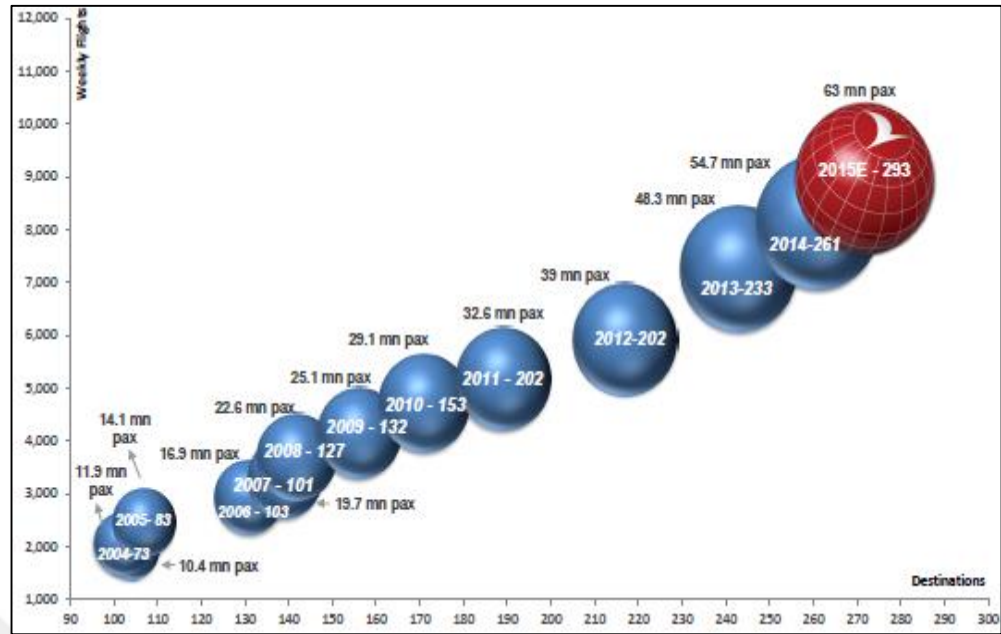


Figure 4.1 Network development of THY (Kılıc & Inceöz, 2015)

Related with the above Figure 4.1, Figure 4.2 gives details about total passenger traffic distribution for domestic and international lines.

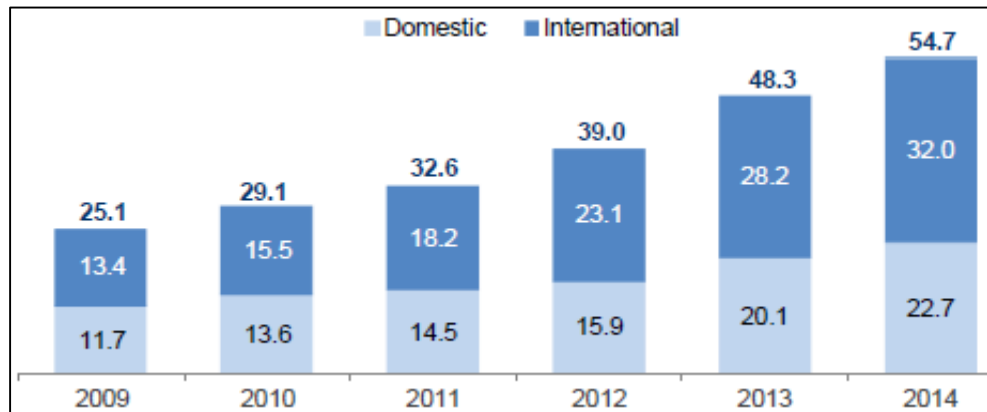


Figure 4.2 Total passenger traffic distribution (mn) of THY (Kılıc & Inceöz, 2015)

While global aviation grew 5.6%, THY got ahead of it with the capacity increment by 16.3% and company increased its global share from 1.6 to 1.8 in 2014. Following Figure 4.3 displays THY's share in global markets.

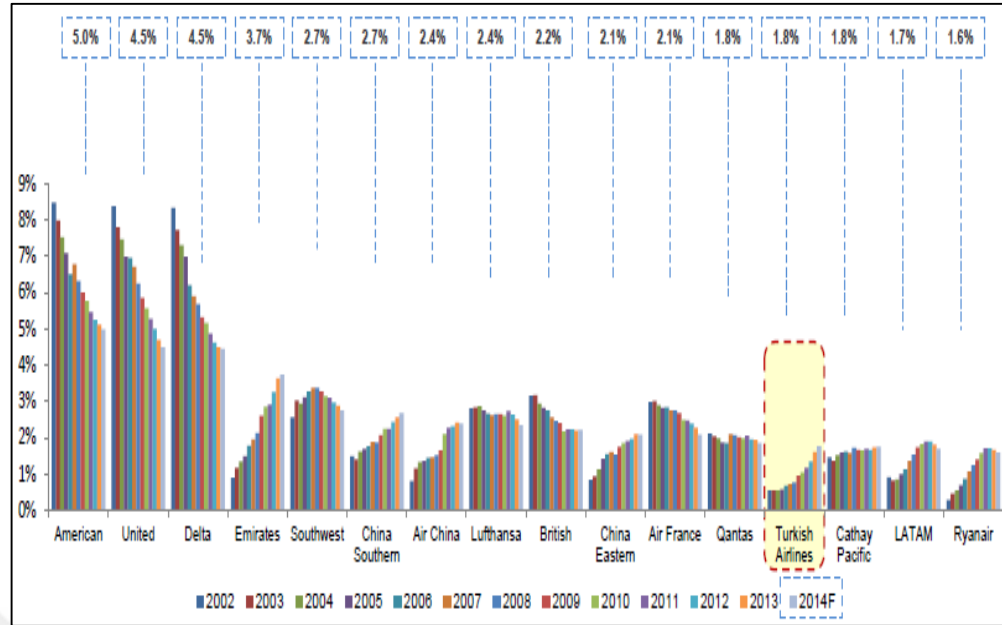


Figure 4.3 Global market share trends (in ASK) (Kılıc & Inceoz, 2015)

THY revealed that their aim was to reach 63.2 million passengers with 15% capacity increment and seat occupancy rate more than 80% by the end of 2015. Having a 293 planes fleet and flying 273 different points by adding 2 domestic and 7 international lines to its flight network is another purpose of the company. With its profitable and consistent growth, THY tripled its global marketplace share for the last ten years and it is constantly increasing its service quality and brand awareness every passing day. In accordance with making Istanbul one of the preeminent aviation centers purpose, THY continues adding value to Turkish economy with its 43,000 employees including group companies (Milliyet , 2015).

4.2 Problem Definition

Demand forecasting is a crucial step for the constitution of future strategies of a company, this study aims to show uncertainty theory's success by forecasting the passenger demand of THY. Airline industry has one of the areas which has rapidly changing factors. Unexpected events make hard to predict the demand fluctuations. Remind that, making an optimal demand forecasting has crucial importance because strategic decisions are based on reliable forecast solutions. Decisions such as crew

assignment, network optimization, aircraft purchase, investment, corporation, etc. Can be taken after forecasting the demand. It can be said that all these things unroll the importance of forecasting. In this thesis, THY's passenger demand forecasting is taken as the problem and with the solution, importance of uncertainty theory will be emphasized.

THY's passenger traffic data were examined in Minitab 11. Autocorrelation function (ACF) tests and partial auto correlation (PACF) tests were done to see if three types of traffic data are stationary or non-stationary. Results showed that all traffic data are non-stationary, that's why ARIMA or Box-Jenkins methods are not suitable for the data. Forecast results were obtained by using time series methods under certain environment. Figure 4.4 shows ACF and PACF tests for domestic lines and Figure 4.5 shows the same tests for international lines. All figures emphasize that passenger traffic data are not suitable to apply any auto regressive method because all traffic data are nonstationary. Time series methods seems proper to use.

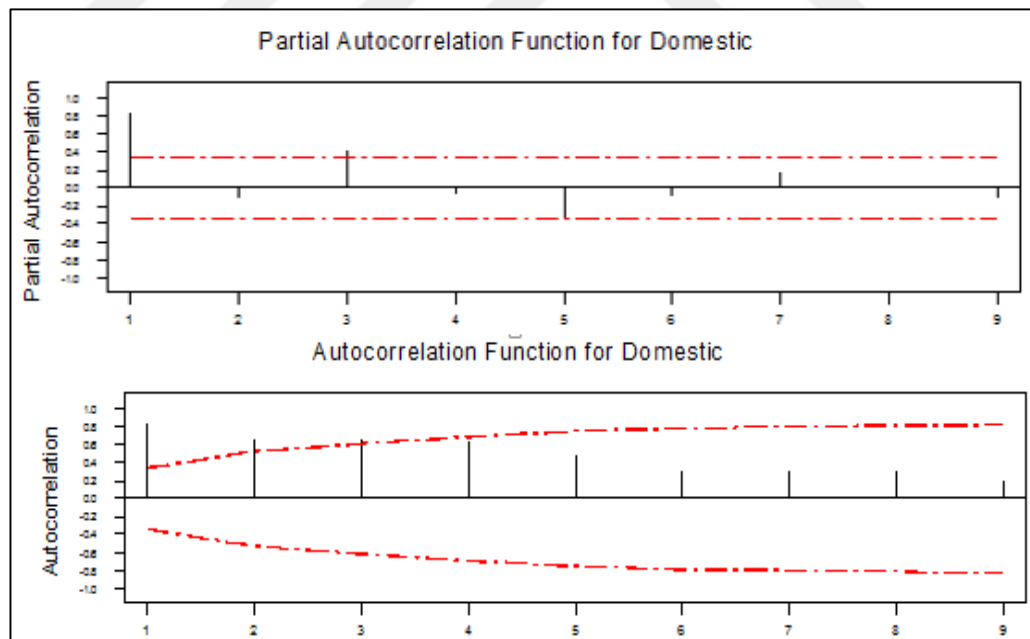


Figure 4.4 PACF and ACF tests for domestic lines passenger traffic data

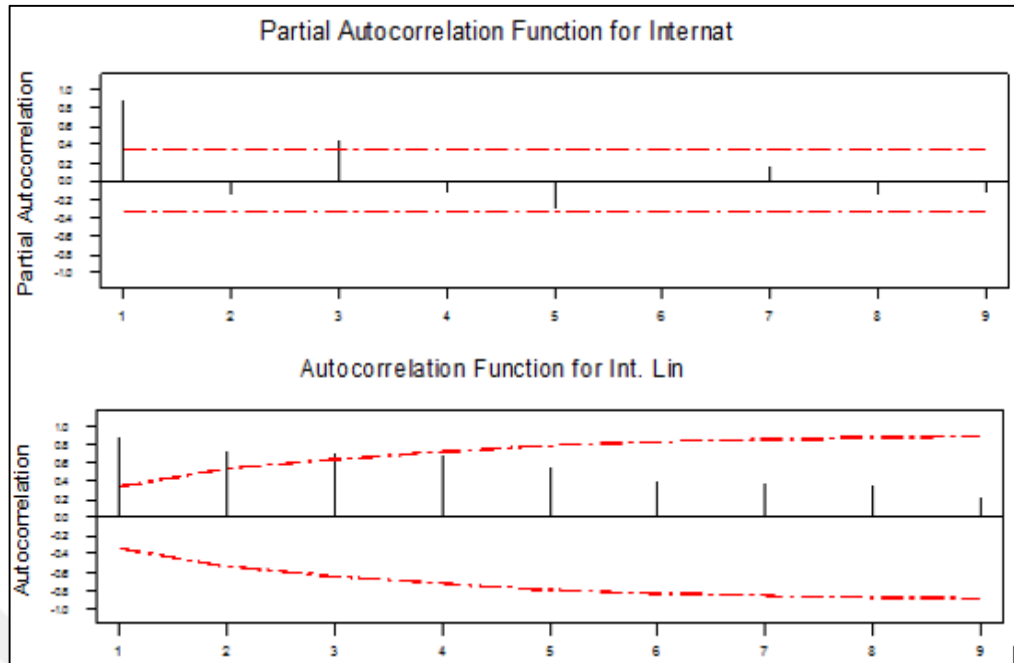


Figure 4.5 PACF and ACF tests for international lines passenger traffic data

Finally Figure 4.6 displays ACF and PACF tests for total passenger traffic data.

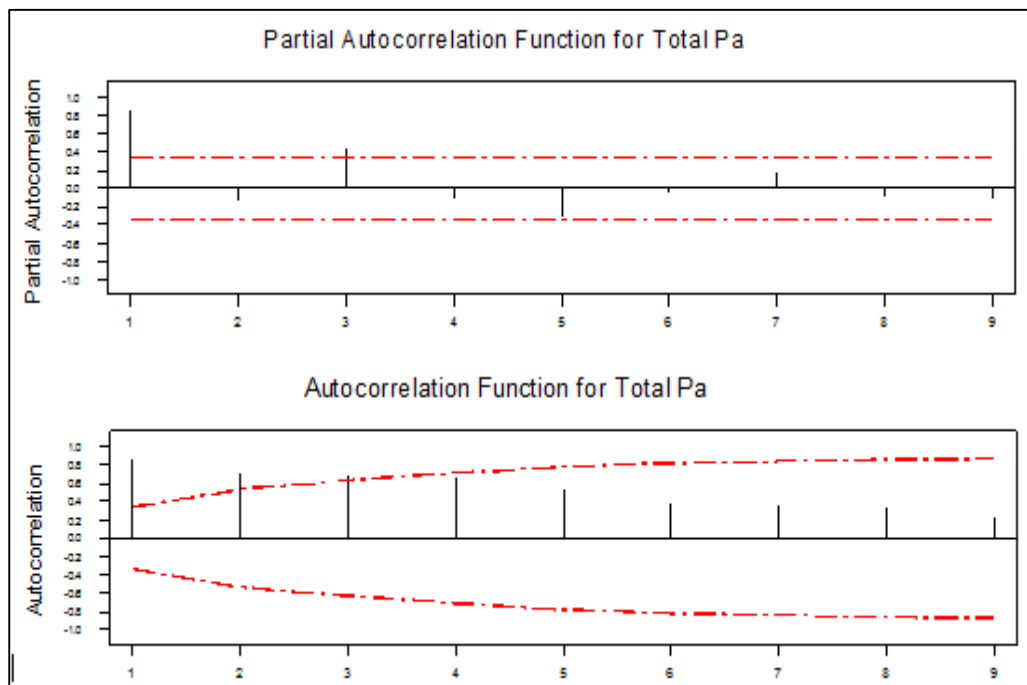


Figure 4.6 PACF and ACF tests for total passenger traffic data

4.3 Case Definitions

This thesis tackles the forecasting in two different contexts. One for certain environment and the other is uncertain environment. The reason that the study was divided into two different environments is showing the techniques' superiority that is used in uncertain environment. Uncertain environment consideration is very important for obtaining the optimum results for every problem. Traditional methods ignore uncertainties and behave like everything is certain in the problem environment but it is forgotten that these factors which are rapidly changing have crucial importance on the problem. For airline industry, there exist a lot of factors that can cause changes in the passenger demand. Fuel prices, terror attacks, weather changes, natural events, etc. can rapidly change passenger demand. They can effect ticket prices, flight schedule or flight network and they are directly related with the demand.

4.4 Methodologies

In certain environment sections, four traditional quantitative methodologies are studied. By using MA, ES, Holt's two parameter and Holt-Winters methodology passenger demand of THY for domestic lines, international lines and total passenger number has been forecasted. Combined method is applied to passenger data. MA and Holt-Winters methodologies are combined, because they give the best results among each four methods. Combination helps having the stronger sides of MA and Holt-Winters.

Grey theory is chosen to make the passenger demand forecasting in uncertain environment and it is mentioned in chapter 6 in detail. This methodology has a lot of implementations in many different research areas. Grey forecasting is one of its popular branches in making forecasting in uncertain environments. So it is used to forecast the same passenger demand with the existing passenger traffic data.

In chapter 7, another uncertain environment implementation is mentioned which is a branch of uncertainty theory. Uncertainty theory implementation is the highlight of

this thesis, because this thesis wants to show the usability and utility of uncertainty theory. It can be used in so many different areas and gives reliable solutions. By using empirical uncertainty distribution, ES parameters are decided and demand forecasting is studied again. Error analysis methods AE, MAD, MSE and MAPE are used for the purpose of evaluating each method's results and deciding the best method that gives the optimum result. Every methodologies' calculation steps and solution tables are mentioned in related sections in the following.

4.5 Data

Data has been taken from THY's web site for the study. All data can be reached from under the following titles corporate, investor relations, financial & operational and traffic results, the link that is related with the data is <http://investor.turkishairlines.com/en/financial-operational/traffic-results/1/2006> . To forecast the passenger demand data, passenger traffic flow between the years 2006 and 2014 has been used. Annual data has been divided to four quarters for calculations. Even though, the purpose is forecasting the passenger demand of 2015's first quarter, every year's passenger demand was forecasted from 2006 to 2015 and those data were accepted as test data. In the following Table 4.1 shows the data that will be used in the forecasting problem.

Table 4.1 Passenger numbers of THY's domestic lines, international lines and total

Years	Quarters	Domestic Lines	International Lines	Total Passenger Numbers
2006	Q1	1670880	1489497	3160377
	Q2	2292658	2030287	4322945
	Q3	2726588	2603194	5329782
	Q4	2165145	1965482	4130627
2007	Q1	2091423	1836948	3928371
	Q2	2607814	2396145	5003959
	Q3	2867671	2994741	5862412
	Q4	2367868	2493356	4861224
2008	Q1	2334853	2205749	4540602
	Q2	2806424	2943571	5749995
	Q3	3176875	3408181	6585056
	Q4	2675077	2985583	5660660
2009	Q1	2413921	2493716	4907637
	Q2	2965643	3363367	6329010
	Q3	3335202	4062937	7398139
	Q4	2976802	3489885	6466687
2010	Q1	3015122	3141713	6156835
	Q2	3421327	3816609	7237936
	Q3	3905756	4611520	8517276
	Q4	3240845	3946520	7187365
2011	Q1	3189019	3513280	6702299
	Q2	3614101	4472552	8086653
	Q3	4067279	5488045	9555324
	Q4	3639141	4666771	8305912
2012	Q1	3449719	4519337	7969056
	Q2	3959336	5816170	9775506
	Q3	4556418	6833003	11389421
	Q4	3940719	5970525	9911244
2013	Q1	4001032	6011770	10012802
	Q2	5135566	7266135	12401701
	Q3	5800794	7996335	13797129
	Q4	5115260	6953113	12068373
2014	Q1	5138869	6955685	12094554
	Q2	5832040	8329294	14161334
	Q3	6178788	8963890	15142678
	Q4	5557813	7718588	13276401

CHAPTER FIVE

CASE 1: FORECASTING IN CERTAIN ENVIRONMENT

5.1 Methods Used for Forecasting in Certain Environment

In certain environments, methods will be implemented as if there was nothing happened unexpectedly. There exists no rapidly changing conditions in the forecasting environment. By pretending there is nothing that causes fluctuations in passenger demand, to forecast the passenger demand of THY, four traditional time series methods MA, ES, Holt's Two Parameter and Holt-Winters Method will be mentioned in the context of certain environments. These four methods were defined briefly in section 3.3.1, but in this chapter will deeply define the methods. Besides these methods, combined method will be used in this environment. This method has advantages of the methods it combines. Two methods which give reasonable results according to others are chosen for combined method. Details of the method will be told in section 5.6. After every section, the results of the study will be shown in tables. In evaluation of methods section, all four methods's solutions will be investigated with the help of error analysis techniques AE, MAD, MSE and MAPE.

5.2 Forecasting with MA

It is the most popular and widely used technique for demand forecasting in the literature. MA technique takes away the market complexity and helps to focus on the main goal such as demand of the next periods (Christou, 2012). In the computation of this technique, while the number of past period values stays constant, the time frames change. This method is also known for rolling calculation period. It calculates the next period's forecast by taking the average of determined number of past period values. When calculating the MA of a demand data series like $d_1, d_2, d_3, \dots, d_t$ under the observation of m parameters, at time frame t , the following formula is used:

$$MA_{t+1} = \frac{d_{t-m+1} + d_{t-m+2} + \dots + d_t}{m} = \frac{1}{m} * \sum_{i=1}^m d_{t-i+1}, \quad m \leq t \quad (5.1)$$

An example to implementation of MA on a data set, starting from the origin and by using four recent points, states in following (Kaufmann, 2013).

$$MA_5 = \frac{d_1+d_2+d_3+d_4}{4} \quad (5.2)$$

$$MA_6 = \frac{d_2+d_3+d_4+d_5}{4} \quad (5.3)$$

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$$MA_t = \frac{d_{t-1}+d_{t-2}+d_{t-3}+d_{5t-4}}{4} \quad (5.4)$$

It has an advantage that it takes the latest periods and creates closer forecasting results to the recent changes that can catch up the trend/cycle of that period. This model generates a new average by adding the latest new observation while the oldest period drops (Larson, 2001). An important part of the MA method is deciding the number of periods that will be included because degree of smoothing that forecast included is effected by that numbers. Such that, accuracy of the calculated values increases as the number of periods in the MA calculation increase. This method is however unsufficient for dealing with trend or seasonality although it is more useful than a mean. MA also can forecast only one period ahead with accuracy. Even if it is easy for implementation, it is not enough for demand forecasting because of its inability in catching up the sudden shifts of demand (Chase, 2013).

In this case, MA will be used to forecast the passenger traffic demand of THY's domestic, international and total lines. Every line is shown in different excel tables. Data is on a quarterly basis, so MA is calculated with four periods. In the following, tables for domestic and international lines and also total passenger numbers are placed. Table 5.1 shows the passenger traffic movement of domestic lines of THY.

Table 5.1 Passenger demand forecasting results of domestic lines with four periods MA

Period	Quarters	Traffic	Forecast	Error
1	2006 Q1	1670880	-	-
2	2006 Q2	2292658	-	-
3	2006 Q3	2726588	-	-
4	2006 Q4	2165145	-	-
5	2007 Q1	2091423	2213818	122395
6	2007 Q2	2607814	2318954	-288861
7	2007 Q3	2867671	2397743	-469929
8	2007 Q4	2367868	2433013	65145
9	2008 Q1	2334853	2483694	148841
10	2008 Q2	2806424	2544552	-261873
11	2008 Q3	3176875	2594204	-582671
12	2008 Q4	2675077	2671505	-3572
13	2009 Q1	2413921	2748307	334386
14	2009 Q2	2965643	2768074	-197569
15	2009 Q3	3335202	2807879	-527323
16	2009 Q4	2976802	2847461	-129341
17	2010 Q1	3015122	2922892	-92230
18	2010 Q2	3421327	3073192	-348135
19	2010 Q3	3905756	3187113	-718643
20	2010 Q4	3240845	3329752	88907
21	2011 Q1	3189019	33957623	206744
22	2011 Q2	3614101	3439237	-174864
23	2011 Q3	4067279	3487430	-579849
24	2011 Q4	3639141	3527811	-111330
25	2012 Q1	3449719	3627385	177666
26	2012 Q2	3959336	3692560	-266776
27	2012 Q3	4556418	3778869	-777549
28	2012 Q4	3940719	3901154	-39566
29	2013 Q1	4001032	3976548	-24484
30	2013 Q2	5135566	4114376	-1021190
31	2013 Q3	5800794	4408437	-1392360
32	2013 Q4	5115260	4719528	-395732
33	2014 Q1	5138869	5013163	-125706
34	2014 Q2	5832040	5297622	-534418
35	2014 Q3	6178788	5471741	-707048
36	2014 Q4	5557813	5566239	8426
37	2015 Q1	5116201	5676878	560677

Data belongs to passenger numbers between the years 2006-2014. Three months are accepted as one period or one quarter. Calculations have been made by four period and previous quarters forecastings were used as test data so that it gives a chance to

compare the forecasting results with the actual values. First column represents the periods, second column represents the quarters, domestic passenger numbers and corresponding forecast results are in the third and fourth column. Errors are in the last column. The Aim is to forecast the first quarter of 2015. This result is shown in the last row and it is highlighted with yellow.

Table 5.2 contains the international passenger traffic movement data and their forecasting results, while Table 5.3 represents the total passenger numbers that change according to different periods of different years and their forecasting results. Same as the Table 5.1 forecasting results are calculated by using MA method with four time periods. The reason that it is chosen to be calculated with four time period is that annual data is collected under four periods. Calculations are made in MS Excel 2010. Tables are placed respectively; periods, quarters, traffic data, related forecasting results and the errors. The last rows which are highlighted show forecasting results for the first quarter of 2015. Previous data and their forecasting results are used as test data. All methods' aims are forecasting the first quarter of 2015 passenger demand so all results will be evaluated according to this time period. Results are evaluated in details in the section 5.7 Evaluation of Methods.

Table 5.2 Passenger demand forecasting results of international lines with four periods MA

Period	Quarters	Traffic (D)	Forecast (F)	Error
1	2006 Q1	1489497	-	-
2	2006 Q2	2030287	-	-
3	2006 Q3	2603194	-	-
4	2006 Q4	1965482	-	-
5	2007 Q1	1836948	2022115	185167
6	2007 Q2	2396145	2108978	-287167
7	2007 Q3	2994741	2200442	-794299
8	2007 Q4	2493356	2298329	-195027
9	2008 Q1	2205749	2430298	224549
10	2008 Q2	2943571	2522498	-421073
11	2008 Q3	3408181	2659354	-748827
12	2008 Q4	2985583	2762714	-222869
13	2009 Q1	2493716	2885771	392055
14	2009 Q2	3363367	2957763	-405604
15	2009 Q3	4062937	3062712	-1000225
16	2009 Q4	3489885	3226401	-263484
17	2010 Q1	3141713	3352477	210763
18	2010 Q2	3816609	3514476	-302134
19	2010 Q3	4611520	3627786	-983734
20	2010 Q4	3946520	3764932	-181588
21	2011 Q1	3513280	3879091	365811
22	2011 Q2	4472552	3971982	-500570
23	2011 Q3	5488045	4135968	-1352077
24	2011 Q4	4666771	4355099	-311672
25	2012 Q1	4519337	4535162	15825
26	2012 Q2	5816170	4786676	-1029494
27	2012 Q3	6833003	5122581	-1710422
28	2012 Q4	5970525	5458820	-511705
29	2013 Q1	6011770	5784759	-227011
30	2013 Q2	7266135	6157867	-1108268
31	2013 Q3	7996335	6520358	-1475977
32	2013 Q4	6953113	6811191	-141922
33	2014 Q1	6955685	7056838	101153
34	2014 Q2	8329294	7292817	-1036477
35	2014 Q3	8963890	7558607	-1405283
36	2014 Q4	7718588	7800496	81908
37	2015 Q1	7413782	7991864	578082

Table 5.3 Passenger traffic forecasting results of total passengers with four periods MA

Period	Quarters	Traffic	Forecast (F)	Error
1	2006 Q1	3160377	-	-
2	2006 Q2	4322945	-	-
3	2006 Q3	5329782	-	-
4	2006 Q4	4130627	-	-
5	2007 Q1	3928371	4235933	307562
6	2007 Q2	5003959	4427931	-576028
7	2007 Q3	5862412	4598185	-1264227
8	2007 Q4	4861224	4731342	-129882
9	2008 Q1	4540602	4913991	373390
10	2008 Q2	5749995	5067049	-682946
11	2008 Q3	6585056	5253558	-1331498
12	2008 Q4	5660660	5434219	-226441
13	2009 Q1	4907637	5634078	726441
14	2009 Q2	6329010	5725837	-603173
15	2009 Q3	7398139	5870591	-1527548
16	2009 Q4	6466687	6073861	-392826
17	2010 Q1	6156835	6275368	118533
18	2010 Q2	7237936	6587668	-650268
19	2010 Q3	8517276	6814899	-1702377
20	2010 Q4	7187365	7094684	-92682
21	2011 Q1	6702299	7274853	572554
22	2011 Q2	8086653	7411219	-675434
23	2011 Q3	9555324	7623398	-1931926
24	2011 Q4	8305912	7882910	-423002
25	2012 Q1	7969056	8162547	193491
26	2012 Q2	9775506	8479236	-1296270
27	2012 Q3	11389421	8901450	-2487971
28	2012 Q4	9911244	9359974	-551270
29	2013 Q1	10012802	9761307	-251495
30	2013 Q2	12401701	10272243	-2129458
31	2013 Q3	13797129	10928792	-2868337
32	2013 Q4	12068373	11530719	-537654
33	2014 Q1	12094554	12070001	-24553
34	2014 Q2	14161334	12590439	-1570895
35	2014 Q3	15142678	13030348	-2112331
36	2014 Q4	13142678	13366735	224057
37	2015 Q1	12833776	13635311	801535

5.3 Forecasting with ES

In real life for so many cases, demand data has a trend or seasonal effect that changes according to different times of the year. For the purpose of having more accurate forecasting results, MA is not enough to catch the seasonal patterns of demand data. To solve this issue, there improvement has been made on MA models and different smoothing techniques were developed to forecast the demand of next period. These smoothing techniques that are called ES methods need specific constant parameter that takes value between $[0, 1]$ to weigh the past demand (Chase, 2013).

ES model is used when there is no trend or no seasonality in the demand data. Past demand data is weighed by exponential weights that decrease going through the past. This means that more recent data has the greater weight (Mun, 2010). In other words, simple ES uses the previous demand period's forecast and set it by the help of estimation error. The forecast of the next period:

$$F_{t+1} = \alpha * D_t + (1 - \alpha) * F_t \quad (5.5)$$

α that range between $[0, 1]$ means that if it takes a value which is closer to 0, the forecasting results does not reflect the fluctuation of past demand exactly. But if it takes a value closer to 1, next period's forecast is generated more related to the past period's patterns. It can be said that α has an effect on the forecastin results and for this reason it is important to choose the value of α . Even ES model is useful for estimating the future demand when product has short demand history, it has a disadvantage in forecasting more than one period ahead exponentially (Chase, 2013).

In the following, demand forecasting results that are gained by using ES for domestic lines, international lines and total passenger numbers of THY will be shown. In the above Table 5.4 is about forecasting results of domestic passenger numbers.

Table 5.4 Passenger demand forecasting results of domestic lines with ES ($\alpha = 0.99$)

Period	Quarters	Traffic	Forecast (F)	Error
1	2006 Q1	1670880	2259085	588205
2	2006 Q2	2292658	1676762	-615896
3	2006 Q3	2726588	2286499	-440089
4	2006 Q4	2165145	2722187	557042
5	2007 Q1	2091423	2170715	79292
6	2007 Q2	2607814	2092216	-515598
7	2007 Q3	2867671	2602658	-265013
8	2007 Q4	2367868	2865021	497153
9	2008 Q1	2334853	2372840	37987
10	2008 Q2	2806424	2335233	-471191
11	2008 Q3	3176875	2801712	-375163
12	2008 Q4	2675077	3173123	498046
13	2009 Q1	2413921	2680057	266137
14	2009 Q2	2965643	2416582	-549061
15	2009 Q3	3335202	2960152	-375050
16	2009 Q4	2976802	3331451	354650
17	2010 Q1	3015122	2980348	-34774
18	2010 Q2	3421327	3014774	-406553
19	2010 Q3	3905756	3417261	-488495
20	2010 Q4	3240845	3900871	660026
21	2011 Q1	3189019	3247445	58426
22	2011 Q2	3614101	3189603	-424498
23	2011 Q3	4067279	3609856	-457423
24	2011 Q4	3639141	4062705	423564
25	2012 Q1	3449719	3643377	193658
26	2012 Q2	3959336	3451656	-507680
27	2012 Q3	4556418	3954260	-602159
28	2012 Q4	3940719	4550396	609677
29	2013 Q1	4001032	3946816	-54216
30	2013 Q2	5135566	4000490	-1135076
31	2013 Q3	5800794	5124215	-676579
32	2013 Q4	5115260	5794028	678768
33	2014 Q1	5138869	5122048	-16821
34	2014 Q2	5832040	5138701	-693339
35	2014 Q3	6178788	5825107	-353681
36	2014 Q4	5557813	6175251	617438
37	2015 Q1	5116201	5563987	447786

Results are reached by using Minitab 16. Parameter α changes according to different lines's data. For domestic lines it is chosen as $\alpha = 0.99$. In Table 5.4, first column is periods and second is quarters that belong to different years. Following

columns show the domestic lines passenger traffic, their forecasting results and the errors. Like in the studies in MA method, the aim is to forecast the passenger demand of 2015's first quarter and it is emphasized in the last row of table, also one period ahead forecasting (Fits) results of previous quarters are calculated to see the method's consistency.

Following tables are the other implementations of ES method. Table 5.5 contains the information about international lines passenger traffic movement and their forecasting results. For international lines demand forecasting calculations α is chosen equal to 0.8. Minitab 16 calculations constituted the forecasting results. Columns are arranged like periods, quarters, international lines passenger traffic data, related forecasting results and errors. The last row emphasizes the 2015's first quarters international lines passenger demand and in the previous quarters Fits results are shown as test data.

Forecasting studies of total passenger numbers are shown in Table 5.6. The table is arranged just as the previous ones. Again, ES forecasting studies are done by using Minitab 16 and α is accepted 0.7. All three parameters that are used there different ES implementations are decided by trial and error method. Different parameter values that change in the range [0,1] are tested by looking at the results's MAPE and the parameter that causes the min MAPE in the forecasting results is decided upon. 2015 first quarter's forecasting solution is in the last row of the table. The comparison of the forecasting results that are calculated by ES with other methods will be shown in section 5.6. In the following tables which are given, Table 5.5 and Table 5.6, information is placed.

Table 5.5 Passenger demand forecasting results of international lines with ES ($\alpha = 0.8$)

Period	Quarters	Traffic	Forecast (F)	Error
1	2006 Q1	1489497	2053592	564095
2	2006 Q2	2030287	1602316	-427971
3	2006 Q3	2603194	1944693	-658501
4	2006 Q4	1965482	2471494	506012
5	2007 Q1	1836948	2066684	229736
6	2007 Q2	2396145	1882895	-513250
7	2007 Q3	2994741	2293495	-701246
8	2007 Q4	2493356	2854492	361136
9	2008 Q1	2205749	2565583	359834
10	2008 Q2	2943571	2277716	-665855
11	2008 Q3	3408181	2810400	-597781
12	2008 Q4	2985583	3288625	303042
13	2009 Q1	2493716	3046191	552475
14	2009 Q2	3363367	2604211	-759156
15	2009 Q3	4062937	3211536	-851401
16	2009 Q4	3489885	3892657	402772
17	2010 Q1	3141713	3570440	428726
18	2010 Q2	3816609	3227458	-589151
19	2010 Q3	4611520	3698779	-912741
20	2010 Q4	3946520	4428972	482452
21	2011 Q1	3513280	4043010	529730
22	2011 Q2	4472552	3619226	-853326
23	2011 Q3	5488045	4301887	-1186158
24	2011 Q4	4666771	5250813	584042
25	2012 Q1	4519337	4783579	264242
26	2012 Q2	5816170	4572185	-1243985
27	2012 Q3	6833003	5567373	-1265630
28	2012 Q4	5970525	6579877	609352
29	2013 Q1	6011770	6092395	80625
30	2013 Q2	7266135	6027895	-1238240
31	2013 Q3	7996335	7018487	-977848
32	2013 Q4	6953113	7800765	847652
33	2014 Q1	6955685	7122643	166958
34	2014 Q2	8329294	6989077	-1340217
35	2014 Q3	8963890	8061251	-902640
36	2014 Q4	7718588	8783362	1064774
37	2015 Q5	7413782	7931543	517761

Table 5.6 Passenger traffic forecasting results of total passengers with ES ($\alpha = 0.7$)

Period	Quarters	Traffic	Forecast (F)	Error
1	2006 Q1	3160377	4312677	1152300
2	2006 Q2	4322945	3506067	-816878
3	2006 Q3	5329782	4077882	-1251900
4	2006 Q4	4130627	4954212	823585
5	2007 Q1	3928371	4377702	449331
6	2007 Q2	5003959	4063170	-940789
7	2007 Q3	5862412	4721722	-1140690
8	2007 Q4	4861224	5520205	658981
9	2008 Q1	4540602	5058918	518316
10	2008 Q2	5749995	4696097	-1053898
11	2008 Q3	6585056	5433826	-1151230
12	2008 Q4	5660660	6239687	579027
13	2009 Q1	4907637	5834368	926731
14	2009 Q2	6329010	5185656	-1143354
15	2009 Q3	7398139	5986004	-1412135
16	2009 Q4	6466687	6974498	507811
17	2010 Q1	6156835	6619030	462195
18	2010 Q2	7237936	6295494	-942442
19	2010 Q3	8517276	6955203	-1562073
20	2010 Q4	7187365	8048654	861289
21	2011 Q1	6702299	7445752	7434523
22	2011 Q2	8086653	6925335	-1161318
23	2011 Q3	9555324	7738258	-1817066
24	2011 Q4	8305912	9010204	704292
25	2012 Q1	7969056	8517200	548144
26	2012 Q2	9775506	8133499	-1642007
27	2012 Q3	11389421	9282904	-2106517
28	2012 Q4	9911244	10757466	846222
29	2013 Q1	10012802	10165111	152309
30	2013 Q2	12401701	10058495	-2343206
31	2013 Q3	13797129	11698739	-2098390
32	2013 Q4	12068373	13167612	1099239
33	2014 Q1	12094554	12398145	303591
34	2014 Q2	14161334	12185631	-1975703
35	2014 Q3	15142678	13568623	-1574055
36	2014 Q4	13142678	14670462	1527784
37	2015 Q5	12833776	13601013	767237

5.4 Forecasting with Holt's Two-Parameter

This method which is an extension of ES was developed by Charles C. Holt to forecast the demand that has a trend but no seasonal pattern. The main idea of Holt's

two parameter method which is also known for “Linear ES” is implementing the ES twice to have more accurate forecasting results. It can be thought that, this method creates a control mechanism on the recently controlled estimation results (Christou, 2012). As the name suggests holt’s two parameter method uses two different smoothing parameters α and β that are range in $[0, 1]$. While ES uses α , the second part of the model, linear ES, uses β . Just like in the ES, identifying the optimum parameters has a great importance and sometimes choosing the parameters value that help to get the minimum MAPE can be a way to find the optimum parameter combination (Mun, 2010). The equation for this method is:

$$L_{t+1} = \alpha * D_{t+1} + (1 - \alpha) * (L_t + T_t) \quad (5.6)$$

$$T_{t+1} = \beta * (L_{t+1} - L_t) + (1 - \beta) * T_t \quad (5.7)$$

$$F_{t+1} = L_t + T_t \quad (5.8)$$

where

L_t = prediction of the series’ level at time t

T_t = prediction of data series’ slope at time t

F_{t+1} = the forecast at time $t + 1$

The first step creates a linear trend for the current data’s level and removes any lateness. After that, trend will be updated otherwise the trend can make the new values upper or lower according to the previous period. In terms of trend updating, it looks like the original ES method. For the forecasting results, the trend T_t added to the level L_t . To start calculating two-parameter ES, there needs to be two calculations, one for finding the smoothed value for level 1, L_1 , and one for having the trend 1, T_1 . When it is compared with the ES, it can be seen that it gives more accurate and reasonable solutions for the next period demand with a less error because of considering the trend fluctuations in its forecasting process (Chase, 2013).

Holt’s two parameter method’s implementation to the thesis’s passenger traffic data will be displayed after the explanation of it. All Holt’s two parameter calculations for three types of passenger numbers data are calculated by using Minitab 16. The main

goal is forecasting the passenger demand of 2015's first quarter and the previous years's Fits results are calculated by means of having the test data.

Below, Table 5.7 shows the domestic passenger demand traffic, their forecasting results and errors. Periods and quarters according to years are in the first and second columns of the table. Third and the last columns are the domestic line passenger traffic flow and forecasting results that are calculated with Holt's two parameters, and errors are placed in the last column. Smoothing parameters α and β are decided by trial and error technique. They are given different values in the range of [0.1] and forecasting results are evaluated according to MAPE. The parameter set that give the minimum MAPE was chosen to calculate the forecasting results for this study. For domestic line passenger demand forecasting calculation α was chosen as 0.1 and β was chosen as 0.6. The last row that contains the forecasting result of 2015's first quarter is highlighted. Here is the mentioned Table 5.7.

Table 5.7 Passenger demand forecasting results of domestic lines with Holt's two parameter

Period	Quarters	Traffic	Forecast (F)	Error
1	2006 Q1	1670880	1750442	79562
2	2006 Q2	2292658	1841233	-451425
3	2006 Q3	2726588	2012207	-714381
4	2006 Q4	2165145	2252340	87195
5	2007 Q1	2091423	2407084	315661
6	2007 Q2	2607814	2520042	-87772
7	2007 Q3	2867671	2678609	-189062
8	2007 Q4	2367868	2858649	490781
9	2008 Q1	2334853	2941258	606405
10	2008 Q2	2806424	2975920	169496
11	2008 Q3	3176875	3044103	-132772
12	2008 Q4	2675077	3150479	475403
13	2009 Q1	2413921	3167514	753593
14	2009 Q2	2965643	3111514	145871
15	2009 Q3	3335202	3107534	-227668
16	2009 Q4	2976802	3154568	177766
17	2010 Q1	3015122	3150393	135271
18	2010 Q2	3421327	3142351	-278976
19	2010 Q3	3905756	3192472	-713284
20	2010 Q4	3240845	3328821	87976
21	2011 Q1	3189019	3379765	190746
22	2011 Q2	3614101	3408988	-205113
23	2011 Q3	4067279	3490103	-577176
24	2011 Q4	3639141	3643055	3914
25	2012 Q1	3449719	3737664	287945
26	2012 Q2	3959336	3786592	-172744
27	2012 Q3	4556418	3891954	-664464
28	2012 Q4	3940719	4086356	145637
29	2013 Q1	4001032	4191010	189978
30	2013 Q2	5135566	4279830	-855736
31	2013 Q3	5800794	4524567	-1276227
32	2013 Q4	5115260	4887926	-227334
33	2014 Q1	5138869	5160036	21166,65
34	2014 Q2	5832040	5406025	-426015
35	2014 Q3	6178788	5722294	-456494
36	2014 Q4	5557813	6069000	511187
37	2015 Q1	5116201	6288267	1172066

Table 5.8 is about the passenger demand forecasting results for international lines. Same as the others its columns are located as periods, quarters, international lines passenger numbers, related forecasting results and errors. Parameters are changed

according to different data sets. For international lines, Holt's two parameter method is calculated on Minitab 16 by using the parameters $\alpha = 0.1$ and $\beta = 0.2$.

Table 5.8 Passenger demand forecasting results of international lines with Holt's two parameter

Period	Quarters	Traffic	Forecast (F)	Error
1	2006 Q1	1489497	1144239	-345258
2	2006 Q2	2030287	1373862	-656425
3	2006 Q3	2603194	1647730	-955464
4	2006 Q4	1965482	1970611	5129
5	2007 Q1	1836948	2197330	360382
6	2007 Q2	2396145	2381317	-14828
7	2007 Q3	2994741	2603121	-391620
8	2007 Q4	2493356	2870436	377080
9	2008 Q1	2205749	3053340	847591
10	2008 Q2	2943571	3172241	228670
11	2008 Q3	3408181	3348461	-59720
12	2008 Q4	2985583	3554714	569131
13	2009 Q1	2493716	3686700	1192984
14	2009 Q2	3363367	3732440	369073
15	2009 Q3	4062937	3853190	-209747
16	2009 Q4	3489885	4036017	546132
17	2010 Q1	3141713	4132334	990621
18	2010 Q2	3816609	4164389	347780
19	2010 Q3	4611520	4253773	-357747
20	2010 Q4	3946520	4420864	474344
21	2011 Q1	3513280	4495259	981979
22	2011 Q2	4472552	4499251	26699
23	2011 Q3	5488045	4598238	-889807
24	2011 Q4	4666771	4806671	139900
25	2012 Q1	4519337	4909335	389998
26	2012 Q2	5816170	4979190	-836980
27	2012 Q3	6833003	5188482	-1644521
28	2012 Q4	5970525	5511418	-459107
29	2013 Q1	6011770	5724995	-286775
30	2013 Q2	7266135	5927075	-1339060
31	2013 Q3	7996335	6261164	-1735171
32	2013 Q4	6953113	6669568	-283545
33	2014 Q1	6955685	6938480	-17205
34	2014 Q2	8329294	7181102	-1148192
35	2014 Q3	8963890	7559787	-1404103
36	2014 Q4	7718588	7992145	273557
37	2015 Q1	7413782	8251265	837483

Table 5.9 Passenger demand forecasting results of total passengers with Holt's two parameter

Period	Quarters	Traffic	Forecast (F)	Error
1	2006 Q1	3160377	2901507	-258870
2	2006 Q2	4322945	3223682	-1099263
3	2006 Q3	5329782	3651881	-1677901
4	2006 Q4	4130627	4171502	40875
5	2007 Q1	3928371	4518427	590056
6	2007 Q2	5003959	4798634	-205325
7	2007 Q3	5862412	5162485	-699927
8	2007 Q4	4861224	5589795	728571
9	2008 Q1	4540602	5859683	1319081
10	2008 Q2	5749995	6044139	294144
11	2008 Q3	6585056	6325206	-259850
12	2008 Q4	5660660	6666869	1006209
13	2009 Q1	4907637	6861802	1954165
14	2009 Q2	6329010	6922856	593846
15	2009 Q3	7398139	7108066	-290073
16	2009 Q4	6466687	7387468	920781
17	2010 Q1	6156835	7527370	1370535
18	2010 Q2	7237936	7594885	356949
19	2010 Q3	8517276	7756620	-760656
20	2010 Q4	7187365	8045329	857964
21	2011 Q1	6702299	8155016	1452717
22	2011 Q2	8086653	8176174	89521
23	2011 Q3	9555324	8331861	-1223463
24	2011 Q4	8305912	8643315	337403
25	2012 Q1	7969056	8791935	822879
26	2012 Q2	9775506	8875550	-899956
27	2012 Q3	11389421	9149447	-2239974
28	2012 Q4	9911244	9602146	-309098
29	2013 Q1	10012802	9867939	-144863
30	2013 Q2	12401701	10120206	-2281495
31	2013 Q3	13797129	10631766	-3165363
32	2013 Q4	12068373	11295020	-773353
33	2014 Q1	12094554	11734540	-360014
34	2014 Q2	14161334	12139926	-2021408
35	2014 Q3	15142678	12751880	-2390798
36	2014 Q4	13142678	13448589	305911
37	2015 Q1	12833776	13869509	1035733

Last calculation of Holt's two parameter method is done for the data of THY's total passenger numbers. Forecasting results that are reached with this technique is in the above Table 5.9. Parameters are chosen so that α is equal to 0.1 and β is equal to 0.2.

The table's column settings are just like the previous tables. The last row is highlighted for showing the forecasting results of 2015's first quarter.

5.5 Forecasting with Holt-Winters Model

When the demand data does not have any trend or seasonal fluctuation it is proper to use MA or ES method to forecast, on the other hand, in case of demand data having a trend Holt's two-parameter model can be used. Furthermore, some demand data changes according to different seasons of the year, in this case it can be said that demand has seasonal patterns and that time to time series models for forecasting that are mentioned beforehand cannot handle this seasonal data. To get over this, Holt's two-parameter model was developed by adding a seasonal parameter by Peter R. Winters and named Holt-Winters technique or just The Winters' Model. It sets the seasonal fluctuation by two different ways; one is multiplicative and the other is additive. Seasonal length is known in two types and is expressed with parameter s . Winters's model has the third equation in addition to Holt's two-parameter. The Holt-Winters model equation in multiplicative type is (Chase, 2013; Christou, 2012).

$$L_t = \alpha * \left(\frac{D_t}{S_{t-s}} \right) + (1 - \alpha) * (L_{t-1} + T_{t-1}) \quad (5.9)$$

$$T_t = \beta * (L_t - L_{t-1}) + (1 - \beta) * T_{t-1} \quad (5.10)$$

$$S_t = \gamma * \left(\frac{D_t}{L_t} \right) + (1 - \gamma) * S_{t-s} \quad (5.11)$$

$$F = (L_t + T_t * m) * S_{t-s+m} \quad (5.12)$$

where

L_t = the series' level

s = seasonal length (number of weeks, etc.)

T_t = trend

S_t = seasonal component

F_t = m periods ahead forecasting result

The first step of the method calculates a smoothed forecast for the time series' level, while the second step predicts the trend of the data. Just like in the ES, predicted seasonality S_t is calculated in the third step. As the last step, to forecast the next period's demand, seasonal factor is multiplied with the summation of level and demand (Christou, 2012).

Additive seasonality is an another form of Holt-Winters' model and it has equations as in the following;

$$L_t = \alpha * (Y_t - S_{t-s}) + (1 - \alpha) * (L_{t-1} + T_{t-1}) \quad (5.13)$$

$$T_t = \beta * (L_t - L_{t-1}) + (1 - \beta) * T_{t-1} \quad (5.14)$$

$$S_t = \gamma * (Y_t - L_t) + (1 - \gamma) * S_{t-s} \quad (5.15)$$

$$F = L_t + T_t * m + S_{t-s+m} \quad (5.16)$$

When a time series's seasonal fluctuations are not to be realized in magnitude and it is not dependent on the series' average level, it can be said that this time serie is suitable for additive seasonal winters model. The main difference between the multiplicative and additive seasonality is adding the seasonal component to the sum of level and trend and subtracting the seasonal component in the first equation instead of taking the ratio. That's because real life problems are more proper to multiplicative form, additive version is not be used in common. In general, ES methods are simple to use just they have a lack of consideration of price, promotions, etc. (Chase, 2013).

After telling the Holt-Winters method, now the usage of the method for this study will be shown. Multiplicative Winters method is chosen for the study. Next three tables display the THY's passenger forecasting results for domestic and international lines, also for the total passenger numbers. All forecasting results are calculated by using Minitab 16, and three parameters of Holt-Winters method are decided by trial and error technique just as the parameters of ES and Holt's two parameter. Seasonal length is accepted four for each three calculations, because when the passenger traffic data is investigated it is seen that seasonal pattern has occured every four periods. For domestic lines parameters are decided to be $\alpha = 0,82$, $\beta = 0,45$ and $\gamma = 0,99$.

Passenger demand forecasting results for domestic lines are in the Table 5.10. First 36 period's forecasting results are Fits results, and the 37th is the aimed forecasting result which is the first quarter of 2015.

Table 5.10 Passenger demand forecasting results of domestic lines with Holt-Winters method

Period	Quarters	Traffic	Forecast	Error
1	2006 Q1	1670880	1651914	-18966
2	2006 Q2	2292658	2189788	-102870
3	2006 Q3	2726588	2810962	84374
4	2006 Q4	2165145	2561617	396472
5	2007 Q1	2091423	2012301	-79122
6	2007 Q2	2607814	2585764	-22050
7	2007 Q3	2867671	2985961	118290
8	2007 Q4	2367868	2477996	110129
9	2008 Q1	2334853	2194024	-140829
10	2008 Q2	2806424	2836017	29593
11	2008 Q3	3176875	3151194	-25681
12	2008 Q4	2675077	2726277	51200
13	2009 Q1	2413921	2544650	130729
14	2009 Q2	2965643	2872074	-93569
15	2009 Q3	3335202	3274223	-60979
16	2009 Q4	2976802	2819248	-157554
17	2010 Q1	3015122	2824798	-190324
18	2010 Q2	3421327	3768809	347482
19	2010 Q3	3905756	3896021	-9735
20	2010 Q4	3240845	3343476	102631
21	2011 Q1	3189019	3048707	-140312
22	2011 Q2	3614101	3771424	157323
23	2011 Q3	4067279	4103892	36613
24	2011 Q4	3639141	3417586	-221555
25	2012 Q1	3449719	3476426	26707
26	2012 Q2	3959336	4052640	93304
27	2012 Q3	4556418	4536109	-20309
28	2012 Q4	3940719	3909879	-30840
29	2013 Q1	4001032	3722530	-278501
30	2013 Q2	5135566	4708031	-427535
31	2013 Q3	5800794	6108075	307281
32	2013 Q4	5115260	5187787	72527
33	2014 Q1	5138869	5010890	-127979
34	2014 Q2	5832040	6135875	303835
35	2014 Q3	6178788	6669704	490916
36	2014 Q4	5557813	5335362	-222451
37	2015 Q1	5116201	5293812	177611

Table 5.11 represents international lines passenger traffic forecast. Parameters for level, trend and seasonality are $\alpha = 0.98$, $\beta = 0.21$, $\gamma = 0.53$. Table arranged like periods, quarters, traffic data, forecasting results and errors. Highlighted row is the 2015's first quarter's forecasting result and the previous periods are the Fits results.

Table 5.11 Passenger demand forecasting results of international lines with Holt-Winters method

Period	Quarters	Traffic	Forecast	Error
1	2006 Q1	1489497	1396840	-92657
2	2006 Q2	2030287	2089315	59028
3	2006 Q3	2603194	2600036	-3159
4	2006 Q4	1965482	2422246	456764
5	2007 Q1	1836948	1701753	-135195
6	2007 Q2	2396145	2448505	52360
7	2007 Q3	2994741	2941994	-52747
8	2007 Q4	2493356	2686087	192731
9	2008 Q1	2205749	2127801	-77948
10	2008 Q2	2943571	2886547	-57024
11	2008 Q3	3408181	3575564	167383
12	2008 Q4	2985583	2999368	13785
13	2009 Q1	2493716	2528767	35051
14	2009 Q2	3363367	3218727	-144640
15	2009 Q3	4062937	4043116	-19821
16	2009 Q4	3489885	3572836	82951,5
17	2010 Q1	3141713	2947063	-194650
18	2010 Q2	3816609	4090789	274180
19	2010 Q3	4611520	4552197	-59323
20	2010 Q4	3946520	4022429	75909
21	2011 Q1	3513280	3313526	-199754
22	2011 Q2	4472552	4538264	65712
23	2011 Q3	5488045	5348461	-139584
24	2011 Q4	4666771	4807029	140258
25	2012 Q1	4519337	3933136	-586201
26	2012 Q2	5816170	5912287	96117
27	2012 Q3	6833003	7054023	221020
28	2012 Q4	5970525	6008304	37778,9
29	2013 Q1	6011770	5073718	-938052
30	2013 Q2	7266135	7926611	660476
31	2013 Q3	7996335	8811736	815401
32	2013 Q4	6953113	6956532	3419
33	2014 Q1	6955685	5855570	-1100115
34	2014 Q2	8329294	9074877	745583
35	2014 Q3	8963890	10023146	1059256
36	2014 Q4	7718588	7727181	8593
37	2015 Q1	7413782	6444855	-968927

Table 5.12 Passenger demand forecasting results of total passengers with Holt-Winters method

Period	Quarters	Traffic	Forecast	Error
1	2006 Q1	3160377	3036885	-123492
2	2006 Q2	4322945	4281806	-41139
3	2006 Q3	5329782	5431319	101537
4	2006 Q4	4130627	4970834	840207
5	2007 Q1	3928371	3775969	-152402
6	2007 Q2	5003959	4994772	-9187
7	2007 Q3	5862412	5950491	88079
8	2007 Q4	4861224	5080717	219493
9	2008 Q1	4540602	4434269	-106333
10	2008 Q2	5749995	5671487	-78508
11	2008 Q3	6585056	6733731	148675
12	2008 Q4	5660660	5621422	-39238
13	2009 Q1	4907637	5177430	269793
14	2009 Q2	6329010	6092541	-236469
15	2009 Q3	7398139	7262993	-135146
16	2009 Q4	6466687	6298631	-168056
17	2010 Q1	6156835	5865854	-290981
18	2010 Q2	7237936	7839116	601180
19	2010 Q3	8517276	8439882	-77394
20	2010 Q4	7187365	7244930	57565
21	2011 Q1	6702299	6502270	-200029
22	2011 Q2	8086653	8267021	180368
23	2011 Q3	9555324	9461324	-94000
24	2011 Q4	8305912	8104093	-201819
25	2012 Q1	7969056	7575145	-393911
26	2012 Q2	9775506	9834664	59158
27	2012 Q3	11389421	11635550	246129
28	2012 Q4	9911244	9797897	-113347
29	2013 Q1	10012802	9121809	-890993
30	2013 Q2	12401701	12317753	-83948
31	2013 Q3	13797129	14900447	1103318
32	2013 Q4	12068373	12050578	-17795
33	2014 Q1	12094554	11236161	-858393
34	2014 Q2	14161334	14646332	484998
35	2014 Q3	15142678	16662291	1519613
36	2014 Q4	13142678	13179390	36712
37	2015 Q1	12833776	12138033	-695743

Table 5.12 shows the result of forecasting calculations of total passenger numbers of THY. Parameters are accepted as $\alpha = 0.83$, $\beta = 0.33$, $\gamma = 0.90$. Periods, quarters, total passenger traffic data, their forecasting results and errors are listed in the table.

Just like the previous calculations, Minitab 16 is appealed to. Fits results up until the 2015's first quarter are placed in the table as test data. And the main forecasting study, 2015's first period is placed in the last row and highlighted.

5.6 Combined Method

It is known that different methods can be used to model and forecast any kind of historical data. It is possible to use ARIMA or ES method to make the forecast of a time serie which has trend pattern. In this case, it is not proper to forecast by using just one method without considering the other method's information. And it creates to need of methods' combination. When the two different forecasting method exist that is applicable to that time serie, a new forecasting technique is created by combining them. This new technique has advantages because it has the both methods' strengths and information. New combined method's error is better than one method's. Bates and Granger (1969) proposed combining the two forecasting method linearly. When it is considered $\hat{y}_{1,T+t}(T)$ and $\hat{y}_{2,T+t}(T)$ are the different two techniques' forecast results and k_1 and k_2 are the weights, combined forecast is constituted as in the following:

$$\hat{y}_{T+t}^c = k_1 \hat{y}_{1,T+t}(T) + k_2 \hat{y}_{2,T+t}(T) \quad (5.17)$$

Determination of weights must be thorough, thus, features of forecast results $\hat{y}_{T+t}^c$ can be good. If it is considered that two forecast results are different other word results are not related with each other, k_2 can be chosen as means of k_1 and it can be expressed as $k_2 = 1 - k_1$. And, when it is assumed $k = k_1$, the combined forecast is expressed (Montgomery, Jennings, & Kulahci, 2008):

$$\hat{y}_{T+t}^c = k \hat{y}_{1,T+t}(T) + (1 - k) \hat{y}_{2,T+t}(T) \quad (5.18)$$

It is important to choose the proper weight factor to combine the two methods. Properly chosen k makes the combined method's error variance minimum. Otherwords, when two different methods are combined according to that k , new forecast error's variance is obtained equal or less than the each individual forecast

error's variance. Accepting that, methods in the combination process' error variances are σ_1^2 and σ_2^2 , correlation coefficient between two different methods' forecasting errors is ρ , then calculation of k which will minimize the combined methods variance is;

$$k^* = \frac{\sigma_2^2 - \rho\sigma_1\sigma_2}{\sigma_1^2 + \sigma_2^2 - 2\rho\sigma_1\sigma_2} \quad (5.19)$$

In this context, MA and Holt-Winters method will be combined as it is mentioned above. The reason that these two techniques are chosen is that they are the methods that give the minimum MAPE. Comparing time series methods that are used in this study can be seen in section 5.6. MA use the last four passenger demand data while calculating next period's forecast, so that, it can catch up the latest fluctuations and give closer results to actual data. And Holt-Winters' Method is successful in showing both trend and seasonal pattern in the data. By thinking these powerful sides of two techniques, it is accepted to be proper combining them. It is thought that, combination of these methods's strength give more reasonable forecasting results, if it is compared with individual ones. For Holt-Winters' method all calculations are done as it is mentioned in section 5.4, by using same parameters. That's because MA method's forecasting results starts from the 5th period, in calculating variance of two methods's and correlation to find the optimum k , Holt-Winters's forecasting results are taken into consideration from the 5th period, although its forecasting results start from the beginning. This combined method forecasting study is done for domestic and international lines, and also for total passenger numbers. Following tables shows the results in details. And method's evaluation and comparison with the other time series techniques which are in this study will be investigated in the next section.

Following Table 5.13 displays the combined method forecasting solutions for domestic lines passenger demand of THY. MA and Holt-Winters method solutions are same as with the solutions in section 5.1 and 5.4. By using domestic passenger traffic lines forecasting results and errors of MA and Holt-Winters, variance and correlation calculations help to constitute the weight k . All calculations are done with the help of MS Excel 2010. Two methods are combined with the absolute value of weight $k =$

0.0268. Forecasting solutions starts from the 4th period because of MA. Detailed comparison of this method will be done in section 5.6.

Table 5.13 Passenger demand forecasting results of domestic lines with combined method

Period	Quarters	Traffic	Forecast	Error
1	2006 Q1	1670880	-	-
2	2006 Q2	2292658	-	-
3	2006 Q3	2726588	-	-
4	2006 Q4	2165145	-	-
5	2007 Q1	2091423	2017692	-73731
6	2007 Q2	2607814	2578626	-29188
7	2007 Q3	2867671	2970226	102555
8	2007 Q4	2367868	2476793	108925
9	2008 Q1	2334853	2201773	-133080
10	2008 Q2	2806424	2828220	21796
11	2008 Q3	3176875	3136294	-40581
12	2008 Q4	2675077	2724812	49735
13	2009 Q1	2413921	2550098	136177
14	2009 Q2	2965643	2869292	-96351
15	2009 Q3	3335202	3261748	-73454
16	2009 Q4	2976802	2820003	-156799
17	2010 Q1	3015122	2827422	-187700
18	2010 Q2	3421327	3750200	328873
19	2010 Q3	3905756	3877058	-28698
20	2010 Q4	3240845	3343108	102263
21	2011 Q1	3189019	3057991	-131028
22	2011 Q2	3614101	3762537	148436
23	2011 Q3	4067279	4087401	20122
24	2011 Q4	3639141	3420534	-218607
25	2012 Q1	3449719	3480465	30746
26	2012 Q2	3959336	4043008	83672
27	2012 Q3	4556418	4515852	-40566
28	2012 Q4	3940719	3909646	-31073
29	2013 Q1	4001032	3729326	-271706
30	2013 Q2	5135566	4692150	-443416
31	2013 Q3	5800794	6062609	261815
32	2013 Q4	5115260	5175261	60001
33	2014 Q1	5138869	5010951	-127918
34	2014 Q2	5832040	6113451	281411
35	2014 Q3	6178788	6637658	458870
36	2014 Q4	5557813	5341538	-216275
37	2015 Q1	5116201	5304060	187859

Table 5.14 represents the forecast solutions of international lines traffic movement. After the two methods' variance of errors and correlation calculations, weight is found $k = 0.120769$ for international lines. Forecast and error results are shown besides the periods, quarters and passenger traffic data in the following table;

Table 5.14 Passenger demand forecasting results of international lines with combined method

Period	Quarters	Traffic	Forecast	Error
1	2006 Q1	1489497	-	-
2	2006 Q2	2030287	-	-
3	2006 Q3	2603194	-	-
4	2006 Q4	1965482	-	-
5	2007 Q1	1836948	1740443	-96505
6	2007 Q2	2396145	2407501	11356
7	2007 Q3	2994741	2852437	-142304
8	2007 Q4	2493356	2639258	145902
9	2008 Q1	2205749	2164333	-41416
10	2008 Q2	2943571	2842581	-100990
11	2008 Q3	3408181	3464914	56733
12	2008 Q4	2985583	2970787	-14796
13	2009 Q1	2493716	2571882	78166
14	2009 Q2	3363367	3187210	-176157
15	2009 Q3	4062937	3924713	-138224
16	2009 Q4	3489885	3530998	41113
17	2010 Q1	3141713	2996024	-145689
18	2010 Q2	3816609	4021188	204579
19	2010 Q3	4611520	4440557	-170963
20	2010 Q4	3946520	3991332	44812
21	2011 Q1	3513280	3381829	-131451
22	2011 Q2	4472552	4469875	-2677
23	2011 Q3	5488045	5202029	-286016
24	2011 Q4	4666771	4752450	85679
25	2012 Q1	4519337	4005842	-513495
26	2012 Q2	5816170	5776348	-39822
27	2012 Q3	6833003	6820764	-12239
28	2012 Q4	5970525	5941943	-28582
29	2013 Q1	6011770	5159590	-852180
30	2013 Q2	7266135	7713001	446866
31	2013 Q3	7996335	8535008	538673
32	2013 Q4	6953113	6938980	-14133
33	2014 Q1	6955685	6000646	-955039
34	2014 Q2	8329294	8859659	530365
35	2014 Q3	8963890	9725505	761615
36	2014 Q4	7718588	7736036	17448
37	2015 Q1	7413782	6631686	-782096

Table 5.15 Passenger demand forecasting results of total passengers with combined method

Period	Quarters	Traffic	Forecast	Error
1	2006 Q1	3160377	-	-
2	2006 Q2	4322945	-	-
3	2006 Q3	5329782	-	-
4	2006 Q4	4130627	-	-
5	2007 Q1	3928371	3784669	-143702
6	2007 Q2	5003959	4984051	-19908
7	2007 Q3	5862412	5924913	62501
8	2007 Q4	4861224	5074109	212885
9	2008 Q1	4540602	4443343	-97259
10	2008 Q2	5749995	5660055	-89940
11	2008 Q3	6585056	6705735	120679
12	2008 Q4	5660660	5617881	-42779
13	2009 Q1	4907637	5186067	278430
14	2009 Q2	6329010	6085605	-243405
15	2009 Q3	7398139	7236657	-161482
16	2009 Q4	6466687	6294379	-172308
17	2010 Q1	6156835	5873599	-283236
18	2010 Q2	7237936	7815446	577510
19	2010 Q3	8517276	8409147	-108129
20	2010 Q4	7187365	7242088	54724
21	2011 Q1	6702299	6516883	-185416
22	2011 Q2	8086653	8250834	164181
23	2011 Q3	9555324	9426561	-128763
24	2011 Q4	8305912	8099910	-206002
25	2012 Q1	7969056	7586255	-382801
26	2012 Q2	9775506	9809027	33521,4
27	2012 Q3	11389421	11583837	194416
28	2012 Q4	9911244	9789614	-121630
29	2013 Q1	10012802	9133905	-878897
30	2013 Q2	12401701	12279064	-122637
31	2013 Q3	13797129	14825327	1028198
32	2013 Q4	12068373	12040745	-27628,1
33	2014 Q1	12094554	11251933	-842621
34	2014 Q2	14161334	14607446	446112
35	2014 Q3	15142678	16593596	1450918
36	2014 Q4	13142678	13182933	40255
37	2015 Q1	12833776	12166985	-666791

Table 5.15 shows the forecasting results of total passenger numbers that are obtained by combining MA and Holt-Winters methods. Absolute value of k is equal

to 0.01891. Forecasting results start from 5th period, and 2015's first quarter's passenger forecast takes place in the last row and it is highlighted.

5.7 Evaluation of Methods

In the previous five subsections, all five methods and their forecast solution tables for domestic and international lines also total passenger numbers are mentioned. All the tables contain periods, quarters according to different years, passenger traffic data, their forecasting results and the errors. Now, it is time to evaluate all the methods which were used and to compare them with each other. For three different kinds of passenger traffic data and forecast results, different error analysis are implemented. Results from these analysis help the decisionmaker to decide which forecasting technique is suitable for the studied data. The study's main purpose is to forecast the 2015's first quarter's passenger traffic demand, so all the comparisons are made according to the error analysis of the 37th period which belongs to that quarter. AE, MSE, MAD, percentage error (PE) and MAPE calculations are made by using all 36 periods' Fits results between the years 2006-2014 and forecast result of 2015's first quarter. In the comparison tables, column names are constituted as passenger traffic data of related line, and the method's names respectively MA, ES, Holt's two parameter, Holt-Winters and combined method. And the rows show actual data of related line and its forecast result for 37th period, error of 37th period, AE of 37th period, MSE, MAD, PE of 37th period and MAPE.

First of all, the methods will be compared for domestic lines' solutions. Table 5.16 gives chance to evaluate and compare the methods. All analysis solutions matter for the study but final decision for which method is more reasonable and optimum to choose will be given consideration to MAPE value.

Table 5.16 Error analysis and comparison of five methods for domestic lines passenger traffic

	Domestic Passenger Traffic	MA	ES	Holt's Two Parameter	Holt- Winters	Combined Method
Actual Value and Forecast Results	5116201	5676878	5563987	6288267	5293812	5304060
Error	-	560677	447786	1172066	177611	187859
AE	-	560677	447786	1172066	177611	187859
MSE	-	2.19E+11	2.41E+11	2.30E+11	3.65E+10	3.31E+10
MAD	-	348006	433141	370385	146167	141922
PE	-	10.96	8.75	22.91	3.47	3.67
MAPE	-	8.8	12.84	10.51	4.08	3.68

The solutions in the Table 5.16 is clearly show that error and PE values are minimum with the Holt-Winters method. While MA gives the minimum MSE value, minimum MAD value is found with combined method and Holt-Winters' method comes after 146617. For MAPE values, Holt-Winters comes first with 4.08 and MA is second with 8.8 in time series method. According to MAPE results, MA choice and Holt-Winters seem proper to choose for combination. Combined method's MAPE value is the best of all with 3.68.

Holt's two parameter methods error and therefore PE is the maximum of all. When ES is compared with Holt's two parameter, it is seen that its MAPE value is bigger than Holt's two parameter. Figure 5.1 shows that these two methods are successful in showing trend, also ES method successfull in catching the seasonal fluctuations. As a result of the first period's forecast error, its solutions keep deviating and give a lot more error than the other techniques. Both two methods cannot be assessed for the choice of best method for domestic lines fort his reason. Some improvement on their parameters or evaluation for first forecasting value, can help to get better results. But for now, evaluation will continue for other time series methods in the study.

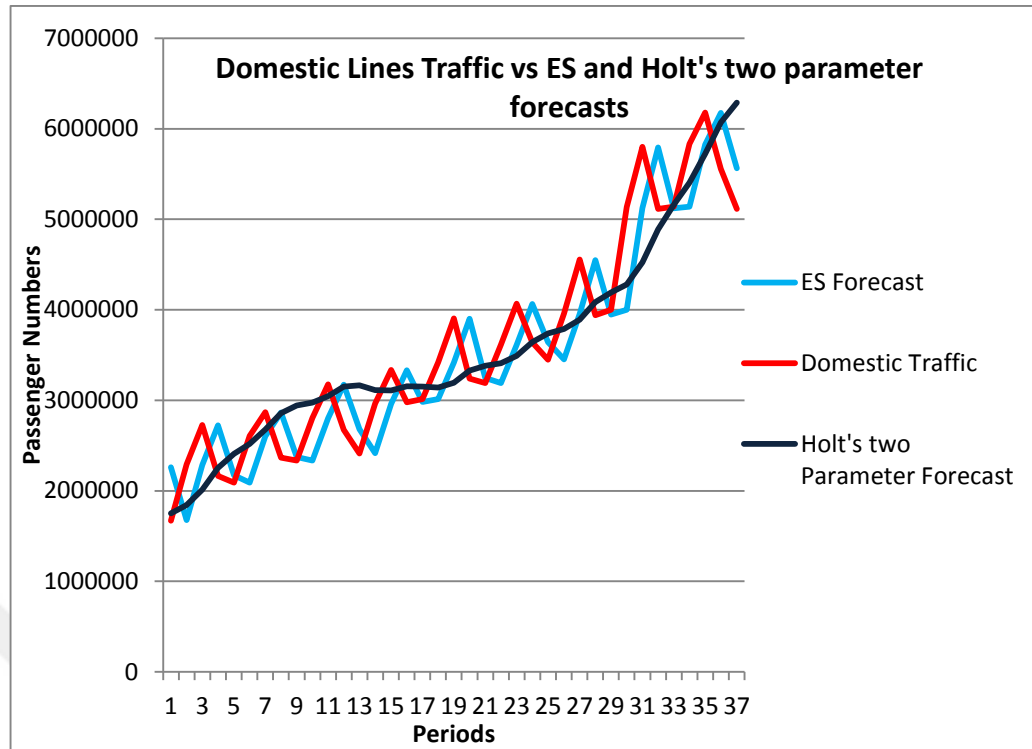


Figure 5.1 Domestic lines traffic vs ES and Holt's two parameter forecast results

It is told in section 5.1 that, MA uses last four actual value to forecast the next period. It gives chance to catch up the latest fluctuations and constitute forecast results closer to latest values by means of taking the average of last four periods. It can be seen in the following Figure 5.2 that MA is good at catching up the trend pattern but not successful for seasonal pattern, in this point Holt-Winters method comes to play because it is successful in catching up both trend and seasonal fluctuations. Its forecast results nearly match up with the actual traffic data.

By considering these powerful sides of the two methods, it is wise to combine them. So, new combined method proves this foresight by giving the best MAPE result and being reasonable for other analysis solutions. Figure 5.2 shows that combine method forecast solutions catch trend and seasonal pattern properly. Its pattern is better than Holt-Winters, also it can be seen that actual traffic data, Holt-Winters and combined method's patterns are intersecting. Combine method's forecast error for domestic line's first quarter of 2015 is more than accruing passenger traffic numbers. It forecasts 187859 more passengers, it is better than being less, otherwise company managers

have lack of ability to supply the extra demand. So, this extra passenger forecast is sufferable number for a company in case of being disrepute for not suplying the demand. After these evaluations, it can be said that combine method can be chosen for domestic lines passenger demand forecast.

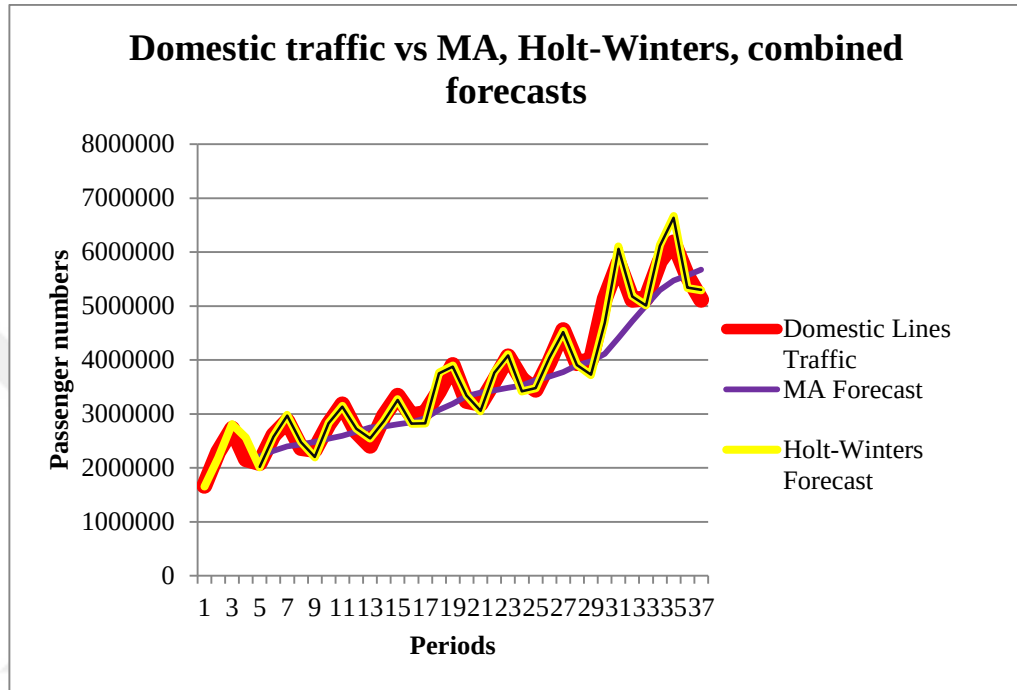


Figure 5.2 Domestic lines traffic vs MA, Holt-Winters and combined methods forecast results

Now, evaluation will be continue for international lines. Following Table 5.17 shows the error analysis of five different forecast methods which are implemented to international lines traffic passenger numbers.

Table 5.17 Error analysis and comparison of five methods for international lines passenger traffic

	International Passenger Traffic	MA	ES	Holt's Two Parameter	Holt-Winters	Combined Method
Actual Value and Forecast Results	7413782	7991864	7931543	8251265	6444855	6631686
Error	-	578082	517761	837438	-968927	-782096
AE	-	578082	517761	837438	968927	782096
MSE	-	5.33E+11	5.44E+11	5.65E+11	1.83E+11	1.27E+11
MAD	-	17518	663257	594427	271177	230548
PE	-	7.8	6.98	11.3	13.07	10.55
MAPE	-	0.24	16.3	14.7	5.5	4.3

It can be seen from the table 5.17 that, forecast results of Holt-Winters and combined method are less than actual passenger traffic. At first look, these solutions can leave a bad impression because companies do not prefer making a forecast below the actual value. Otherwise, they can face the condition of not supplying passenger demand and losing their customers. But these two methods give better solutions against ES and Holt's two parameter, if they are compared according to MSE and MAD values. Even the PE of Holt-Winters is the maximum of all with 13.07 as a solution of maximum AE, its MAPE result ranks number two by 5.5, ignoring the combined method.

Even though minimum error, AE and PE, ES gives the maximum MAPE value with 16.3 and it loses the chance of being chosen for the optimal method. Holt's two parameter' forecast surplus is a lot more than the others, it makes the method come second for AE, MAD, PE and MAPE, also it has the maximum MSE value. It is told before that, companies prefer having forecast values bigger than actual value but not so much. It must be remembered that they are trying to reach optimal solutions all the time. So much surplus can cause the waste of sources in case forecast results come to

nothing. To take a better decision, Figure 5.3 which is constituted in MS Excel 2010, can be screened. The figure helps to see the patterns of ES, Holt's two parameter against international lines' actual passenger traffic pattern.

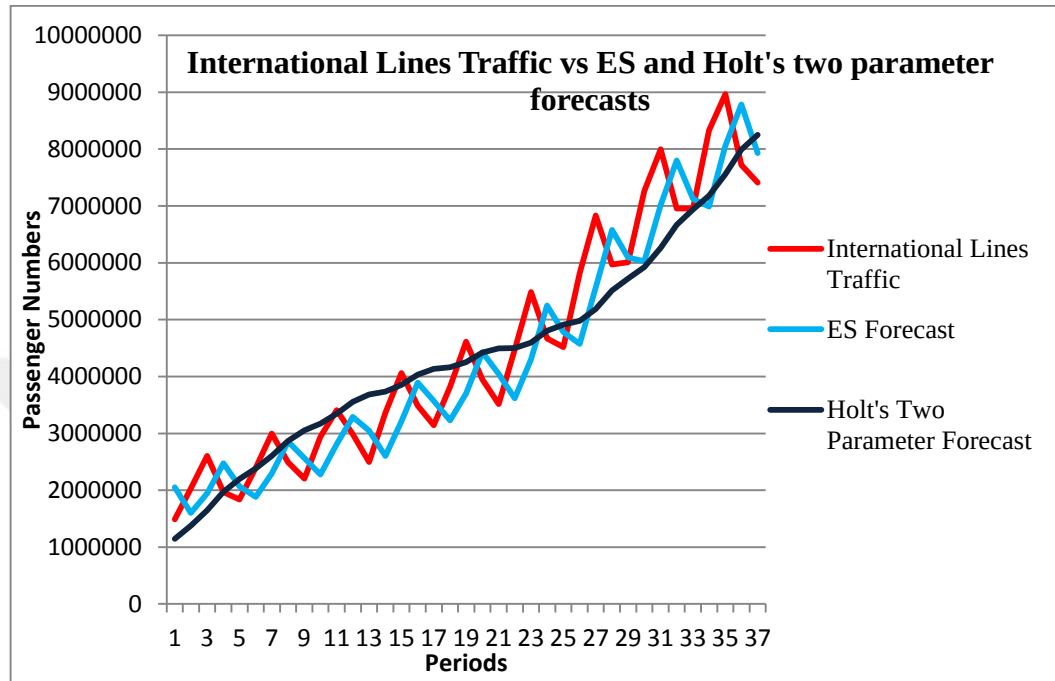


Figure 5.3 International lines traffic vs ES and Holt's two parameter forecast results

Just like it is in the domestic lines' traffic forecast, ES and Holt's two parameter shows the expected patterns. At first view, ES pattern looks almost same with the actual traffic pattern, because it is clear that ES catches up with the trend and seasonal pattern. But its patterns do not intersect with the actual one despite the similarity, again it can be said that first period's error can cause this deviation. And as a result of this, ES's gives the maximum MAPE value. It is known that Holt's two parameter method is not good at mimicing seasonal patterns and it is clearly seen in the figure. Even if it is not an exact pattern, it just shows trend fluctuation. Considering error analysis solutions and their pattern, ES and Holt's two parameter can not be evaluated as the optimal method or they can not be the candidates for combination.

As a result of making forecasting for the next period considering last four actual value, MA method comes second after ES for AE and PE. It follows Holt-Winters

method's MSE with $5.33E+11$. MA gives the minimum MAD value as 17518. Its MAPE value is incredibly less than others that it equals to 0.24. When the MSE, MAD and MAPE values are considered MA and Holt-Winters seems proper to combine. When the combined method is evaluated it can be seen that its MSE is the minimum of all. Also MAD value and PE are between the results of MA and Holt-Winters. 4.3 is a reasonable MAPE value, comparing with others and again this value is between the MAPE value of MA and Holt-Winters.

Figure 5.4 displays MA, Holt-Winters and combined methods' forecast results' pattern as against the international lines' traffic pattern. It is not surprising that MA is only successful in catching the trend, in spite of its minimum MAPE value. But Holt-Winters is good at both, because of its seasonal parameter, it can mimic the seasonal pattern. The power of Holt-Winters' trend and seasonal adjustments and MA's minimum MAPE, their combination catches trend and seasonal patterns with smaller MAPE value than Holt-Winters. Figure 5.4 shows how Holt-Winters and combined method intersect with international lines' traffic pattern. Besides, combined method's pattern is better than Holt-Winters'. Although, its forecast result for the first quarter of 2015 is lower than the actual value, it can be ignored when its superiority is considered in the comparison with the other methods. So, combined method can be preferred to forecast the international lines' passenger traffic movement.

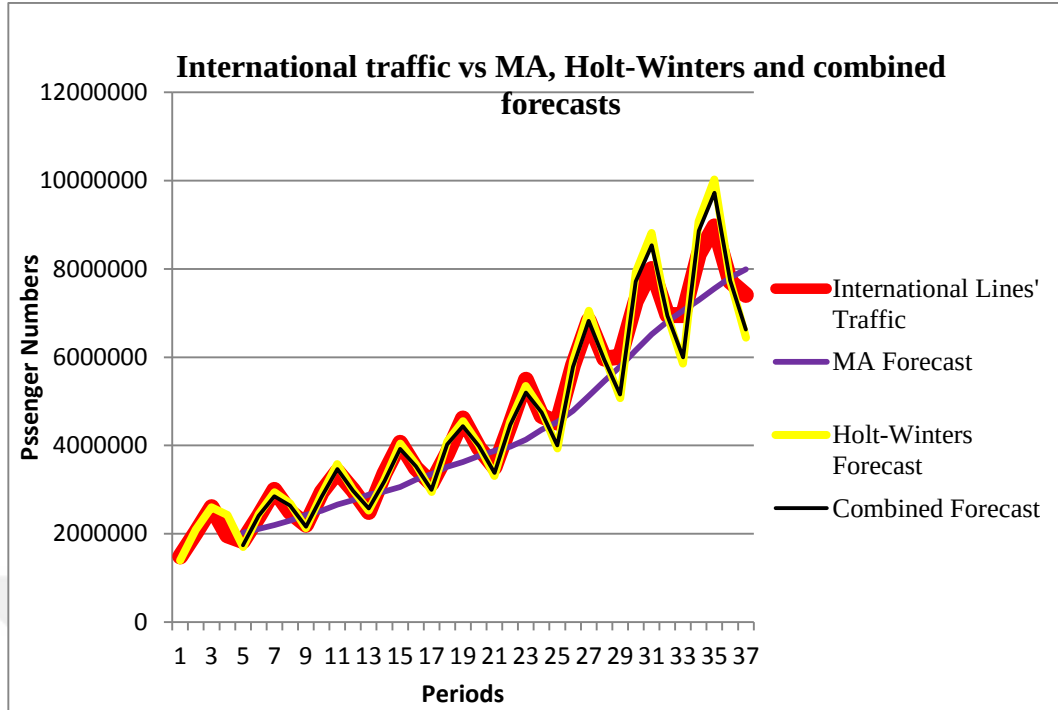


Figure 5.4 International lines traffic vs MA, Holt-Winters and combined methods forecast results

Lastly, comparison of methods to forecast the total passenger numbers will be done. 37th period's actual total passenger number and related forecasting solutions of used methods, their error, AE, MSE, MAD, PE and MAPE solutions will be shown on the Table 5.18.

Table 5.18 Error analysis and comparison of five methods for total passenger numbers' traffic

	Total Passenger Traffic	MA	ES	Holt's Two Parameter	Holt-Winters	Combined Method
Actual Value and Forecast Results	12833776	13635311	1360101 3	13869509	12138033	12166985
Error	-	801535	767237	1035733	-695743	-666791
AE	-	801535	767237	1035733	695743	666791
MSE	-	1.36E+12	1.44E+1 2	1.46E+12	2.06E+11	1.92E+11
MAD	-	889638	1074743	949703	296355	290596
PE	-	6.25	5.98	8.07	5.42	5.2
MAPE	-	0.19	14.25	12.38	3.61	3.16

If it is looked at the values of AE, seen that combined method has the minimum of all. In the sense of error, it is seen that combined method and Holt-Winters forecasted the total passenger traffic less than the actual value. It is mentioned before that companies do not want to make forecasts below the actual number because of customer loss possibility. In error regard, ES gives the optimal forecasting solution. But ES is ranked at second in MSE ranking, after the MA which gives 1.36E+12 MSE value. MAD value and especially MAPE of ES is the maximum of all the methods' solutions. Because of its 14.25 MAPE result, ES is removed from the list of optimal forecasting methods.

Holt's two parameter follows ES with MAPE value equal to 12.38, also it has the maximum error, AE and PE values. ES and Holt-Winters are not preferred for combination because of their big MAPE values, also it can be seen in the Figure 5.5 that Holt's two parameter is not successful in catching the seasonal fluctuations and can not be said that catching trend success is not exact. Same as the domestic and international forecasting results of ES, its total passenger forecasting results' pattern seems proper in regard of showing trend and seasonal fluctuations at first sight. But it

is clear that ES forecast results and real passenger numbers do not intersect. Of course, it is a forecast process and forecast does not have to be same with the real value, but forecast must be close to it. ES results are very different than real values even if it mimics the actual passenger traffic. Because of these difference, ES's MAPE value is the maximum. So other methods are kept evaluating for choosing the optimum method. Also both of these two methods lost their chance for combination.

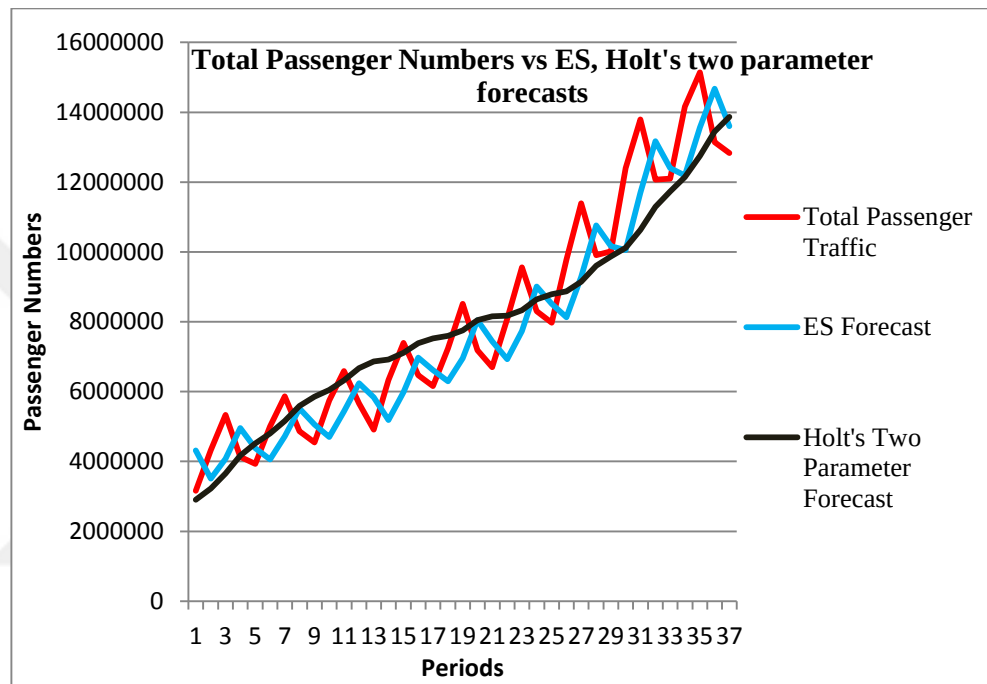


Figure 5.5 Total passenger numbers vs ES and Holt's two parameter forecast results

Surprisingly, combined method and Holt-Winters are ranked at the end for the comparison of MSE. But it is clear that these two methods have superiority to others by a long way, if we analysis their MAD values. Combined method is ranked at first by 290596 and Holt-Winters follows it by 296355. Related with their AE, PE of combined method is minimum and Holt-Winters comes after it with 5.42. MAPE of MA is the minimum of all with 0.19, despite this, Figure 5.6 displays that MA is not able to catch the seasonal pattern. It is good at catching the trend because it uses last four actual values to forecast the next period. Ignoring combined method, the second minimum value of MAPE belongs to Holt-Winters with 3.61 and these values makes two methods suitable for combination. If it is analysed according to the combined

method's MAPE, it is found 3.16 which is between MA's and Holt-Winters's MAPE results. Even though the MSE result of Holt-Winters is the maximum, it is ranked second for AE, MAD and PE. Combined method proves with its minimum AE, MAD and PE and also optimal MAPE value that MA and Holt-Winters are the right choices to combine. Holt-Winters mimics the seasonal and trend pattern properly. But Figure 5.6 shows that combined method is the best considering its seasonal and trend fluctuations. It can be said that combined method is the optimal forecasting method for three types of data which are domestic lines, international lines and total passenger numbers' traffic movement considering both the error analysis solutions and results' distribution pattern.

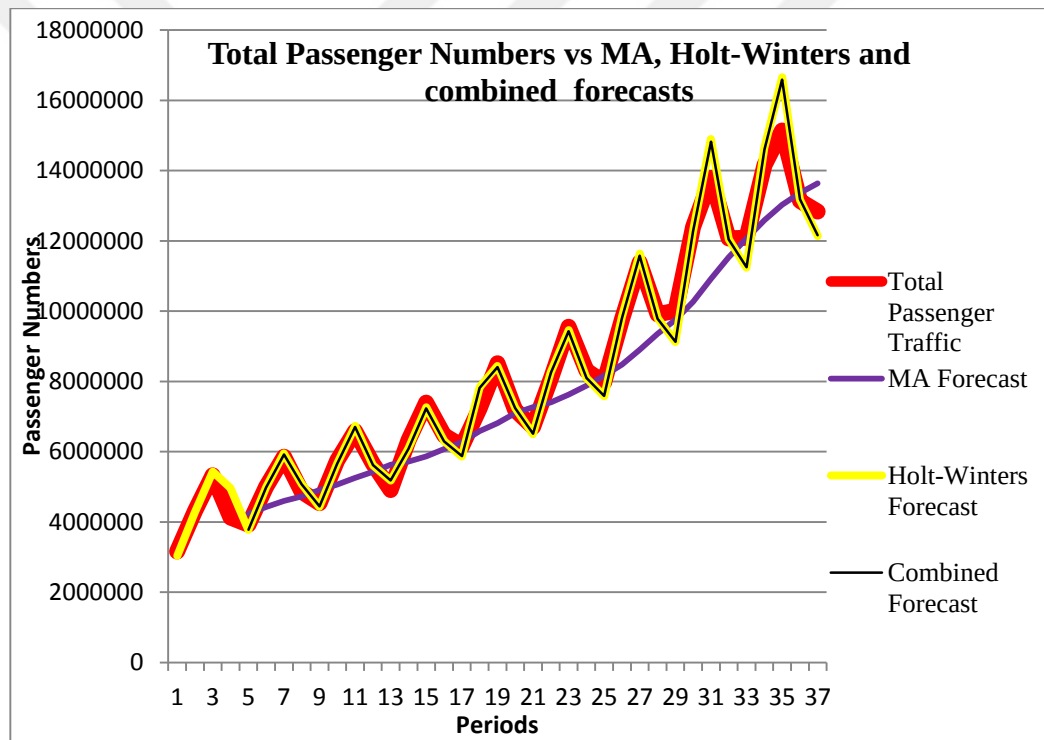


Figure 5.6 Total passenger number vs MA, Holt-Winters and combined methods forecast results

CHAPTER SIX

CASE 2: FORECASTING IN UNCERTAIN ENVIRONMENT WITH GREY THEORY

As it is mentioned in previous sections uncertain environment must be considered in forecasting studies with the purpose of having more clear solutions. Rapidly changing conditions of today's World makes it hard to catch the latest conditions. Especially for forecasting studies, environment and its conditions are so important to predict the target within the requested range. Grey forecasting is one of the methods that is used for different research subjects in uncertain environment. After giving information about the grey forecasting technique and its steps, combination method will be defined. Combination method brings different point of view, it combines two different techniques. With this combination of two different techniques' benefits, stronger and clearer forecasting solutions are obtained. Following the expressions, method evaluations and comparisons will be given by using error analysis techniques AE, MSE, MAD, PE and MAPE.

6.1 Information About Grey Forecasting

Deng (1989) developed Grey System Theory and from that time to now, it has found a large field of application such as engineering, management, finance, agriculture, transportation, military, meteorology, medical, etc. The main reason that it gains such a huge popularity is it can cope with the systems whose parameters are not completely known. Grey theory accepts three different systems. First one is define the systems whose information is quite known is white systems and on the contrary if the information is not quite clear in other words unknown it is named black system. And the last one is between them, its information not all totally known nor all totally unknown is grey systems (Pi et al., 2010). Grey system theory has an advantage when comparing the traditional statistical models, that is, a limited set of information is enough for grey prediction. Actually, grey system theory can show an acceptable success by using at least four known inputs to forecast the unknown systems (Deng, 1989; Kayacan, Ulutaş, & Kaynak, 2010). Grey prediction model takes its place in the

grey system theory by its efficiency on forecasting the character of unknown systems with little observation.

Grey prediction method is implemented in four basic steps. Data regenerating is the first step and it has four widely known models, which are the grey relational generating operation (GRGO), the accumulated generating operation (AGO), the inverse accumulated generating operation (IAGO) and the last one is the interpolation generating. In general, AGO is used in grey prediction because of its advantage of requiring less observation. The second step of prediction is Grey Model identification with the aim of constructing a grey differential equation (Hung, Huang, Lin, & Hou, 2010). Grey model is shown as $GM(n, m)$, and here n corresponds difference equation's order while m corresponds variables' number.

The basic grey prediction model $GM(1,1)$ is widely used and implemented in the short term estimations by its computational advantages (L. Liu, Wang, M. Liu, & Li, 2014). Furthermore, in this study we used $GM(1,1)$ too, which is also known Grey Model First Order One Variable. This type of grey model is updated when the new data comes to the estimation model with the help of time-varying coefficients that it has. And the last two steps are for finding the different elements in the middle of the series and data generating. According to these explanations, the general implementation of grey prediction algorithm is as in the following:

Step 1: Original data collection and data sequence construction. When i is the i^{th} sample $X^{(0)}(i)$ defines the non-negative original data. The sequence of n samples is

$$X^{(0)} = (x^{(0)}(1), x^{(0)}(2), x^{(0)}(3), \dots, x^{(0)}(n)), x^{(0)}(k) > 0, k = 1, 2, \dots, n \quad (6.1)$$

Step 2: AGO creates $X^{(1)}$ which is the new sequence that is transformed from the original data sequence.

$$X^{(1)} = (x^{(1)}(1), x^{(1)}(2), x^{(1)}(3), \dots, x^{(1)}(n)) \quad (6.2)$$

The derivation of $x^{(1)}(k)$ is,

$$x^{(1)}(k) = \sum_{i=1}^k x^{(0)}(i), \quad k = 1, 2, \dots, n \quad (6.3)$$

Step 3: Calculation of mean value of the AGO sequence also named the background value.

$$z^{(1)}(k) = 0.5 \left(x^{(1)}(k) + x^{(1)}(k-1) \right) \quad k = 2, 3, \dots, n \quad (6.4)$$

Step 4: Construction of first order differential equation of GM (1, 1) model. The least square prediction sequence of the grey difference equation of GM (1, 1) is defined as in the following (Deng, 1989) :

$$x^{(0)}(k) + az^{(1)}(k) = b \quad (6.5)$$

The grey differential equation is:

$$\frac{dx^{(1)}}{dt} + ax^{(1)} = b \quad (6.6)$$

In this equation a is the development coefficient, while b is the grey input. And they can be calculated like,

$$[a, b]^T = (B^T B)^{-1} B^T Y \quad (6.7)$$

where

$$Y = [x^{(0)}(2), x^{(0)}(3), \dots, x^{(0)}(n)]^T \quad (6.8)$$

$$B = \begin{bmatrix} -z^{(1)}(2) & 1 \\ -z^{(1)}(3) & 1 \\ \vdots & \vdots \\ -z^{(1)}(n) & 1 \end{bmatrix} \quad (6.9)$$

Another way to calculate the a and b is;

$$a = \frac{D \times C - (n-1) \times E}{(n-1) \times F - D^2} \quad (6.10)$$

$$b = \frac{F \times C - D \times E}{(n-1) \times F - D^2} \quad (6.11)$$

C, D, E and F are shown in the next equations

$$C = \sum_{k=2}^n x^{(0)}(k) \quad (6.12)$$

$$D = \sum_{k=2}^n z^{(1)}(k) \quad (6.13)$$

$$E = \sum_{k=2}^n z^{(1)}(k) \times x^{(0)}(k) \quad (6.14)$$

$$F = \sum_{k=2}^n (z^{(1)}(k))^2 \quad (6.15)$$

Step 5: Having the estimated value as $\hat{x}^{(0)}(k+1)$ with the help of grey prediction.

$$\hat{x}^{(0)}(k+1) = (1 - e^a)(x^{(0)}(1) - b/a)(e^{-ak}) \quad (6.16)$$

6.2 Evaluation of Method

After giving information about grey forecasting process, now it is time to use it for the passenger forecasting of THY. In section 5 and its subsections, different forecasting methods' implementations are shown in certain environment. According to their results, combined method which is the combination of MA and Holt-Winters is the optimum to choose for certain environment.

In this case, uncertain conditions like weather changes, terror attacks, economic fluctuations, fuel prices, etc. are considered, and as a result of this grey forecasting process is used to forecast the traffic movement of domestic lines, international lines and total passenger numbers. All calculations and tables are constituted by using MS Excel 2010. The following Table 6.1 shows the result of grey forecasting for domestic lines passenger traffic movement. Columns are ranked like periods, quarters, domestic lines passenger traffic, grey forecasting results and error. Last row which is highlighted, is the passenger forecast of 2015's first quarter. This is the aim of the thesis that all methods under uncertain environments are used to forecast the 37th period. For domestic lines' grey forecasting process to find the parameters " a " and " b " equation 10 and 11 is used. First of all calculations are done like it is told to find the C, D, E and F. After they are found, " a " is obtained equal to -0.0301034 and " b " is obtained equal to 1977428 . As it is seen in the Table 6.1 that, grey forecasting forecast the target period bigger than the actual value.

Table 6.1 Passenger demand forecasting results of domestic lines with grey forecasting

Period	Quarters	Traffic	Grey Forecasting	Error
1	2006 Q1	1670880		
2	2006 Q2	2292658	2058555	-234103
3	2006 Q3	2726588	2121467	-605121
4	2006 Q4	2165145	2186301	21156
5	2007 Q1	2091423	2253117	161694
6	2007 Q2	2607814	2321975	-285839
7	2007 Q3	2867671	2392937	-474734
8	2007 Q4	2367868	2466067	98199
9	2008 Q1	2334853	2541433	206580
10	2008 Q2	2806424	2619102	-187322
11	2008 Q3	3176875	2699145	-477730
12	2008 Q4	2675077	2781634	106557
13	2009 Q1	2413921	2866643	452722
14	2009 Q2	2965643	2954251	-11392
15	2009 Q3	3335202	3044536	-290666
16	2009 Q4	2976802	3137581	160779
17	2010 Q1	3015122	3233469	218347
18	2010 Q2	3421327	3332287	-89040
19	2010 Q3	3905756	3434125	-471631
20	2010 Q4	3240845	3539076	298231
21	2011 Q1	3189019	3647234	458215
22	2011 Q2	3614101	3758698	144597
23	2011 Q3	4067279	3873568	-193711
24	2011 Q4	3639141	3991948	352807
25	2012 Q1	3449719	4113946	664227
26	2012 Q2	3959336	4239673	280337
27	2012 Q3	4556418	4369242	-187176
28	2012 Q4	3940719	4502771	562052
29	2013 Q1	4001032	4640381	639349
30	2013 Q2	5135566	4782196	-353370
31	2013 Q3	5800794	4928345	-872449
32	2013 Q4	5115260	5078961	-36299
33	2014 Q1	5138869	5234180	95310
34	2014 Q2	5832040	5394142	-437898
35	2014 Q3	6178788	5558992	-619796
36	2014 Q4	5557813	5728881	171068
37	2015 Q1	5116201	5903962	787761

Forecast results seem proper but to get a lot more details about this forecasting process' solutions following error analysis Table 6.2 and pattern which is shown in Figure 6.1 will help.

Table 6.2 Error analysis of grey forecasting method for domestic lines passenger traffic

		Error	AE	MSE	MAD	PE	MAPE
Domestic Passenger Traffic	5116201	-	-	-	-	-	-
Grey Forecasting Result	5903962	787761	787761	1.54E+11	325230	15.40	9.05

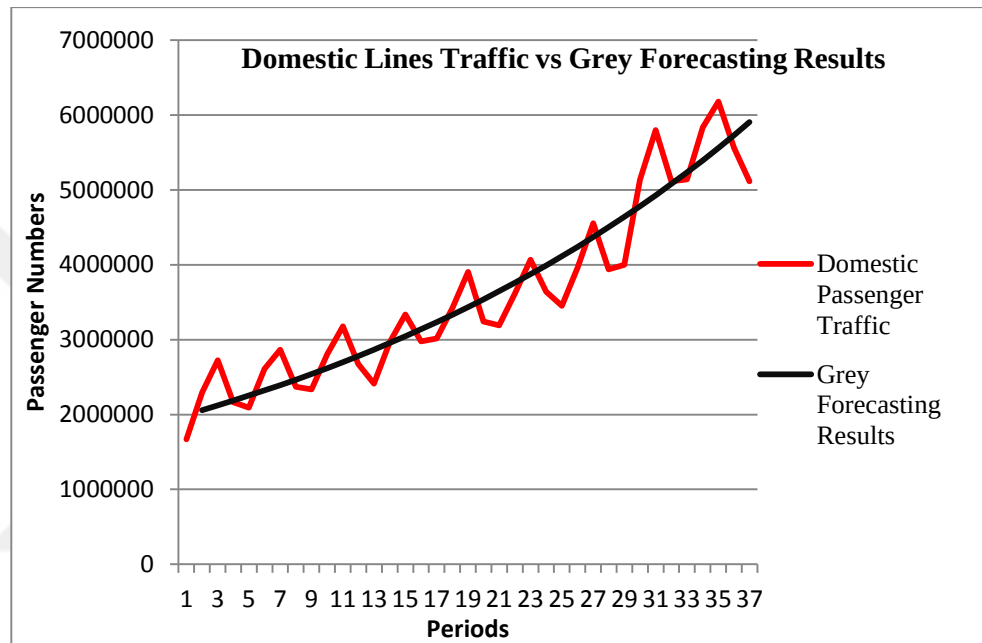


Figure 6.1 Domestic lines passenger traffic vs grey forecasting results

According to the error analysis table, it can be said that grey forecast result of 2015's first quarter exceeds the actual value with a value of 787761. This is a sufferable number for a company within uncertain environments if it wants to meet unexpected demand increase. Although, 15.04 is great number for PE, MAPE which is equal to 9.05 makes grey forecasting method reasonable for forecasting process. Reminded that, this method is implemented for a case under uncertain conditions, it is hard to constitute a foresight about demand fluctuations. So, MAPE under 10% seems reasonable, also getting forecast result bigger than the actual value is another plus of the process.

On the other side, if Figure 6.1 is investigated, grey forecasting solutions catch the trend pattern in the actual domestic passenger traffic. But as a minus, it has a lack of ability to catch seasonal fluctuations. For further studies, it can be thought to make some modifications on the method. With these modifications or hybridization process with other methods, grey forecasting process can gain characteristics to catch seasonal fluctuations. For existing conditions, it can be said that grey forecasting can be preferred to forecast domestic lines' passenger traffic movement under uncertain conditions.

Continue to search grey forecasting method, this time its implementation to international lines passenger traffic movement will be shown. Same as the domestic lines' table, Table 6.3 will show the periods, quarters, international lines' passenger numbers, grey forecasting results for international lines and errors. Also the last row is highlighted again to emphasize the passenger numbers of 2015's first quarter.

All calculations for grey forecasting are done by using MS Excel 2010 and tables and figures are constituted with the help of it, too. That it is mentioned in steps of grey forecasting process, calculations are done to obtain the parameter " a " and " b ". And grey forecasting process is worked by taking " a " is equal to $-0,043992$ and " b " is equal to 1827388 . Proportional to increment of previous periods, grey forecasting method forecasts the 2015's first quarter bigger than the real value. Even though, previous periods forecast results and errors seem reasonable, 37th period's error obtained a lot more than expected with 1610454 . More detailed interpretation will be done in Table 6.4 with the help of error analysis solutions. Before that, forecasting solutions can be viewed on the following table.

Table 6.3 Passenger demand forecasting results of international lines with grey forecasting

Period	Quarters	Traffic	Grey Forecasting	Error
1	2006 Q1	1489497		
2	2006 Q2	2030287	1935167	-95120
3	2006 Q3	2603194	2022199	-580995
4	2006 Q4	1965482	2113145	147663
5	2007 Q1	1836948	2208182	371234
6	2007 Q2	2396145	2307493	-88652
7	2007 Q3	2994741	2411270	-583471
8	2007 Q4	2493356	2519714	26358
9	2008 Q1	2205749	2633036	427287
10	2008 Q2	2943571	2751454	-192117
11	2008 Q3	3408181	2875198	-532983
12	2008 Q4	2985583	3004507	18924
13	2009 Q1	2493716	3139632	645916
14	2009 Q2	3363367	3280834	-82533
15	2009 Q3	4062937	3428386	-634551
16	2009 Q4	3489885	3582574	92689
17	2010 Q1	3141713	3743697	601984
18	2010 Q2	3816609	3912066	95457
19	2010 Q3	4611520	4088007	-523513
20	2010 Q4	3946520	4271861	325342
21	2011 Q1	3513280	4463984	950704
22	2011 Q2	4472552	4664747	192196
23	2011 Q3	5488045	4874540	-613505
24	2011 Q4	4666771	5093767	426997
25	2012 Q1	4519337	5322855	803518
26	2012 Q2	5816170	5562245	-253925
27	2012 Q3	6833003	5812401	-1020602
28	2012 Q4	5970525	6073808	103283
29	2013 Q1	6011770	6346972	335201
30	2013 Q2	7266135	6632420	-633715
31	2013 Q3	7996335	6930707	-1065628
32	2013 Q4	6953113	7242409	289296
33	2014 Q1	6955685	7568129	612444
34	2014 Q2	8329294	7908498	-420796
35	2014 Q3	8963890	8264175	-699715
36	2014 Q4	7718588	8635848	917260
37	2015 Q1	7413782	9024236	1610454

Table 6.4 Error analysis of grey forecasting method for international lines passenger traffic

		Error	AE	MSE	MAD	PE	MAPE
International Passenger Traffic	7413782	-	-	-	-	-	-
Grey Forecasting Result	9024236	1610454	1610454	3.45E+11	472667	21.7	10.74

As it is mentioned before, forecast result is 1610454 bigger than actual value. Although it is said that, bigger forecast value is better than being less, this value must be reasonable and sufferable. This time, PE with a value of 21.7 clearly shows that surplus of forecast error is a lot more than expected. On the other hand, MAPE can be sufferable if it exceeds 10%, but reasonable MAPE reveals that, despite the big error of the last period, forecasting process can be preferred for the uncertain cases. Eventually, process is taking in an uncertain environment, and considering unexpected events, 10.74 MAPE value can be supposed to be succesful. Also, following Figure 6.2 displays the pattern of grey forecast results and international lines passenger movement. It can be interpreted that, its success in catching trend is not applicable for catching seasonal fluctuations. Still, all these things can not change that grey forecasting process is suitable for this data type in uncertain environments.

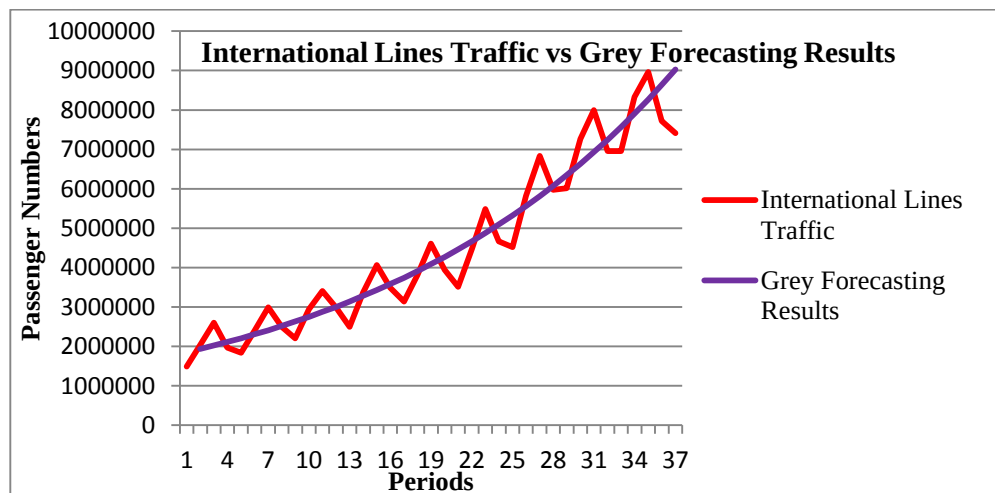


Figure 6.2 International lines passenger traffic vs grey forecasting result

Finally, grey forecasting process will be implemented to total passenger numbers' forecast. Table 6.5 will show the periods, quarters, actual and forecasted passenger numbers and errors. Last row is emphasized for taking attention to the 37th period.

Table 6.5 Demand forecasting results of total passenger numbers with grey forecasting

Period	Quarters	Traffic	Grey Forecasting	Error
1	2006 Q1	3160377		
2	2006 Q2	4322945	3955419	-367526
3	2006 Q3	5329782	4107784	-1221998
4	2006 Q4	4130627	4266019	135392
5	2007 Q1	3928371	4430348	501977
6	2007 Q2	5003959	4601008	-402951
7	2007 Q3	5862412	4778241	-1084171
8	2007 Q4	4861224	4962302	101078
9	2008 Q1	4540602	5153452	612850
10	2008 Q2	5749995	5351966	-398029
11	2008 Q3	6585056	5558127	-1026929
12	2008 Q4	5660660	5772229	111569
13	2009 Q1	4907637	5994579	1086942
14	2009 Q2	6329010	6225493	-103517
15	2009 Q3	7398139	6465303	-932836
16	2009 Q4	6466687	6714350	247663
17	2010 Q1	6156835	6972991	816156
18	2010 Q2	7237936	7241594	3658
19	2010 Q3	8517276	7520545	-996731
20	2010 Q4	7187365	7810240	622875
21	2011 Q1	6702299	8111095	1408796
22	2011 Q2	8086653	8423539	336886
23	2011 Q3	9555324	8748019	-807305
24	2011 Q4	8305912	9084998	779086
25	2012 Q1	7969056	9434957	1465901
26	2012 Q2	9775506	9798397	22891
27	2012 Q3	11389421	10175837	-1213584
28	2012 Q4	9911244	10567816	656572
29	2013 Q1	10012802	10974894	962092
30	2013 Q2	12401701	11397653	-1004048
31	2013 Q3	13797129	11836698	-1960432
32	2013 Q4	12068373	12292654	224281
33	2014 Q1	12094554	12766174	671620
34	2014 Q2	14161334	13257934	-903400
35	2014 Q3	15142678	13768637	-1374041
36	2014 Q4	13142678	14299013	1156335
37	2015 Q1	12833776	14849819	2016043

Calculations are done by using MS Excel 2010. Parameter a and b are calculated as $a = -0.0377972$ and $b = 3761688$. As it is seen, grey forecasting result of last period is bigger than the actual passenger number once more. For a lot more details, Table 6.6 will be examined from the point of error analysis results.

Table 6.6 Error analysis of grey forecasting method for total passenger traffic

		Error	AE	MSE	MAD	PE	MAPE
Total Passenger Traffic	12833776	-	-	-	-	-	-
Grey Forecasting Result	14849819	2016043	2016043	8.56E+11	770504	15.71	9.62

For total passengers, situation does not change, either. Once again, forecast result of 2015's first period is obtained larger than the actual value. Although, the error value is more than 2 million and 15.71% PE, from the point of MAPE the forecasting process seems proper for the data set. 9.62 % is a reasonable value, for uncertain environment cases and it does not change the truth of big values of error, MSE, MAD and PE. Also Figure 6.3 reflects that grey forecasting pattern does not intersect with the real data's pattern. All three grey forecasting processes can be used for case data. Reminded that, their error analysis results are not reasonable except the MAPE values. Weakness in catching seasonal patterns is another point, and reflecting trend pattern is not enough for success. For better results in uncertain environment, grey forecasting process for this data type must be improved by doing some modifications on the method or hybridizing with other methods. It can be preferred for case of uncertain environment forecasting process for now. Details about total passenger numbers' and grey forecast results' pattern can be taken from the Figure 6.3 in the following.

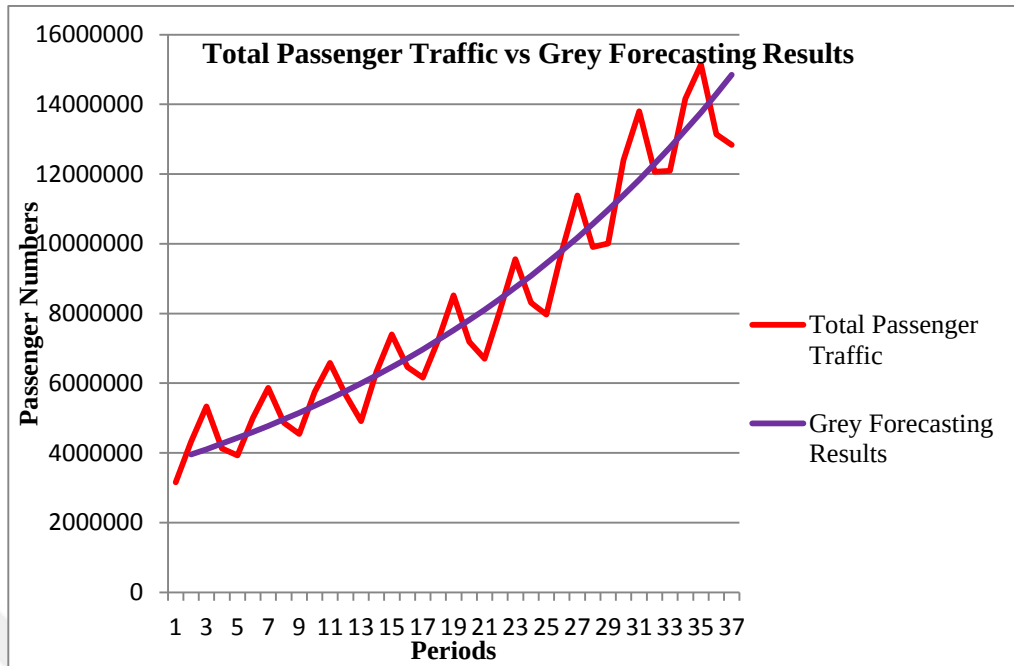


Figure 6.3 International lines passenger traffic vs grey forecasting results

CHAPTER SEVEN

CASE 3: FORECASTING IN UNCERTAIN ENVIRONMENT WITH UNCERTAINTY THEORY

Until this chapter, different methods and their solutions were pointed out in certain and uncertain environments. As the stronger and distinctive part of this thesis uncertainty theory and its implementation to forecasting data will be mentioned in the following sections. Uncertainty theory is gaining popularism in the solution of uncertain environment problems. It has superiorities against to traditional methods and other methods such as grey or fuzzy techniques. This chapter will give information about uncertainty theory and its difference from probability theory. Also another important point of uncertainty theory degree of belief or belief degree will be defined. Empirical uncertainty distribution will be introduced and it will be hybridized with ES method. The details of this study, solution tables and error analysis are placed in the following.

7.1 General Information About Uncertainty and Probability Theory

In real life, so many times people take their decisions under uncertain conditions. One of the ways that describes an uncertain situation is probability theory (Kolmogorov, 1933) and it is usually defined as frequency (Liu, 2015). As uncertainty becomes a vitally important topic of human's life, with a purpose of understanding and modelling the uncertainty, Liu (2007) proposed uncertainty theory in 2007 and reformed it in 2010. Recently, uncertainty theory comes into use to help people cope with uncertainty in their lives and this theory is accepted as a mathematical branch. It is commonly held that uncertainty and probability is almost the same but in every aspect this is a wrong idea. There is no doubt that their concepts are different from each other (Liu, 2012).

Analysing the random phenomena is in the focus of probability theory. It concerns with identifying range of possible values and possibility of random variables. Standard statistical techniques are used for gathering and describing the historical data with related information in a system and these techniques are developed with a purpose of

constituting a decision support system for the probability distribution (Wang & Peng, 2014).

Cumulative frequency is a function that represents the percentile of samplings belonging to an undeterminate quantity and situated leftward of actual point. Information and choices do not change frequency. It means; frequency is for a long period of time and it is stationary. Long-term cumulative frequency and predicted probability distribution must be close to each other. In that case, using probability theory is the basic assumption. When there are so many samples, it can be believed that long term cumulative frequency and predicted probability theory are close and it means predicted probability distributions based problems can be solved by using probability theory. But what if there are not enough samples to predict a probability distribution? In that case uncertainty theory comes into front and belief degrees of every case that will happen are defined by relevant experts.

It can be said that, uncertainty theory and probability theory are used to model uncertainty. Reminded that, while probability theory is implementable for frequency modelling, uncertainty theory models degree of belief. So, using these theories instead of each other can cause having inadequate solutions. Especially, it can not be thought about using probability theory for modelling degree of belief. Otherwise, result can be terribly unreasonable. Figure 7.1 displays that, only rational approach in the situation of there exist enough samples is probability theory, because in that case cumulative frequency and predicted probability distribution can be close to each other. And if there exist no samples, in other words, belief degrees are only data that are hold, cumulative frequency and uncertainty distribution diverges from each other. In that situation, uncertainty theory is accepted as the validate procedure (Liu, 2015).

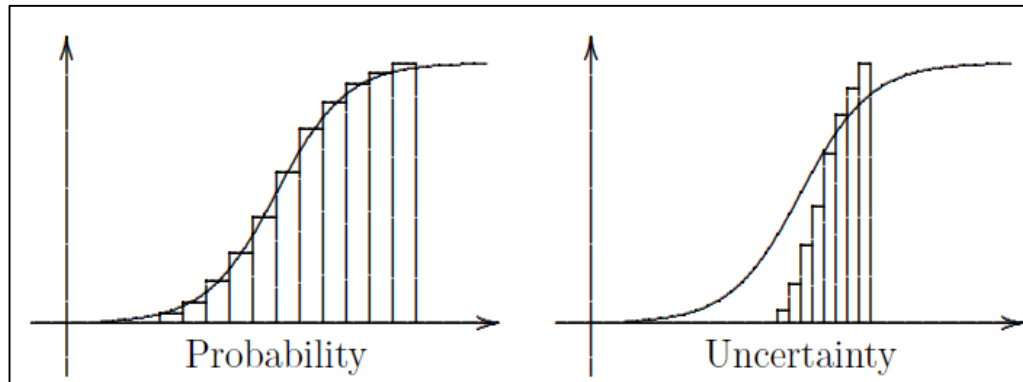


Figure 7.1 Probability and uncertainty distributions vs cumulative frequencies (Liu, 2015)

The situation that the system has one variable differs from the case mentioned above. In that condition, because of not considering the product measure, solutions of uncertainty and probability theories will be the same. This means theories can be used instead of each other. It must be remembered that degree of belief and frequency are different, in case of accepting belief degree instead of probability can cause big problems in the proceedings of the study. But the good point is uncertainty theory can not let small errors turn to large ones (Liu, 2015).

7.2 Indeterminacy

It is not possible to estimate some case's consequences beforehand, and the word corresponding this kind of situations is indeterminacy. For instance, the side of a coin in heads or tails game can not be estimated before tossing the coin. So, it can be said that heads or tails can be an example of indeterminate situation. Adding the examples, passenger demand, stock price, weather conditions, fuel price, etc..

Determinacy is accepted comparative, but however indeterminacy is infinite. It is clear that people generally take their decisions under indeterminate conditions. Because of hardness of modelling indeterminacy, engineering and science study this subject besides mathematics. Frequency that is constituted with the help of previous data and experts' evaluation belief degree can help to model indeterminacy. In the following subsections, these two terms will be told in details (Liu, 2015).

7.3 Frequency

Accept that change rate of fuel prices is an undeterminate quantity and a sample set is constituted for that quantity. The function which symbolizes all the samples' percentage that are located in the current point's left side, represents the cumulative frequency. It can be seen in the Figure 7.2 that cumulative frequency is a ladder function. Its values are getting bigger when the current point goes from left side to right side (Liu, 2015).

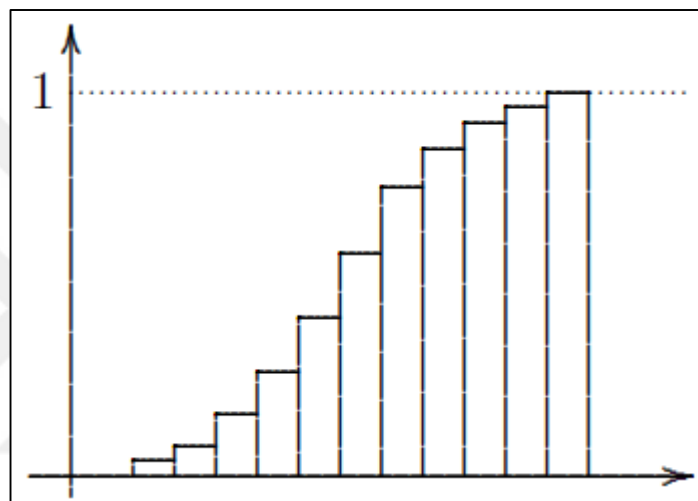


Figure 7.2 Cumulative frequency histogram (Liu, 2015)

Personel choices can not change frequency because of it is based on facts. It can be said that, frequency appears in longtime and is unvarying; it does not matter if it is accepted by decisionmakers or not (Liu, 2015).

7.4 Belief Degree

Actually, people use degree of belief in their daily lives without noticing. For instance, “Jane is an old woman”, “tomorrow will be rainy” and “next week it will snow” are some of the examples of belief object. To express how strong we believe that an event will occur, the expression “degree of belief” is used. When it is believed completely that an event will occur, it can be said that degree of belief is 1. On the contrary, if it is thought not possible to happen, then we can say that degree of belief

is 0. And in the case that events are thought equally likely events, 0.5 is given as the events' degree of belief. The value of each event's degree of belief changes in the range of $[0, 1]$. When the degree of belief's value gets higher, the belief we have, that an event will occur, gets stronger.

Supposing that a box has 15 matchsticks in it, some of them are shorter than others but number of shorter or longer matchsticks is not known. Because of this reason, probability theory can not be used for the purpose of deciding for drawing the short matchstick. In this situation, degree of belief can help us. Because it is clear that drawing a short or long matchstick is equally likely events and their degree of belief is 0.5. It should not be forgotten that degree of belief is related with personal information; it means it can change as the personal information changes (Liu, 2015).

7.4.1 Belief Degree Function

To define an indecisive quantity like a bridge' tolerability, it is needed more than one degree of belief. Of course, it is not possible to get information about all possible cases' degree of belief. For these kinds of situations, belief degree function is referred. It defines the degree of belief according to which side of current point' the indecisive quantity takes place.

To exemplify, belief degree function is equal to 1, if it is believed that indecisive quantity falls into the current point's left side, and if it falls into the current point' right side, then the belief degree function is equal to 0. Values that the belief degree function takes changes in the range of $[0,1]$, and this value is getting bigger while the current point changes left side to right side (Liu, 2015).

7.4.2 Obtaining Degree of Belief

For understanding the usage of degree of belief, think about a bridge and its strength. Suppose that we do not have any knowledge about the strength of the bridge. It means that the bridge strength's probability distribution can not be predicted by

statistical methods. To deal with this problem, consulting bridge engineers is the only way for constituting degree of belief about bridge strength. Of course, engineers can not perfectly define every possible case' degree of belief. Engineers can not go beyond the subjective ideas, for instance if an engineer is asked about bridge strength, he says that he thought the strength changes in the range of 90 and 140 tons. Now, we can have the degree of believes from the expert's data. According to previous statements, he is 100% sure that strength is not more than 140 tons. So, its degree of belief is 1 and experimental data is (140, 1). Also bridge strength is less than 90 tons with 0% trustingly. And our second experimental data is (90, 0). So, degree of belief $\Phi(x)$ is stated as in the following:

$$\Phi(x) = \begin{cases} 0, & \text{if } x < 90 \\ \frac{x-90}{50}, & \text{if } 90 \leq x \leq 140 \\ 1, & \text{if } x > 140 \end{cases} \quad (7.1)$$

From this equation $\Phi(x)$, it may be concluded that in case strength is less than 100 tons, degree of belief equals to 0.20 (Liu, 2015). Following Figure 7.3 shows the belief degree function of bridge strength.

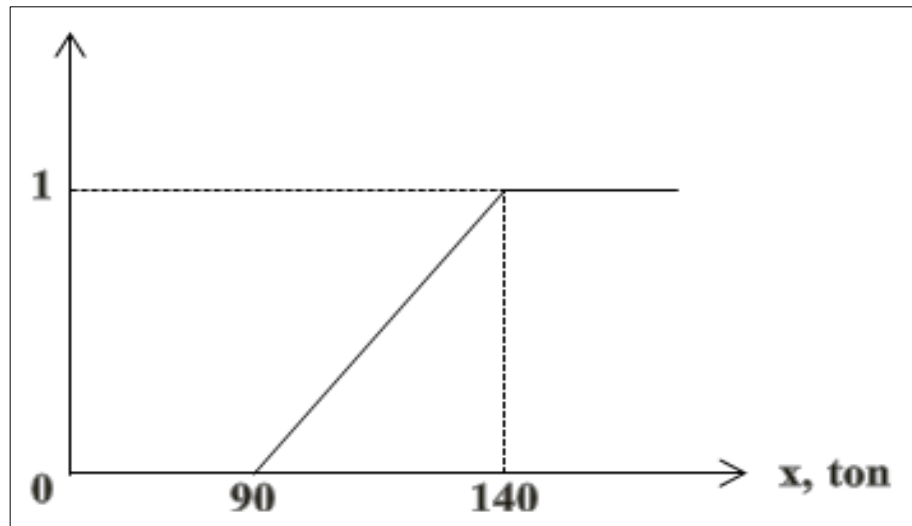


Figure 7.3 Belief degree function of bridge strength (Liu, 2015)

7.5 Uncertain Statistics

Uncertainty theory can help collecting and expounding experimental data that are obtained from the experts. Starting from this point of view, Liu (2010) started to study uncertain statistics. After collecting expert's experimental data with questionnaire study for constituting uncertainty distributions and membership functions from the data, empirical uncertainty distribution, method of moments, principle of least squares, multiple domain experts and Delphi method were introduced (Liu, 2015).

Following subsection will be about expert's experimental data. For determining the uncertainty distribution, empirical uncertainty distribution has been chosen. Only this distribution method will be told in detail in the context of this thesis. More information about other methods can be obtained from Liu's book Uncertainty Theory (Liu, 2015).

7.5.1 Expert's Experimental Data

Expert's experimental data is preferred instead of historical data as a basis of uncertain statistics. But the main question must be about the way that these expert's experimental data are obtained. Questionnaire study is one of the ways which Liu (2010) suggested for the purpose of gathering these data. To implement this process, authorities in related subjects are found and referred to. They are requested to study a questionnaire whose subject is determining an uncertain variable's " ξ " meaning, for example "how long does it take to travel from İzmir to Istanbul by plane".

First of all, the authority or expert must state an expectative x value to the uncertain variable ξ , for instance 60 minutes, then he must be questioned as to how much possible is ξ less than or equal to x ? Indicate that α is the belief degree of the expert and is equal to 0.7. Related with uncertain measure's self-duality feature, it can be said that $1 - \alpha$ expresses the belief degree of the expert that ξ is bigger than x . So the experimental data that is obtained from the expert is represented as

$$(x, \alpha) = (60, 0.7) \quad (7.2)$$

Process that is mentioned above is iterated and with the help of questionnaire study, expert's experimental data are constituted as in the following, $(x_1, \alpha_1), (x_2, \alpha_2), (x_3, \alpha_3), \dots, (x_n, \alpha_n)$.

Reminded that, it must not be given a value for x, α or n , without consulting an expert. In the opposite case, expert can be under the influence and his experience may not be enough (Liu, 2015). In the following, Figure 7.4 shows expert's experimental data.

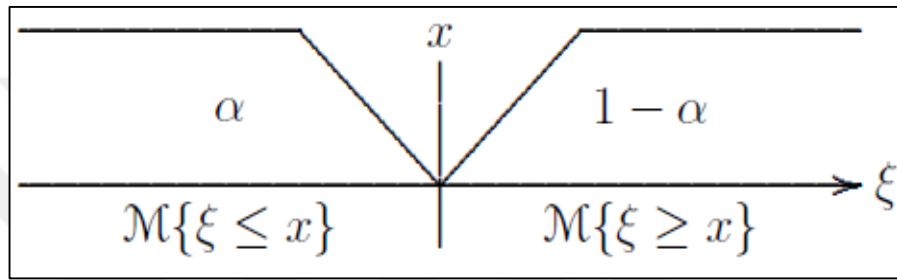


Figure 7.4 Expert's experimental data (Liu, 2015)

7.5.2 Empirical Uncertainty Distribution

After obtaining uncertain variables from the experts, the next step must be determining the uncertain variable's uncertainty distribution. This subsection will tell the empirical uncertainty distribution or with its other name linear interpolation method. Suppose that an expert's experimental data set is like $(x_1, \alpha_1), (x_2, \alpha_2), (x_3, \alpha_3), \dots, (x_n, \alpha_n)$ and they have the persistence condition that,

$$x_1 < x_2 < x_3 < \dots < x_n, \quad 0 \leq \alpha_1 \leq \alpha_2 \leq \alpha_3 \leq \dots \leq \alpha_n \leq 1. \quad (7.3)$$

Liu proposed an empirical uncertainty distribution whose basis is expert's experimental data (Liu, 2010; 2015). Following equation shows the empirical uncertainty distribution in the light of experimental data that are obtained from the experts with the help of questionnaire study.

$$\phi(x) = \begin{cases} 0, & \text{if } x < x_1 \\ \alpha_i + ((\alpha_{i+1} - \alpha_i)(x - x_i)/(x_{i+1} - x_i)), & \text{if } x_i \leq x \leq x_{i+1}, 1 \leq i < n \\ 1, & \text{if } x > x_n \end{cases} \quad (7.4)$$

After defining the uncertainty distribution by using the equation 7.4, expected value of it will be found with the following equation 7.5 (Liu, 2015),

$$E[\xi] = \frac{\alpha_1 + \alpha_2}{2}x_1 + (\sum_{i=2}^{n-1} \frac{\alpha_{i+1} - \alpha_{i-1}}{2}x_i) + (1 - \frac{\alpha_{n-1} + \alpha_n}{2})x_n \quad (7.5)$$

The following Figure 7.5 shows an empirical uncertainty distribution who has an expert's experimental data set with five factors.

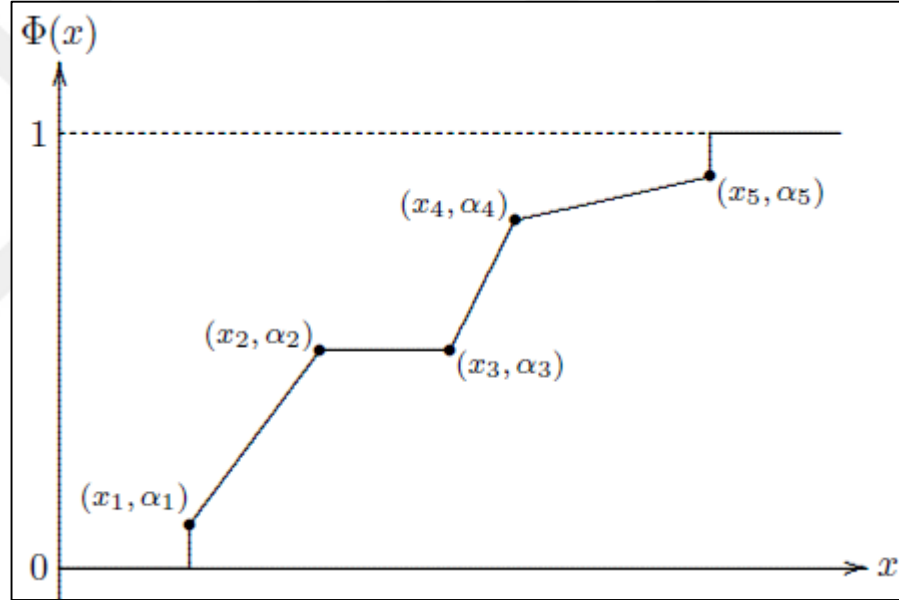


Figure 7.5 Empirical uncertainty distribution (Liu, 2015)

7.6 Forecasting with Uncertainty Theory

Until this section, different quantitative demand forecasting methods were exemplified, and they were studied under the consideration of certain and uncertain environments. This subsection will also study the forecasting process under uncertain environments. Uncertainty theory is the main focus of this thesis and this subsection

will make forecasting with the help of it. Uncertainty theory can have a large implementation area, although it gains popularity, its examples are not so many.

In this study, a hybrid model will be used. Namely, ES method's implementation was studied in section 5.3, and that time it was said that its parameters were chosen by trial and error method. Also there exists a chance to identify these parameters with the help of Minitab 16, because Minitab 16 offers a chance to assign a value for ES's parameter by using optimal ARIMA segment. This study chooses uncertainty theory's empirical uncertainty distribution to assign a parameter value of ES method. Of course, to collect the experimental data set, expert's experimental data technique of uncertainty theory will be used.

After determining the parameter with empirical uncertainty distribution, forecast will be done by using this parameter with ES. So, it will be a hybrid study in terms of using uncertainty theory technique with traditional time series method. Also, collection of expert's experimental data is a qualitative method, while ES is quantitative. The forecasting technique that will be used in the following will be not only the combination of uncertainty theory and traditional time series method, but also will be the combination of qualitative and quantitative method.

At the end of study, there will be a chance to compare ES forecasting solutions with three different parameters that are obtained with three different ways. The purpose is to show how possible to get reasonable solutions by using uncertainty theory and to encourage researchers for using uncertainty theory in their future studies.

7.6.1 Questionnaire Study for ES Parameter

It is referred an expert whose field of study is statistics and forecasting. With the help of questionnaire study, it is constituted an experimental data set of ES's parameter for domestic lines, international lines and also total passenger demand forecast. In the following, questionnaire study for the ES method's parameter of domestic lines will be shown. THY's passenger traffic of domestic lines will be shown to a forecast expert.

He puts forward ideas about the parameter values by investigating the traffic data because he is an expert about parameter values that are used in these kind of forecasting process. He defined his candidate parameter values with their belief degrees and considered uncertainties that passenger traffic demand can face with. Different scenarios were considered and instead of saying an only one parameter, different parameter sets were proposed. Process was repeated for international lines and total passenger numbers, too. Their questionnaire study will not be displayed, instead, only the expert's experimental data set will be given. In the following, questions and answers of questionnaire study can be investigated.

Q1: After investigating the domestic passenger lines passenger traffic movement, what do you think is the minimum value of the ES's parameter that will be used in this forecasting process?

A1: With a belief degree of 0, its minimum value is 0.6. (it means expert's experimental data is $(0.6, 0)$)

Q2: What do you think is the maximum value of parameter?

A2: With a belief degree of 1, its maximum value is 1. (an expert's experimental data is $(1, 1)$)

Q3: In your opinion what is the likely value?

A3: 0.8

Q4: What is the belief degree that the ES's value is less than 0.8?

A4: I am 60% sure that it is less than 0.8. (an expert's experimental data is $(0.8, 0.6)$)

Q5: Is there any value that ES's parameter may take?

A5: It may take the value of 0.9.

Q6: What is the belief degree that the ES's value is less than 0.9?

A6: I am %80 sure that it is less than 0.9. (an expert's experimental data is $(0.9, 0.8)$)

Q7: Is there another value that ES's parameter may take?

A7: It may be 0.7.

Q8: What is the belief degree that the ES's value is less than 0.7?

A8: My belief degree that it is less than 0.7, is 0.3. (an expert's experimental data is (0.7, 0.3))

Q9: Is there another value that ES's parameter may take?

A9: I have no idea.

As a solution of this questionnaire study, five expert's experimental data are obtained. Data set to use ES process of domestic lines passenger traffic forecast can be seen here in the following,

(0.6, 0), (0.7, 0.3), (0.8, 0.6), (0.9, 0.8), (1, 1)

This questionnaire study process was repeated for constituting ES's parameters that will be used in forecasting passenger numbers of international lines and total.

For international lines, expert's experimental data set of ES's parameter is defined by the expert that,

(0.5,0), (0.6,0.4), (0.7,0.8), (0.8, 1)

And for total passenger numbers, forecasting process will be start by using expert's experimental data set in the following (Liu, 2015),

(0.5,0), (0.6,0.4), (0.7,0.8), (0.8, 1)

7.6.2 Forecasting with Hybrid Method

This subsection will tell the hybrid method's implementation to domestic lines, international lines and total passenger numbers. In the forecast process, the first step which is the collection of data to use in empirical uncertainty distribution was carried out with the help of questionnaire study.

First of all, forecast of domestic lines passenger traffic movement will be studied. Empirical uncertainty distribution will use expert's experimental data and determine expected value of smoothing parameter. Like in the section 5.3, ES will forecast the domestic lines passenger traffic movement by taking the help of Minitab 16. Remind that, expert's experimental data set is (0.6, 0), (0.7, 0.3), (0.8, 0.6), (0.9, 0.8), (1, 1). Calculation of smoothing parameter's expected value is done by using equation (7.6) as in the following,

$$E[\xi] = \frac{0+0.3}{2} 0.6 + \frac{0.6-0}{2} 0.7 + \frac{0.8-0.3}{2} 0.8 + \frac{1-0.6}{2} 0.9 + (1 - \frac{0.8+1}{2}) 1 \quad (7.6)$$

As a result of this calculation, expected value of ES parameter is obtained as equal to 0.78. In section 5.3, smoothing parameter was found by trial and error method and α was determined as equal to 0.99. It is also possible to assign a smoothing parameter by using optimal ARIMA segment for the calculation of ES. Optimal ARIMA finds α as equal to 0.62. Following Table 7.1 shows three ES methods' evaluation with three smoothing parameters that were obtained in different ways. First one is the result of ES whose smoothing parameter was obtained by trial and error method (TES). Second one is the uncertain ES (UES) whose smoothing parameter was obtained by empirical uncertainty distribution and the last one is the ES with the smoothing parameter obtained by Minitab 16's optimal ARIMA (AES). Besides, actual domestic traffic data of 2015's first quarter and every method's forecast result for this period, MAPE, MAD and MSE will be shown in the table. For three types of smoothing parameter, ES calculation was done in Minitab 16.

Table 7.1 Comparison of UES vs TES and AES for domestic lines

ES Forecast Results				
	Actual Number of 37th Period's Passengers for Domestic Lines	$\alpha=0.99$ (by trial and error method)	$\alpha=0.78$ (by empirical uncertainty distribution)	$\alpha=0.62$ (by optimal ARIMA)
	5116201			
Forecast of 37th period		5563987	5670459	5707344
MAPE		12.84	12.89	12.31
MAD		433141	434020	417732
MSE		2.41E+11	2.36E+11	2.31E+11

As it can be seen from Table 7.1, smoothing constant that was obtained by uncertainty theory is in the between of others that were obtained by trial and error method and optimal ARIMA method. It is closer to constant of AES. All of three different calculations' forecasts are higher than the actual passenger numbers. Although MAD value of UES is the maximum of all, its forecast solution, MAPE and MSE values take place between the solutions of TES and AES.

AES has the minimum MAPE, MAD and MSE values, so this solutions makes 0.62 optimum as smothing parameter for the ES forecast process of domestic lines. UES which uses 0.78 that was obtained by emprical uncertainty distribution as smoothing constant comes after it. TES has the closest forecast result to actual traffic data, but considering previous forecast studies in this thesis, MAPE is the key factor to evaluate the forecast method. So, this makes AES the best of three. Reminded that, the better solutions of UES against to TES are the result of uncertainty factor in forecast process of UES. It brings the idea that uncertainty theory can improve the process.

In the following, this three forecast process will be conducted for international lines passenger forecast traffic data. Table 7.2 will show their forecast result for 37th period and error analysis solutions to benchmark UES with TES and AES. To constitute

expert's experimental data, questionnaire study in subsection 7.6.1 is repeated, and to obtain smoothing constant that will be used in UES process for international lines passenger traffic movement, empirical uncertainty distribution is referred. According to questionnaire study result, expert's experimental data set is obtained like $(0.5, 0)$, $(0.6, 0.4)$, $(0.7, 0.8)$, $(0.8, 1)$. After making calculations for empirical uncertainty distribution by using this experimental data set, smoothing constant, that will be used in UES forecasting process, is found as equal to 0.63. While this smoothing constant had found as equal to 0.8 by trial and error method, Minitab 16 optimal ARIMA segment in single ES found this value for the same international traffic data set as equal to 0.63.

For the forecasting calculations of domestic lines passenger traffic movement, AES which uses optimal ARIMA smoothing parameter gave the optimum results in terms of MAPE, MAD and MSE. Considering this, smoothing parameter values that are approaching optimal ARIMA's value can be accepted as reasonable. This time notice that, empirical uncertainty distribution has reached nearly the same smoothing parameter value with optimal ARIMA. If the Table 7.2 is studied, it is seen that when 0.64 is used as smoothing parameter for ES forecasting process, error analysis solutions are optimum. Although, TES method with smoothing parameter 0.80 forecasts the 37th period in other words first quarter of 2015 better than the UES and AES, its error analysis solutions are the highest of all. But in assessing the overall forecasting process, like it is mentioned before, MAPE, MAD and MSE are the important factors, especially MAPE is used to determine the optimum forecasting method in this thesis. UES method's error analysis results are between the error results of TES and AES just as it happened in domestic lines passenger traffic forecast, but this time it is clear that UES results are so close to results of AES. This trial shows once more that uncertainty theory and its branches are effective when they are implemented to a process. Here is the table about above mentioned solutions.

Table 7.2 Comparison of UES vs TES and AES for international lines

ES Forecast Results of International Lines				
	Actual Number of 37th Period's Passengers for International Lines	$\alpha=0.80$ (by trial and error method)	$\alpha=0.63$ (by empirical uncertainty distribution)	$\alpha=0.64$ (by optimal ARIMA)
	7413782			
Forecast of 37th period		7931543	8027045	8025294
MAPE		16.3	15.54	15.17
MAD		663257	635398	632070
MSE		5.44E+11	5.42E+11	5.39E+11

Finally, the questionnaire study will be carried out for comparing forecasting methods to take attention uncertainty theory and its implementation. To forecast the 2015's first quarter's passenger traffic movement, these three types of ES will be studied. Remind that, in subsection 5.3 smoothing parameter for total passenger numbers forecast was taken as $\alpha = 0.7$. When Minitab 16 is used for ES calculation and optimal ARIMA segment is chosen to assign a smoothing parameter, α is found as equal to 0.62. For UES it is known that smoothing parameter is assigned by using empirical uncertainty distribution and it was said before that, questionnaire study was performed to gather expert's experimental for empirical distribution. As a result of (0.5, 0), (0.6, 0.4), (0.7, 0.8), (0.8, 1). Remind that, this set is same with the experimental data set for international lines. After calculating uncertain empirical distribution according to this set, smoothing parameter α is found as equal to 0.63. According to these parameters, ES forecast calculations are made by using Minitab 16. Solutions and error analysis results are shown in Table 7.3 which is constituted in MS Excel 2010.

Table 7.3 Comparison of UES vs TES and AES for total passengers

	ES Forecast Results of Total Passengers			
	Actual Number of 37th Period's Passengers for Total	$\alpha=0.70$ (by trial and error method)	$\alpha=0.63$ (by empirical uncertainty distribution)	$\alpha=0.62$ (by optimal ARIMA)
	12833776			
Forecast of 37th period		13601013	13649343	13654467
MAPE		14.25	14.07	13.62
MAD		1074743	1.06E+06	1.04E+06
MSE		1.44E+12	1.45E+12	1.44E+12

For the forecast solutions of total passengers, it is clearly seen that table does not change. TES is the method whose forecast result of 2015's first quarter approaches the actual value most. But its error analysis results show that for the overall forecast process, TES is the last one to chose with its highest MAPE result. Uncertainty distribution assigned the smoothing parameter 0.63 which is very close to parameter of optimal ARIMA 0.62. AES gives the optimum error analysis solutions and this makes it the best ES type with 0.62 smoothing parameter. UES's MAPE value takes place with 14.07 between the TES with 14.48 and AES with 13.62.

The purpose of this thesis is to show how reasonable it is to choose uncertainty theory methods for any kind of problems. All of three types traffic data ES studies show that uncertainty theory's empirical uncertainty distribution assigns smoothing parameter values better than studying the same process with trial and error method, also parameter values are so close to ones optimal ARIMA found. ES gives reasonable and sufferable solutions with the constant empirical uncertainty distribution assigned by using expert's experimental data. Even if the MAPE of UES is a bit higher than AES, UES must be chosen for the study because it has already known that UES has the power of handling uncertainties in the problem environment. It can be said that uncertainty theory is a useful tool for problem solving in many research areas.

CHAPTER EIGHT

COMPARISON OF ALL FORECASTING METHODOLOGIES

Until this subsection, different methods were used to forecast the passenger traffic demand of THY. While traditional methods were evaluated in certain environment, others were evaluated under uncertain environment. Their comparisons were made between each other, but now all solutions for each type of data will be shown in one table. Based upon the forecast results, MAPE, MAD and MSE, a benchmarking will be done. Following Table 8.1 shows the comparison of MA, ES, Holt's two parameter, Holt-Winters, combined method, grey forecasting and UES.

Table 8.1 Comparison of all methodologies for domestic lines passenger demand

	Actual Traffic	Forecast Result	MAPE	MAD	MSE
	5116201				
MA		5676878	8.8	348006	2.19E+11
ES		5563987	12.84	433141	2.41E+11
Holt's Two Parameter		6288267	10.51	370385	2.30E+11
Holt-Winters		5293812	4.08	146167	3.65E+10
Combined Method		5304060	3.68	141922	3.31E+10
Grey Forecasting		5903962	9.05	325230	1.54E+11
UES		5670459	12.89	434020	2.36E+11

This table shows that combined method is the best forecasting method for domestic lines passenger traffic data whereas UES is the worst of all, when they are evaluated according to their MAPE. MAPE of UES is higher than ES. Generally, error results of the methods in certain environment seem better than methods in uncertain environment, especially better than proposed uncertain hybrid method. Reminded that, first five methods assumed that nothing affects the next period's passenger demand in other words they ignore the uncertainties in forecasting environment and give solutions about historical data. This brings the idea that uncertainty consideration gives a method

superiority and decision of the best method will be taken with this context. Another uncertain environment method grey forecasting's error results are smaller than the hybrid method but its forecast value for the next period is higher than UES. This means, although grey forecasting is better for the whole process, the same thing is not true for the forecasting of next period. It is known that UES process uses both qualitative and quantitative assumptions, assignment of ES's smoothing constant is done according to the methods of uncertainty theory. Smoothing constant is charged for the accuracy of the ES process, when it is assigned according to uncertainty theory' methods it reflects the uncertainty factors. If UES is chosen for the responsible forecasting method of domestic lines passenger demand, it will give trust to decision makers. They will know that according to UES's result they will be ready for even the worst scenarios.

Same comparison will be made for the methods that try to forecast international lines passenger demand for the first quarter of 2015. Table 8.2 gives needed information to evaluate all methods within each other.

Table 8.2 Comparison of all methodologies for international lines passenger demand

	Actual Traffic	Forecast Result	MAPE	MAD	MSE
	7413782				
MA		7991864	0.24	17518	5.33E+11
ES		7931543	16.3	663257	5.44E+11
Holt's Two Parameter		8251265	14.7	594427	5.65E+11
Holt-Winters		6444855	5.5	271177	1.83E+11
Combined Method		6631686	4.3	230548	1.27E+11
Grey Forecasting		9024236	10.74	472667	3.45E+11
UES		8027045	15.54	635398	5.42E+11

Table 8.2 indicates that MA is the best method while ES is the worst according to their MAPE results. MA was calculated according to four periods and it just replicated

the historical data under certain conditions. It was mentioned in section 5.7 that MA is not good at catching seasonal patterns, but UES can catch both trend and seasonal patterns in the data because of ES feature. If the decision maker wants to evaluate forecast results considering uncertainties, he/she can see that UES forecasted the target period with a very close value to MA did, even though UES' MAPE is higher than MA. The idea of whole forecasting process was conducted under uncertain environment can make the decision maker more comfortable while taking strategic decisions because it is known that result includes uncertainties. Grey forecasting may be chosen with its smaller MAPE instead of UES, but conception of UES forecasted the next period by the ES, whose smoothing constant assigned with uncertainty theory, can change the mind. Decision maker must decide which is more important for him/her: smaller errors for whole process or consideration of uncertain environments. Finally, these evaluation will be done in Table 8.3 for total passenger demand.

Table 8.3 Comparison of all methodologies for total passenger demand

	Actual Traffic	Forecast Result	MAPE	MAD	MSE
	12833776				
MA		13635311	0.19	889638	1.36E+12
ES		13601013	14.25	1074743	1.44E+12
Holt's Two Parameter		13869509	12.38	949703	1.46E+12
Holt-Winters		12138033	3.61	296355	2.06E+11
Combined Method		12166985	3.16	290596	1.92E+11
Grey Forecasting		14849819	9.62	770504	8.56E+11
UES		13649343	14.07	1.06E+06	1.45E+12

Methods and their solutions can be interpreted just like the previous Tables 8.1 and 8.2. For certain environments MA is the best of all according to their MAPE but known that it does not catch seasonal pattern. UES forecast result close to MA forecasted, but its MAPE value is higher than MA's. For uncertain environments, grey theory gives more reasonable MAPE value than UES, whereas it forecasted the next period higher

than the UES and actual value. Except the Table 8.1 which contains forecast solutions for domestic lines, it is clearly seen that uncertainty theory combination has gained traditional ES method accuracy. UES method has lower MAPE result than ES has. It gives the reliability of getting ready to uncertainties. Uncertainty theory shows its superiority by reducing MAPE value and increasing forecast accuracy according to traditional ES. For uncertain environment, its MAPE value can be accepted reasonable for all cases. If it is wanted to be decreased, combination of another method with uncertainty theory can be an option. Passenger data that is studied has trend and seasonal patterns. While MA shows trend fluctuations, it is not as successful as ES to reflect the seasonal pattern. Section 5.7 gives clear information about these patterns and chooses the best method in certain environment by explaining on the figures. When it is looked at the traditional ES's MAPE solutions, it does not seem like an appropriate method for this passenger data. If it is asked why UES has higher errors than others, the answer will be the failure of ES to model passenger data, even though it catches both trend and seasonal patterns. However, uncertainty theory impact succeeded reducing the errors and proved that uncertainty theory is good at improving techniques and conditions. There can be another way to show uncertainty theory's power by combining it with another forecast method which is good at modeling the historical data.

CHAPTER NINE

CONCLUSION

Uncertainty concept is mentioned in science environment more than ever before, while indetermined world makes it harder to consider everything around us. A lot of powerful methods fail to propose rational solutions to the problems that they are tackling. In every research area, there exists uncertain conditions that are related directly or indirectly with the problem. Existing traditional methods's results do not satisfy the decision makers because they want to develop their strategies under the consideration of uncertainties. Besides probability theory, fuzzy theory and grey theory arised to meet the requirement in this area. Fuzzy theory, grey theory or their hybrids have being used for many years to provide correct information to decision makers. As time passes by, it is realized that these methods restricted the data or problem and they are mistaken in defining uncertainty concept.

This thesis aimed to develop a novel hybrid uncertain forecasting method for emphasizing the importance of uncertainty theory. Although grey theory and fuzzy system are used in many areas under the consideration of uncertainty, it can be seen that uncertainty theory brings a new perspective to research areas. While grey and fuzzy methods limit the available and target data by identifying them in predetermined borders, uncertainty theory gives the opportunity of identifying data according to how much belief there is for an event to occur.

Expert's experimental data and emprical uncertainty distribution methods are chosen for the study thinking that they will help understanding the basic concepts of uncertainty theory and its success. Withal, expert's experimental data method adds qualitative feature to process and hybrid method becomes more powerfull as a combination of qualitative and quantitative features. Whereas qualitative techniques are subjective and based on experimental data, quantitative techniques are more prefered than others to make more precise forecastings. The important point is sometimes refering to an expert in his/her field can be useful to understand the characteristics of sector.

These two uncertain statistics methods, expert's experimental data and empirical uncertainty distribution are combined with a traditional forecasting method with reason to statistics nature of forecasting and uncertainty sensitivity of the forecasting process. ES is thought to be suitable for this combination after reviewing some studies about combination of ES with fuzzy and grey systems. Detailed information was given in section 1.2. Novel uncertain ES method, UES, assigns the smoothing constant in the first part of the method by using expert's experimental data and uncertainty distribution, and then classic ES procedure is applied by using an assigned constant.

Airline industry is thought to be suitable studying with UES because it has a large amount of factors that can change the passenger demand. Weather conditions, jet fuel and crude oil prices, terror attacks, natural catastrophes, epidemics, economic fluctuations, etc. are some of the events which are hard to know beforehand. So many times, traditional forecasting methods have lack of ability to get over these kind of uncertainties. For tackling this problem, UES is used to forecast domestic and international lines passenger demand and total based passenger demand of THY for 2015's first quarter. Historical data were taken between the year 2006 and 2014.

Besides UES method, MA, ES, Holt's two parameter, Holt-Winters and combined method are applied to three types of passenger data to see the results in certain environments. These methods and their evaluations according to their error analyses were mentioned in chapter 5, in detail. Main results are summarized below:

- Historical traffic data include seasonality and trend.
- Excluding combined method, forecast method with the minimum MAPE is Holt-Winters (MAPE= 4.08) for domestic lines, while it is MA for international lines (MAPE= 0.24) and total passengers (MAPE= 0.19).
- MA catches only the trend pattern whereas Holt-Winters catches both trend and seasonality in the traffic data.
- Combination is done between MA and Holt-Winters methods because of their minimum MAPE success.
- Combined method includes both methods' advantages.

- Combined method not only forecasts the next period's demand accurately but also catches the trend and seasonal pattern of the data.
- Although MA's error analyses are better than combined method, data modelling performance and reasonable MAPE results (3.68 for domestic lines, 4.3 for international lines, 3.16 for total passengers) make combined method optimal forecasting method in certain environments.

It is important to restrain that, these results are obtained under the consideration of certain environments. Managers of airline companies can be dissatisfied with the forecast results because they know that uncertainties can cause fluctuations in passenger demand and consideration of these fluctuations brings success in taking strategic decisions like network optimization, crew assignment, aircraft purchasing, etc.. The same problem is studied in uncertain environment with grey theory. Grey forecasting is mentioned in details in chapter 6. Following statements summarizes grey forecasting results.

- 9.05, 10.74 and 9.62 are the MAPE results of grey forecasting that correspond to domestic lines, international lines and total based passenger demand.
- For all three types passenger traffic data, it only reflects trend pattern.
- Its advantage to traditional method is uncertain environments consideration.
- Its power can be increased by combining it with another method that models data successfully.

Finally, main purpose of this study gives an insight to reseachers. Forecasting in uncertain environments with uncertainty theory indicates theory's power by UES. Besides UES, two other ES methods, whose smoothing constants are assigned with optimal ARIMA and trial and error, are applied to passenger traffic data for comparing them. Detailed explanation is given in section 7.6, but summarized information as in the following:

- TES is chosen to show that UES optimizes smoothing constants.

- AES is chosen to show optimum constants that UES must approach.
- Uncertainty theory achieved changing smoothing constant of TES to obtain better results.
- It assigns smoothing constants as 0.78 for domestic lines passenger demand and 0.63 both for international lines and total passenger demand.
- These constants are very close to the ones assigned by optimal ARIMA which are 0.62, 0.64 and 0.62.
- UES forecast success takes place between AES and TES according to their MAPE.

This process shows that hybridization of uncertainty theory with a traditional method is adequate for optimizing the conditions in problems. Difference between UES and AES is ignorable if it is thought uncertainty theory and being the combination of qualitative and quantitative methods are the positive aspects of UES.

Instead of ES, another forecasting method can be chosen for combining with uncertainty theory to reduce error results, if it is wanted. Remind that, this thesis proves that it is possible to reach optimal solutions under uncertain conditions with uncertainty theory. Researchers can reach more satisfying outputs by using uncertainty theory or its hybrid versions in different problems. Uncertainty theory can be easily adapted to decision taking and planning mechanism for industries in uncertain environments. It gives a chance to think all situations with their degrees of belief which gives the theory its power. It does not bound the decision maker with certain ranges as it happens in some uncertain situation problem solver methods like fuzzy systems by making possible to identify degree of belief. Thesis can be summarized as in the following:

- A novel hybrid uncertain forecasting method is proposed to show uncertainty theory's success.
- Airline industry is chosen to exemplify the method.
- Passenger demand of THY for the first quarter of 2015 is trying to be forecasted by using historical data between the years 2006 and 2014.

- Firstly, five traditional method is applied to passenger data of THY under certain environment conditions, secondly study continues with grey forecasting in uncertain environments.
- Finally, proposed method UES is applied to passenger data by comparing it with AES and TES.
- Results show that uncertainty theory increases a method's power and gives reliability to decision makers.

Thesis achieved its goal by proving the usability and utility of this theory. Hope that it will lead further studies to use uncertainty theory and its techniques in different areas by making clear how much this theory is successful about finding optimal solutions.

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