THE REPUCLIC OF TURKEY
BAHÇEŞEHİR UNIVERSITY

TEMPERATURE DEPENDENT ELECTRICITY LOAD MODELING AND RISK MANAGEMENT

M.S. Thesis

SİMGE ERTEM

İSTANBUL, 2016

THE REPUBLIC OF TURKEY

BAHÇEŞEHİR UNIVERSITY

THE GRADUATE SCHOOL OF NATURAL AND APPLIED SCIENCES

INDUSTRIAL ENGINEERING

TEMPERATURE DEPENDENT ELECTRICITY LOAD MODELING AND RISK MANAGEMENT

M.S. Thesis

SİMGE ERTEM

Supervisor: ASST. PROF. DR. ETHEM ÇANAKOĞLU

İSTANBUL, 2016

THE REPUBLIC OF TURKEY
BAHCESEHIR UNIVERSITY

INSTITUTE OF SCIENCE SCHOOL
INDUSTRIAL ENGINEERING GRADUATE PROGRAM

Name of the thesis: Temperature Dependent Electricity Load Modeling and Risk Management
Name/Last Name of the Student: Simge Ertem
Date of the Defense of Thesis: 12.01.2016

The thesis has been approved by the Graduate School of Natural and Aplied Sciences.

Assoc.Prof.Dr. Nafız ARICA
Graduate School Director
Signature

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

Assist.Prof.Dr. Ethem ÇANAKOĞLU
Program Coordinator
Signature

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

Examining Comittee Members	Signature
Thesis Supervisor Assist.Prof.Dr. Ethem ÇANAKOĞLU	----------------------------------
Member Assoc Prof. Dr. Yaman Ömer ERZURUMLU	---------------------------------
Member Assist.Prof.Dr. Bora ÇEKYAY	----------------------------------

ACKNOWLEDGEMENTS

I would like to express my sincere gratitude to my thesis advisor, Assist. Prof. Dr. Ethem Çanakoğlu, for his patience, continuous support and encouragement during the preparation process of this study.

I also would like to thank my dear friends especially Levent Kirman for his patience and continuous support.

Finally, I dedicate this thesis of mine to my dear family especially my mother Müjde Ertem whose constant ample support enabled me to complete my master thesis.

İstanbul, 2016 Simge ERTEM

ABSTRACT

TEMPERATURE DEPENDENT ELECTRICITY LOAD MODELING AND RISK MANAGEMENT

Simge Ertem

Industrial Engineering Program

Thesis Supervisor: Assist. Prof. Ph. D Ethem Çanakoğlu

February 2016, 94 pages

The essence of life is movement which requires energy both to initiate and maintain activities in all aspect of life. Electricity is a form of energy which is generated from various natural sources such as hydraulic, fossil fuels, nuclear power, solar power and wind power. The invention of electricity accelerated the first industrial revolution. Until recently electricity has been produced and distributed by governmental institutions like other utility services. However after the deregulation of electricity market private companies took over these duties. Since the objective of private companies is to maximize profit and minimize their risks, risk management tools and appropriate models are needed to use.

In this thesis our aim is to model a private electricity distribution company. The electricity distribution company buys electricity either from the electricity market or through bilateral contracts and sells to customers at a fixed price. These companies have two risk factors, one derives from the unknown market price and the other is unknown demand. The demand of electricity has seasonal variations and also affected by the temperature. It is assumed that there is a market for temperature derivatives and the company can use them to hedge its volume risk.

In the first part of this thesis the electricity load is modeled and load simulations are generated. Then in the second part mean-variance type model is derived using the simulations and effects of different hedging strategies are analyzed.

Keywords: Energy, Electricity, Electricity Load, Electricity Distributor, Risk factor

ÖZET

SICAKLIKLA BAĞIMLI ELEKTRİK YÜK MODELLEMESİ VE RİSK YÖNETİMİ

Simge Ertem

Endüstri Mühendisliği

Tez Danışmanı: Yrd. Doç. Dr.Ethem Çanakoğlu

Şubat 2016, 94 sayfa

Yaşamın esası, hayatın bütün aşamalarındaki etkinlikleri hem başlatmak hem de sürdürmek için enerji gerektiren harekettir. Elektrik; hidrolik, fosil yakıtlar, nükleer enerji, güneş enerjisi ve rüzgar enerjisi gibi çeşitli doğal kaynaklardan üretilen bir enerji şeklidir. Elektriğin icat edilmesi ilk sanayi devrimini hızlandırmıştır. Yakın zamana kadar elektriğin üretimi ve dağıtımı, diğer kamu hizmetleri gibi, devlet kurumları tarafından yapılıyordu. Ancak elektrik piyasasının serbestleştirilmesi ile bu hizmetler özel şirketlerin eline geçti. Özel şirketlerin amacı karlarını maksimize etmek ve risklerini minimize etmektir. Bu yüzden risk yönetim araçlarının ve uygun modellerin kullanılması gerekir.

Bu tezde amacımız bir özel elektrik dağıtım şirketi modellemek. Elektrik dağıtım şirketi elektrik piyasasından ya da ikili anlaşmalar yoluyla elektrik satın alır ve sabit bir fiyata müşterilere satar. Bu şirketlerin iki risk faktörü vardır. Biri bilinmeyen piyasa fiyatından türer. Diğeri ise bilinmeyen talep kaynaklıdır. Elektrik talebinin mevsimsel varyasyonları vardır. Ve de ısı değişimlerinden etkilenir. Sıcaklık türevleri için bir pazar olduğunu varsayılır. Ve elektrik dağıtım şirketleri bu sıcaklık türevlerini hacim riskinden korunmak için kullanabilir.

Bu tezin ilk bölümünde elektrik yükü modellenir ve yük simülasyonları oluşturulur. Sonra ikinci kısımda, ortalama-varyans tipi modelleri simülasyonlar kullanılarak türetilir ve farklı korunma stratejilerinin etkileri analiz edilir.

Anahtar Kelimeler: Enerji, Elektrik, Elektrik yükleri, Elektrik Dağıtıcısı, Risk faktörleri

CONTENTS

LIST OF TABLES……………………………………………………………..ix
LIST OF FIGURES…………………………………………………….……x
LIST OF ABBREVIATIONS……………………………………….......xi
LIST OF SYMBOLS……………………………………………….……...xiii
1. INTRODUCTION…………………………………………………....1
2. LITERATURE SURVEY……………………………………………...3
2.1 LITERATURE ON FORECASTING AND SIMULATION……...3
2.2 LITERATURE ON OPTIMIZATION.......……………………...11
2.2.1 Portfolio Optimization……………………………………….14
2.2.2 New Trends On Electricity Market In Turkey…………….16
3. PROBLEM DEFINITION………..…………………………………...17
3.1 LIBERALIZATION…………………………………………………17
3.2 THE MARKETPLACE……………………………………………..18
3.3 WHOLESALE ELECTRICITY MARKET……………………….19
3.4 ELECTRICITY TRADING…………………………………………20
3.4.1 Electricity Power Exchanges and Power Pools……………..21
3.4.1.1 The England and Wales electricity market……......22
3.4.1.2 The Nordic market……………………………...…23
3.4.1.3 Northern America……………………………………23
3.5 THE CHARACTERISTICS OF THE ELECTRICITYLOADS AND PRICES………………………………………….......……23
3.5.1 Price Spikes………………………………………………...25
3.5.2 Seasonality……………………………………………….…26
3.5.3 Seasonal Decompositions………………………………….…27
3.5.4 Mean Reversion………………………………………………28
3.6 MODELING AND FORECASTING ELECTRICITY DEMAND LOADS…………………………………………...…....28
3.6.1 Factors Affecting Load Patterns…………………………….32
3.6.1.1 Time factors………………………………………….33

3.6.1.2 Economic factors……………………………………….33

3.6.1.3 Weather conditions………………………………….34

3.6.1.3.1 *Temperature*………………………………….35

3.6.2 Statistical Methods…………………………………………..36

3.6.2.1 Similar-day method………………………………….37

3.6.2.2 Exponential smoothing……………………………...37

3.6.2.3 Regression methods……………..…………………38

3.6.2.4 Autoregressive model………………...…………..39

3.6.2.5 Autoregressive moving average model………..…..39

3.6.2.6 Autoregressive integrated moving average model..39

3.7 CHALLENGES FOR DISTRIBUTORS…………………………..40

4. PROBLEM DEFINITION…………………………………………………41

4.1 RISK MANAGEMENT…………………………………………….41

4.2 PHASES OF FORECAST AND SIMULATION…………………43

4.2.1 Portfolio Risk Measures…………………………………….50

4.3 THE PHASE OF OPTIMIZATION………………………………..52

5. REAL DATA ANALYSIS…………………………………………………55

5.1 DATA………………………………………………………………...55

5.2 TREND AND SEASONALITY…………………………………….56

5.3 AUTOREGRESSIVE AND DYNAMIC EFFECTS………………59

5.4 UNIT ROOT TEST AND STATIONARY…………………………60

5.5 APPLICATION OF FORECASTING AND SIMULATION……..64

5.6 PRACTICE OF PORTFOLIO OPTIMIZATION………...……70

5.7 OPTIMIZATION RESULT…………………………………………72

6. CONCLUSION………………………………………………………………80

REFERENCES……………………………………………………………………..82

APPENDICES………………………………………………………………….....88

Appendix 1: Figure 1 Histograms for Case 1, 4, 8, 11 in April a month for Spring……………………………………………..……89

Appendix 2: Figure 2 Histograms for Case 1, 4, 8, 11 in July a month for Summer……………………………………………………90

Appendix 3: Figure 3 Histograms for Case 1, 4, 8, 11 in October a month for Fall……………………………………………………………..…91
Appendix 4: Table 1 Expected Value E(x), Variance, Standard Deviation, Value at Risk (VaR), Conditional Value at Risk (CVaR) in April for 11 Different Cases……………………92
Appendix 5: Table 2 Expected Value E(x), Variance, Standard Deviation, Value at Risk (VaR), Conditional Value at Risk (CVaR) in July for 11 Different Cases…………………….93
Appendix 6: Table 3 Expected Value E(x), Variance, Standard Deviation, Value at Risk (VaR), Conditional Value at Risk (CVaR) in October for 11 Different Cases…….……...…..94

LIST OF TABLES

Table 5.1 : Results in Linear Regression Model for Hourly Electricity Load Demand with Matlab…………………………………………………….....58
Table 5.2 : Results in Linear Regression between daily residuals and HDD, CDD with Matlab……………………………………………..………...59
Table 5.3 : Expected Value E(x), Variance, Standard Deviation, Value at Risk (VaR), Conditional Value at Risk (CVaR) in January for 11 Different Cases…………………………………………………………69
Table 5.4 : Expected Value E(x), Variance, Standard Deviation, Value at Risk (VaR), Conditional Value at Risk (CVaR) when bilateral contract price was increased one percent in January for 11 Different Cases……....69
Table 5.5 : For Winter Amounts of 7 Contract Variables Actualized in 17 Models and Values for each Expected Return and Variance……………………...73
Table 5.6 : For Spring Amounts of 7 Contract Variables Actualized in 17 Models and Values for each Expected Return and Variance……………….……...75
Table 5.7 : For Summer Amounts of 7 Contract Variables Actualized in 17 Models and Values for each Expected Return and Variance……………………....76

LIST OF FIGURES

Figure 4.1 : Overview of the electricity load demand forecast and simulation model...43
Figure 4.2 : Overview at Distributors……………………………………………………..52
Figure 5.1 : ACF and PACF correlogram before Differencing………………………...61
Figure 5.2 : ACF and PACF correlogram after Differencing…………………………..62
Figure 5.3: ACF, PACF results and Normality Graph after choosing ARIMA
(3,1,1) Model…………………………………………………………..…63
Figure 5.4 : Normality Graphs after choosing GARCH(1,1) Model…………………...64
Figure 5.5 : Histogram of January Temperature Data which show us have
a Normal Distribution……………………………………………………...…65
Figure 5.6 : Temperature Data Histograms for each Seasons…………………………66
Figure 5.7 : Histograms for Case 1, 4, 8, 11 in Winter………...……………………….68
Figure 5.8 : Efficient frontier curve between expected return (profit) and
standard deviation (risk) and efficient frontier curve between
expected cost and standard deviation (risk)………………………………..…77
Figure 5.9 : Efficient frontier curve for winter…………………………………………78
Figure 5.10 : Efficient frontier curve for spring………………………………………..78
Figure 5.11 : Efficient frontier curve for summer……………………………………...79

LIST OF ABBREVIATIONS

ACF	: Sample Autocorrelation Function
ADF	: Augmented Dickey-Fuller
AGR	: Advanced Gas-cooled nuclear Reactor
AIC	: Akaike Information Criteria
AR	: Autoregressive Model
ARCH	: Autoregressive Conditional Heteroskedasticity Model
ARIMA	: Autoregressive Integrated Moving Average Model
ARMA	: Autoregressive Moving Average Model
BHFL	: British Nuclear Fuels Ltd
BIC	: Bayesian Information Criterion
CDD	: Cooling Degree-days
CEGB	: Central Electricity Generating Board
CHP	: Combined Heat and Power Plants
CVaR	: Conditional Value at Risk
DLR	: Dynamic Linear Regression
EDF	: Electricite de France
EPAct	: Energy Policy Act
ES	: Exponential Smoothing
GARCH	: Generalized AutoRegressive Conditional Heteroskedasticity Process
GDP	: Gross domestic product
GW	: GigaWatt
HDD	: Heating Degree-days
IPP	: Independent Power Producers
KPSS	: Kwiatkowski-Phillips-Schmidt-Shin
KWH	: KiloWatt
LTLF	: Long-term Load Forecasting
MA	: Moving-Average Model
MPT	: Modern Portfolio Theory
MTLF	: Medium-term Load Forecasting

NEM	: Australian National Electricity Market
NP	: National Power
OTC	: Over the Counter
PACF	: Sample Partial Autocorrelation Function
PG	: Power Gen
PURPA	: Public Utilities Regulatory Policies Act
SC	: Schwarz Criterion
STLF	: Short-term Load Forecasting
TSO	: SO-(transmission) system operator
VaR	: Value at Risk

LIST OF SYMBOLS

Agreed threshold	: s
Basis Contract	: W
Bilateral Contract Price	: f_2
Bilateral Contract Variable	: x_2
Carbon Dioxide	: CO^2
Daily element	: D_i
Degree Celsius	: C^o
Degree Fahrenheit	: F^o
Demand Variable	: x_1
Durbin Watson Value	: d
Dynamic linear regression variable (output)	: Y_t
Error Term (Residuals of a model)	: ε_i
Error term	: e_t
Expected Value	: E(x)
Independent Variables	: X_i
Linear combination of the parameters	: Y_i
Market Contract Price	: f_3
Market Contract Price Variable	: x_3
Order of the AR model	: p
Order of the MA model	: q
Permanent element agreed earlier	: k
Process Mean	: μ
Reference temperature	: T_{ref}
Regression variable parameter	: u_t
Sale Price	: f_1
Time	: t
Time Series	: X_t
Time variable parameter	: b_t

Trend component for time t	: T_t
Trend component for time i	: T_i
Weekly element	: W_i
White Noise	: A_t

1. INTRODUCTION

Energy exists within the structure of nature itself in various forms which are called natural energy sources, namely fossil fuels, solar power, wind power, nuclear power and so on. Energy sources are often classified under two headings, such as renewable and nonrenewable natural energy sources. Energy can be generated from natural matter by manipulating those natural sources and forces hidden deep in the core of natural matters under strict control of scientists so as to provide communities with constant forms of energy to satisfy their immediate needs for energy efficiently, effectively and simultaneously. As it is widely known movement is one of the major signs of life, which makes energy both an indispensable and an irrecusable necessity for all living things, running power engines as well as machines. This is because the essence of existence and life is movement because nothing can maintain its existence in space unless it moves around. Human beings have been benefitting from energy both to survive and move so that they can produce what they need to boost their comfort, welfare and happiness. Electricity is one of those energy sources which were invented by Edison only 136 years ago in 1879. It also remained for Edison to distribute electricity loads in a neighborhood of New York in 1882 by erecting electrical wiring post in streets.

In this quantitative research study, it is intended to examine major present researches in order to review various issues regarding to electricity generation, distribution and marketing according to supply and especially demand levels. This study mainly, focuses on electricity demand issues and those factors affecting the matter of electricity loads in many aspects.

To start with, the history of electricity liberalization has been observed and considered to comprehend the structure of electricity market which is viewed in details, with the help of several examples. After that, characteristics of electricity loads and prices are studied and explained briefly.

Moreover, those methods necessary for creating models and forecasting electricity loads have been searched for to find out some major approaches which are applicable to the content of our study are examined.

In addition to this, many articles have been dealt with in details to see and understand different approaches for modeling and forecasting. After studying various modeling approaches to constitute some reliable data for accurate estimations a lot of real life cases are studied. Those cases are studied by performing several research tasks related to those procedures to obtain essential real data analysis as well as some simulations regarding this matter.

Furthermore, Electricity demand levels actualized from 2008 to 2014 are taken into account and thus forecasting of electricity demand for Turkey has been fulfilled in order to predict prospective profit and loss scenarios for electricity distributors in 2015 as well as future contracts to reduce probable risks.

Finally, optimization results have been utilized to discover the best model possible for optimization which will result in highest level of profit but the lowest level of loss being exposed to lowest risk for electricity distributors in 2015. Therefore, the most feasible model for optimization has been obtained and revealed within this context.

Various articles on forecast, simulation and optimization have been scanned, skimmed and considered in Chapter 2 in order to discover essential information to constitute the main structure of this literature survey. In Chapter 3, the following subject matters such as structure of electricity market, characteristic features of electricity loads and prices, modeling of electricity load as well as the relationship between electricity load and temperature factors have been examined throughly. The problem which is our subject matter to be surveyed has been defined and some prior activities have been performed in Chapter 4. Forecast, simulation and optimization methods have been utilized in Chapter 5 to conclude the aim of our problem. Finally, in Chapter 6 all those findings have been considered to generate some suggestions for those electricity load distributors who encounter many challenges within the content of this quantitative literature survey.

2. LITERATURE SURVEY

2.1 LITERATURE ON FORECASTING AND SIMULATION

Many articles and earlier research papers have been studied and analyzed for this literature survey. When the relationship between weather conditions and electricity loads and prices are considered in details, it can easily be seen that these issues have also been studied by many researchers earlier from many different aspects. Among those authors from whose precious ideas I have made great use of are namely (Valor et al 2001) and (Al-Zayer , Al- Ibrahim 1996) studies appear prominently.

It can be seen clearly that weather conditions play a very important role in energy sector because there is a strong relationship between the electricity load and weather conditions, which affect electricity prices indirectly.

(Tol 2009 pp 29-51) cited that climate change is the major cause of all externalities: larger, more complex, and more uncertain than any other environmental issues.

Most researches who conducted various researches in this scope within this respect usually focused on certain countries at a micro-level as cited by the following authors (e.g. Quayle and Diaz 1979; Al-Zayer and Al-Ibrahim 1996; Henley and Peirson 1997,1998; Zarnikau 2003; Mirasgedis et al. 2004; Pezzulli et al. 2006; Giannakopoulos and Psiloglou, 2006; Asadoorian et al. 2007; Cochran et al. 2015).

Nevertheless, all most all of those studies were carried out only for one country, so their research results are often restricted in narrow scope because they consider merely the current range of climates as well as different technologies which were adopted in that country in particular. As a result of this, it is necessary to examine the available data of all countries simultaneously in order to reach more accurate results for generalization but it necessitates us to get involved in working for a long time and spend too much effort as it is known in order to gain much wider insights on certain topics.

According to (Petrick 2010 p. 3-4), the impact of temperature causes various changes on the volume of residential and industrial energy consumption. Consequently, it is possible to conclude that different kinds of energy sources such as oil, gas and electricity usage are directed by a non-linear heating impact. That is to say, the amount of energy consumption do not only decrease with rising temperatures owing to reduced level of demand for energy to heat but also the how fast it goes down go down with the effect of rising temperature rates considerably.

In addition to this, there is enough proof to reveal that temperature fluctuations affect energy usage in various ways depending on inhabitants' economic situation, their income rates as well as current temperature levels. Winter heating is an example for non-linear response. There is not much electricity load demand in winter for heating in countries where moderate climate is widespread whereas electricity load demand for heating decreases to almost zero level if winter season is hot enough to live without the necessity of any heating appliances. Besides, air conditioning exhibits different fluctuations depending on the level of summer heat as well as economic profile of residents because poor people do not use electricity for heating or cooling unless they are exposed to severe weather conditions since they cannot afford it. On the other hand, wealthy people consume electricity extravagantly even if the weather is a little bit hot or cold.

(Sailor and Munoz 1997 pp. 991) cited that the temperature factor was discovered as a dominant independent variable in the method of primitive variable approach. In all of the states of the USA excluding Washington it was observed that summer and winter exhibit clear differences regarding to need for electricity while considering amount of monthly electricity usage versus temperature experienced all over those states in question.

According to another research conducted by (Howden and Crimp [no date] pp. 655-660) in for Australian regions, it was observed that climate has a strong impact on electricity load demand by benefitting from the method of relationships explaining of a large proportion of the observed variance in demand as found for other regions in other countries.

According to (Bessec and Fouquau 2007 pp 2705-2721) a nonlinear connection exists between electricity usage and weather conditions in Europe. In their survey, the connection between electricity load demand and weather conditions in Europe were examined by utilizing a panel model namely threshold which was adopted in 15 countries in Europe during the last twenty years' time.

Among those many primitive variables that affect electricity loads are temperature, humidity, wind speed, solar radiation as well as derived variables including heating degree days (HDD) and cooling degree days (CDD).

Regarding to the usage of heating (HDD) and cooling degree days (CDD), for example as (Al-Zayer and Al-Ibrahim, 1996) cited there are various data on transformation of temperature to consider the issue of non-linearity.

Mostly the connection between electricity load demand, temperature and heating degree days (HDD) and cooling degree days (CDD) were studied by researches who were interested in the connection between weather conditions and electricity usage in details. Similar issues have been examined and practiced during this literature survey. The following factors such as seasonality, effects of serial correlation and of the autoregressive attitude of the weather elements likely to change in calculation of demand proportions are studied from various points of view; therefore, current assumptions have been reached to fulfill efficient forecast outputs.

As it is understood from those previous studies conducted by Valor, et al 2001 pp. 1415 it was released that data related to weather conditions are often among the most prominent weather variables which affect the volume of electricity consumption. This is because almost all of those studies performed within this scope often concentrate on the issue of temperature.

Tol 2009 pp. 29,30 cites that climate changes affect economy significantly which can be observed as definite consequences of temperature variations globally. This case signifies probable effects of weather phenomenon on energy consumption.

According to (Lam et al. 2008 pp. 513-523), energy usage boomed in Hong Kong significantly, electricity usage for ventilation to provide fresh air in domestic and industrial sectors change in particular during the hot, damp summer months. According to the findings in their research in their sector, electricity consumption was in-correlated with the related to two main constituents fixed by benefitting from multiple regression method. Seasonal changes observed in the level of monthly electricity usage in industrial sector were inclined to comply with those of the major constituents more closely than the domestic sector. The regression model is able to yield a clear representation of the yearly electricity usage amount whereas estimation of electricity usage for each month may be different.

There are a lot of important interactions between electricity distribution and weather conditions of a country. The most commonly argued matter among them is the rise in atmospheric CO^2 volume which originates from burning of fossil fuels as a result of this its effects on climate are clearly negative. Here, the effect of climatic fluctuation on energy production and usage is often less usual in research literature. There may be an important effect on energy production capacity in various regions due to climatic variations. This also affects generation of hydroelectricity electricity load. (Sailor and Munoz 1997 pp. 987)

During my literature studies in this field, it has been noticed that the mean daily outdoor temperature has been utilized in almost all research papers from various points of views because it is the best temporal variation of temperature during the course of a day. For that reason, it is necessary to calculate those daily temperature changes by taking into account the factor of population weighted temperature as it is stated in Valor et al. 2001 pp.1415. Many articles were written in this respect. Data related to 11 cities namely Adana, Ankara, Antalya, Diyarbakır, İstanbul, İzmir, Konya, Kars, Malatya, Niğde, Trabzon in Turkey have been taken into account to find out the population weighted temperature index for those cities to come up with some assumptions in this respect for all cities in Turkey in general. In other words, some assumptions and estimations to be utilized for Turkey as values to calculate population weighted temperatures have been gathered by correlating daily temperature data obtained for 11 cities from 2008 to 2014 and their population.

In all of those surveys conducted in this field reveal that researchers mainly observe a large amount of (strong long-term) trend in electricity demand and seasonal variations with peak degrees in summers (highest) and in winters (lowest). Such issues were first studied by Cancelo and Espasa, 2008 pp. 59-83 and it was revealed that the change of demand for electricity load with the effect of temperature is non-linear. That is to say, they increase both increasing and decreasing temperature owing to utilizing of electrical heating apparatus in winter and apparatus for air conditioning in summer but a neutral zone exists which is around 18 C^o where the electricity load demand is not responsively flexible to changes in weather conditions. This non-linear reaction of electricity load demand suggests that utilization of two functions derived from temperature which allow differentiate data regarding to winter and summer. Such a separation action helps us gather much better outcome in the calculation of linear model which may be accomplished by utilizing the degree-day function expressed as heating degree days $HDD_t = max\,(T_{ref} - T_t, 0)$ and cooling degree days $CDD_t = max\,(T_t - T_{ref}, 0)$ where T_{ref} is assumed as a reference temperature. As it is stated earlier neutral area about 18 C^{o} where electricity load demand is inflexible to variations in temperature, 18 C^{o} is regarded as the reference temperature rate.

Yearly regression models may yield more favorable results than a model which takes much longer period of time because many changes occur in weather conditions for longer periods which also affect some other variables likely to increase or decrease electricity consumption for a long time. Therefore, this research reveals that electricity usage rely on variations in temperatures so weather conditions affect the level of demand for electricity considerably. (Al-Zayer ; Al-Ibrahim, 1996 pp.105)

In those articles studied on the issue of a model to determine transfer function intervention to foresee the daily electricity demand rate was described by analyzing the effect of exogenous elements likely to change for determining cooling and heating degree days as well as of those seasonal changeable dummy elements which contain the hours of the day, day of week, holiday, month of year effects.

(Harvey, 1989 pp. 91) This is a linear regression model with or without time variable parameters.

Besides, the importance of varying autoregressive attitudes and dynamic models has been studied in details. As it is mentioned earlier the first problem which has to be responded appears as the reality of a strong trend in the long run observed in the amount of daily load demand for electricity. The common methods utilized to remove those trends in time range are "differencing" and de-trending. That is to say, while implementing the common approach for removing trends in time range necessitates to perform those activities both in correlation and spontaneously.

During this research it has been noticed that another method to be utilized to fulfill the requirements is "Pardo et al 2002 pp. 59 " As it was stated in the article, the daily and monthly seasonality are illustrated by analyzing those related time series at different levels. Calculations in this respect reveal that linear prediction is very important statistically by explaining how and why it happens like that become a trend within this context. In addition to this, it was proved and approved that those following terms or higher terms are not very important in the calculation phase of trend. (Sailor and Munoz, 1997 pp. 989)

Earlier surveys and research texts have revealed important seasonal daily component in electricity load demand ranges (Valor, et al. 2001) (Pardo et al 2002 pp.59)

(Bruhns et al. 2005 pp. 1-8) cited the explanation of the model regarding to non-linear prediction in France for electricity load demand utilized at Electricite de France (EDF). This provides information regarding to dependence of weather and seasonality at various proportions.

The proposed model forces us to bears in mind various seasonal and big impact of different seasons but it also reveals wide serial correlation coefficients with in this respect. Now it is time to mention how to remove the effects of serial correlation coefficients between electricity demand and temperature variations shortly. One of the usual approaches to include autoregressive attitude into models for forecasting are largely based on lagged dependent changeable elements. Although this method is widely used, in the articles surveyed during this literature research study, the second method to remove serial correlation in this model was analyzed by utilizing an autoregressive construction in the error term instead of involving the lagged dependent changeable factor which was first studied by Peirson and Henley, 1994

Different Autoregressive Models (AR) have been experimented by utilizing both Akaike Information Criterion (AIC) and Schwarz Criterion (SC) to decrease the serial correlation seen in the first lags.

Advantages and disadvantages of practices experience by some countries have been explained in the content of recent literature surveys.

(Cancelo et al. 2008 pp 59-83) constructing process and methods utilize by Red Eléctrica de España, the Spanish electricity distribution system operator exhibited in the operation for short-term electricity demand load forecasting. These methods improved in (Cottet and Smith 2003 pp. 839-849) were adapted to various multi-equation methods of half-hourly total electricity load distribution system in New South Wales, Australia. An hourly periodic state space model for modeling French national electricity load was displayed in (Dordonnat et al. 2008 pp 566-587). A lot of models, changing in complexity of functional form and calculation procedures were suggested to enhance correct load forecasting. Double seasonal exponential smoothing models were invented by (Taylor 2003 pp. 799-805) to make univariate electricity demand forecasting for lead times from a half-hour ahead to a day ahead.

(Mohamed and Bodger 2005 pp. 1833-1843) cited that various electricity forecasting models were developed by taking into account some other factors such as economic, social, geographic and demographic issues.

In 6 of the articles studied all of the procedures mentioned above for forecasting have been performed and afterwards different matters have been dealt with in different respects in their fields of studies in details.

In the first article, "Torro et al. 2001 pp. 2-23" the authors performed simulation activity after fulfilling the requirements of forecasting action because temperature is non-tradable and there are not any currently available derivatives for the temperatures of those countries to be studied one by one because weather conditions and temperatures change from country to country every year. That is why, it is impossible to obtain permanent data to avoid the risks of temperature in market prices. Nevertheless, it is possible to simulate some real prospective results of variable temperatures which could be useful when they take positions in assets, or economic activities which are highly connected with temperature rates. It is possible to get expected values either with some real possibilities which come from sample data or unreal possibilities derived through simulation with earlier estimated stochastic models in this field.

In the second article studied " Pardo et al. 2002 pp. 55-70" the authors prepared a model to predict daily electricity load demand in Spain. It has clarified the significance of daily and monthly seasonal construction of electricity load demand. Besides, as a result of pondering both the serial correlation and of the dynamic behavior of the degree-day variables exhibited in the rates of electricity load demand calculation have been underlined. It has been observed that electricity load demand in Spain is highly affected by present and earlier temperatures of the weather mostly before heating degree-days. Therefore, the model devised for Spain displays a high predictive capacity while predicting the amount of daily electricity load demand in Spain.

In the third article titled "Crowley,C. and Joutz,F.L. 2003 p. 1-11" It has been gathered that they have devised special models to determine a standard set of hourly forecasting tools to make estimations accounting for autoregressive structures as well as seasonal cooling degree-day impacts and transaction day change for holidays and weekends.

Therefore, it was possible to calculate short-run flexibilities for the cooling degree-day influences. Afterwards, they applied a simulation over a hot month in particular to consider the effect of a 2 F^0 rise in the daily temperature on the basis of hourly peak loads. The observed consequence is an average electricity load demand rise of 3.8% over all of their forecasting tasks by using real temperature data.

In conclusion, after studying on "(Mirasgedis et al 2006 p. 208-227) that monthly and yearly electricity load predicting in electricity generation plans is a rather challenging job to perform since it is influenced by different elements firstly related to economy and climate conditions of a country directly or indirectly. In their article, they have improved connection of electricity load demand rates directly linked to weather conditions beside seasonal activity patterns by taking into account two multiple regression models together with incorporating autoregressive components to decrease serial correlation. It has been observed that those two models are different on the interval (day or month) basis in order to proceed in time. In general, planning guidance can be achieved through studies on prospective cooler or warmer periods of time than typical years even without any accurate forecast available.

Regarding to literature studies on "Bianco et al 2009 p. 1413-1421" it has been observed that their main objective was to calculated GDP price and GDP per capita flexibilities of residential and industrial electricity consumption roughly as well as to predict the future increase of these consumptions by using various regression models and contrast their outputs with other projections ready to use. It is assumed that the flexibilities, forecast and comments stated would be beneficial to those who make plans for energy and determine policies regarding to future scenarios on the levels of electricity usage in Italy.

Last of all, it is high time to display "Ali et al 2013 p.1-7" article which is the sixth article studied. According to my research, they have inferred the connection between the amount of electricity usage and mean monthly maximum temperature value in Pakistan by making use of a study. ARIMA (Autoregressive Integrated Moving Average) method was selected out of several forecast methods and it was improved to obtain data for the temperature index. It has been understood that the forecast values of mean monthly maximum temperature reveal an increasing trend. Linear trend model for electricity consumption has also been developed as a function of temperature data.

2.2 LITERATURE ON OPTIMIZATION

The reason why optimization approach has been adopted in this literature survey is that electricity load distributors have to foresee their prospective risks and opportunities to increase their profitability and to lower their risks of loss. After the liberalization of electricity market most companies faced various inexperienced cases earlier and risks likely to create irrevocable and irreparable hazards for them. For that reason, they decided to benefit from researches of the following scientists and their articles. (See Harry M. Markowitz (Markowitz 1952 pp. 77)) Because of experiencing too much obscurity in a totally new field of businesses, companies of electricity distribution had to find quick solutions too many problems immediately and they utilized optimization methods to define and to decide what to do in regard to make it clear their positions in respect to their probable risks of loss.

The practice of deregulating and restructuring of electric power industries are widely adopted in most countries nowadays due to various reasons. Turkey has also got involved in these procedures and it is intended to regulate all electricity power generation industry by the end of 2015. Nevertheless, this new trend comes up with various risks due to many reasons. In other words, as in many innovations both advantages and disadvantages occur in the regulation and reconstruction of electricity power generation plants. Because electricity generation firms' priority is to maximize their profits but minimize their risks. Consequently, being aware of those prospective risks and hazards for companies which deal with businesses related to generation and distribution of electricity loads becomes an essential issue to be dealt with initially. When firms determine those hazards and risks, all sorts of effective precautions may be taken to slash those risks. Here it comes the time when to take the first step to determine the weights of their portfolios and optimize it accordingly because investors have to know their risk aversion as soon as possible.

Several risk management methods have been introduced to deal with problems likely to occur in electricity markets in this respect. Risk management may be classified under two headings, such as Risk Control and Risk Evaluation Techniques. As (Liu M et al 2006 pp. 2) cited in their research paper, hedging and portfolio optimization have been explained as a kind of risk control technique. Besides, evaluation of risks and assets of the related company are defined as risk evaluation techniques. Here hedging is essential to offset positions of probable risks, especially in spot markets so that it would be possible for investors to actualize their goals and by some other derivatives such as forward contracts, future contracts, options and swaps and so on. Hedging is divided into two parts namely internal and external. Forward contracts, future contracts, options and swap are constituents of external hedging technique.

In reference (Kaye RJ, et al 1990 pp. 1) and (Tanlapco E, et al 2002 pp. 1-2) hedging the risks of spot price with forward contracts and future contracts have been searched in electricity markets. Forward contracts are the kind of contracts bought by a customer on the condition that providers commit to supply them with an agreed volume of electricity power for a definite period of time in the future. Such contracts are especially beneficial to coordinate both supply and demand side decisions of operations regarding to spot pricing. As a consequence of the terms of their contract, a future contract makes it obligatory for each partner to trade a definite volume of energy at a definite cost/price agreed earlier. Nevertheless, (Liu M, et al 2006 pp. 2) cited that purchaser and merchant/seller of those future contracts have to get involved in and exchange but not with each other.

In my study, future contracts are especially preferred to utilize for both efficient hedging and optimization based on much more realistic data regarding to the matters to estimate optimal electricity load demands. Future contracts are composed of Bilateral contracts, Peak Contracts, Off-peak Contracts and Weather Derivatives Contracts in our research study.

Bilateral Contracts are often based on terms and conditions which are accepted and approved by both parties after tiring and tedious negotiations regarding all terms and conditions of the contract in question one by one.

Peak Contracts can be defined as follows; according to such contracts minimum and maximum electricity load consumption periods are defined according to geographical regions and locations as well as time zones of those countries in question. Afterwards, peak electricity consumption periods are determined clearly by mentioning exact beginning and ending times of those periods on weekdays but weekends and holidays are excluded from this content. According to Enerji Ticareti Derneği, the duration of peak electricity consumption period is from 8.00 am to 8.00 pm Monday to Friday in

Turkey. And if it necessary to mention some other countries, in Germany a similar duration of time for peak hours are accepted but in France this period of time differs.

Off-peak Contracts are just the opposite of peak contracts. That is to say, they bring each other to completion.

Weather Derivative Contracts :

(Zeng 1999 pp. 2075, 2076) Among various factors affecting electricity generation, distribution as well as buying and selling terms and conditions of contracts to be adopted in dealing with matters regarding to finding out how to include and exclude them in terms and conditions of contracts becomes a hot issue to be dealt with carefully, delicately and tactfully during the transactions of such contracts. For that reason, weather phenomenon must be considered in all its aspects to pursue business management in the field of electricity successfully. A weather derivative is a kind of contract between two sides specifies how to handle terms related to buying and selling parts of electricity loads between parties in different weather conditions during the period of contract.

Weather derivatives are composed of three widely used derivatives namely call, put and swap. Therefore, parties of a call contract are buyers and sellers. They come to an agreement on the duration of the contract and weather index which constitutes the basis of the contract defined as W. For instance, W may be regarded as the total amount of precipitation during the period of the contract. Merchant/seller gets a bonus from the purchaser in advance but the seller pays the buyer some money calculated as follows by taking an agreed threshold S as in the following formula $P=k(W-S)$ if W is bigger than S. Here k is a permanent element agreed earlier which makes the volume of remittance/payment for per unit of weather index certain.

A put is similar to a call contract except for the cases when S is more than W. The payment, P is equal to $k(S-W)$ of P_0 for a linear or binary payment plan. A call or put stand for insurance policy. A swap contract transacted between two sides/contractors such as A and B makes it necessary to include no up-front premium at the end of the contract. In this case, the party A pays his utility bill as in the volume of $P= k(W-S)$ but if the value of P comes up negative, B pays back to A. In other words, a swap is a kind of contract as a combination of a call sold to B by A or a put sold to A by B. Here, the S is chosen as a value so that call and put control the same amount of premium. Due to the too much flexibility of the choice of *W* weather derivatives need to be structured to handle various risk management necessities. Here, widely known practices are associated with the consumption of electricity highly affected by temperature changes depending on seasons. Extreme weather conditions do not only lower the number of kilowatt (KWH) hours but they also reduce the price per KWH in contracts transacted according to terms and conditions of deregulated energy trading market which, reduces the revenue of utility companies which trade electricity. Those derivative contracts based on seasonal heating degree days (HDD) and cooling degree days (CDD) are often utilized to manage risks which originated from weather fluctuations. As it was mentioned earlier, those formulas actualized as HDD and CDD and contracts have been put into practice in this scope of this study.

2.2.1 Portfolio Optimization

It is often included among those risk control techniques and it refers to assigning energy purchasing and selling instruments optimally bearing the objective of maximizing profits/benefits in mind while trying to minimize probable risks likely to occur. According to (Vehviläinen and Keppo 2003 pp. 2) and (Sheble 1999 pp. 1,2,3), two types of approaches which may be utilized to deal with prospective portfolio optimization issues existed to deal with matters within in this context. It is called decision analysis and modern portfolio theory. On one hand, decision analysis necessities to determine all probable events with their results, possibilities as well as the constitution of a decision tree in accordance with these data and the assessment of decision tree. On the other hand, modern portfolio theory (MPT) is another technique which may be adopted for portfolio optimization.(Liu and Wu 2006 p.1513; Liu et al. 2006 p. 4; Gökgöz 2009 p.44-45) . The essential part of this approach is mean-variance optimization. There are not adequate number of studies conducted regarding to utilization of MPT in electricity power markets. Although it is a very famous practice in the field of financial literature, a brand new method to deal with issues related to electricity power businesses has been introduced.

Here, modern portfolio theory has been adopted to maintain optimization practices. On one hand, in regard to the classical portfolio theory it is supposed that risks of investment may be avoided by devising portfolio from various shares of different investment instruments such as treasury bills bearing different maturity dates on the bases of various foreign currencies by means of diversification. (Gökgöz 2011 p.359-360) On the other hand, according to modern portfolio theory it is very important to consider relationships such as correlations, motion of portfolio commodities with each other by means of diversification as well as responses to portfolio of risk management. It is possible to build a portfolio which is able to satisfy needs in this respect by considering the factor of motion of securities so that the portfolio owns the same prospective return but it must have lower rates of risks than a portfolio built by neglecting those probable transactions among various securities. Due to the fact that it is not possible for investors to know for sure how much return their assets will yield to them together with some probable risks necessitates it to discover ways how to predict hazards and risks likely to occur. For that reason, scientists introduce some methods to calculate those prospective risks. Investors must be aware of weight percentages of their assets in their portfolio because it is an important problem for them. It is defined as a portfolio selection problem. It remained for Harry M. Markowitz (Markowitz 1952 pp. 77) to come up with a solution to this problem in 1952. Markowitz suggested that portfolio selection must be performed in two steps. The first step consists of making observations and gaining competence as well as giving up old beliefs regarding to future practices about securities ready to use. During the second step, those beliefs related to future practices and their ends are dealt with by choosing the most convenient portfolio.

According to Markowitz's portfolio theory based on mean-variance optimization procedures which investigates adequate portfolios, it is necessary to provide an adequate portfolio which is intended to own minimum risk for a given level of return or maximum return for a given level of risk. Another basic supposition must be accepted so that rational risk-averse investors can choose their portfolios by using merely mean-variance criteria for optimization. Here, major suppositions of mean-variance analysis rely on the following matters

a. Most investors often prefer lower risks to more for the similar volume of prospective return because they are exposed to risk averse.
b. Investors must be aware of the facts related to excepted returns, variances and co-variances of all sorts of commodities/assets/merchandise.

c. Investors must also be aware of both the expected returns, variances and the co-variances of returns to define their optimal portfolios.
d. They neither have to pay any transaction costs nor suffer from limitation for taxes.

2.2.2 New Trends On Electricity Market In Turkey

Global electricity markets are composed of three main types of market structures such as Spot Market, Physical Market as well as Derivatives Markets. Spot markets rely on balance and/or day ahead spot markets but physical markets depend on bilateral and/or physical forward contracts. On the other hand, derivative market which are also adopted as a financial instrument of electricity with futures, options, swap and some other derivatives are benefitted from in several electricity trading transactions.

Here it is important to maintain frequency value of electricity network integrated around a specific value in order to keep interconnected electricity distribution system in a secure and permanent position. Irregular and immediate electricity load changes must be eliminated by load rejection or acceptation of electricity generation plants to compensate for losses for both parties in question because too much electricity power directed into interconnected system is likely to cause hazardous increase in frequency of electricity current but opposite cases reason in decreases in electricity frequency. That is why, balance markets are established to react this sort of cases in a short period of time which is often much shorter than 15 minutes. For that reason, they are called as real time markets. According to the principles of day ahead market, all of the energy generated must be bought and sold within 24hours time but in Turkey this duration is modified as 12 hours and 36 hours before real consumption time. Nowadays Turkish electricity market is composed of mainly two market environments, such as balanced market for keeping load fluctuations in balance as a spot market and bilateral contract implementation. On the other hand, another type of electricity market namely day ahead market has also been introduced in Turkey.

3. PROBLEM DEFINITION

3.1 LIBERALIZATION

Liberalization generally refers to a relaxation of previous government restrictions. Market liberalization was first adopted in many walks of life by several countries approximately forty years ago. Before the Liberalization of the electricity market most of the activities realized in this field were monopolized. Because in those days utility services as well as security, education and providing public transportation for the community were regarded as indispensible rights of the public and compulsory duties and responsibilities of all governments to the society. Soon after the Liberalization, only a few companies got involved in electricity market and thus a new niche was brought into existence which created a complex structure in electricity market by those new actors. One of the major reasons of liberalization of the electricity market was to bring a dynamic and competitive system in the electricity market to encourage initiative entrepreneurs in the field of electricity distribution business because the market liberalization requires a system of competition to supply consumers with electricity in reasonable prices. Finally, energy market regulatory institutions were established in countries where electricity generation and distribution were liberalized to regulate such complex and costly systems because electricity supply is a natural monopoly.

The act of Electricity market relaxation was initiated in Europe at the beginning of 1990s. Electricity demands are still growing all over the world dramatically, as a result of which those old power plants and electricity distribution systems do not serve their purposes efficiently, effectively and properly.

Electricity power market relaxation was first introduced in Chile. The electricity distribution renovation, which was put into practice in 1982, stemmed from the opinion of separating electricity production and dispatch businesses so as to enable those companies to specialize in their own business fields to perform their duties and responsibilities much more efficiently and effectively.

After the introduction of electricity market liberalization in Chile, the reorganization of the British Electricity Sector was commenced in 1990. In the first place, only England was included in the act of the liberalization of the wholesale market solely afterwards, Wales and Scotland also joined in the same system until 2005.

Norway, Sweden, Finland and Denmark in Scandinavia came together to constitute an institution namely the Nordic market in order to operate and regulate the electricity distribution businesses in 1992. After that, liberalization of electricity market was reorganized to deal with production and dispatch of electricity in Victoria and some other places in Australia in 1994. After that the Australian National Electricity Market (NEM) was established in 1998. Similarly, New Zealand followed the example of Australia and reformed their electricity power production businesses at the same time, but they officially launched the electricity market in 1996. Several markets located in the North East regions of the USA namely New York, Pennsylvania and some other states began operating in North America at the end of 1990s. Similarly, electricity production and dispatch businesses were liberalized in California in 1998. In three years time Alberta in Canada followed the same plan.

Nowadays liberalized electricity markets have been consistently developing all around the world. This new temptation to liberalization of electricity markets are more widely observed practices in European countries recently.

A few of the frontiers seen in electricity market reorganization have been working for more than fifteen years effectively. Some other companies have still been striving against various red tape and redtapism to improve their electricity market performance because there are still a few reforms to be introduced in this new business field.

3.2 THE MARKETPLACE

It is hardly possible to store electricity because of its unique nature. Electricity power is a kind of energy which must be ready to use wherever and whenever it is necessary for immediate usage. It is almost impossible to keep electricity in stock under normal operating conditions; otherwise, customers will be deprived of convinces that electricity provide for people. Due to the nature of electricity customers do not queue for it because the exact amount of demand should be available instantly. Moreover, the rate of demand and supply change every minute.

Furthermore, there has to be a transmission system operator in order to coordinate the distribution of energy generated by power plants to meet immediate demand for electricity throughout the region or country. Besides, there are some other factors which affect the rate of electricity to be transmitted within the inter-connective system negatively due to loss of electricity energy for various reasons during the dispatch of the electricity currents because electrical wires and bad weather conditions cause the transmission system lose some of the electricity such as resistance of electrical wires to the flow rate of electricity currents as well as illegal electricity usage as it is widely seen in the Eastern Region of Turkey.

3.3 WHOLESALE ELECTRICITY MARKET

There is a wholesale electricity market which operates throughout a country in order to provide consumers with the benefits of a competitive electricity domestic market all over the country both to regulate and control pricing policies for generators and retailers. Therefore, both regional and local sub-contractors engaged in distribution of electricity in certain areas re-price and sell the electricity to make their on profits to pursue their businesses effectively in those areas where they are assigned for. As it is a widely used practice in New England, some exclusive domains of large suppliers started to open up their services to end-users by offering much more beneficial electricity price rates. Large end-users are also seeking for opportunities to reduce some costly in their energy expenses so they are trying to reorganize the benefits related to buying and selling electricity. According to this new trend those who need to purchase electricity from those firms which are engaged in electricity production businesses is a rather new field of businesses.

Purchasing electricity in large bulks has also some of its drawbacks due to many fluctuations in electricity market, their monthly or annual payments for membership, as well as some other similar costs, because electricity to be used for immediate needs must be bought on a daily basis. In fact, as long as the end-users electricity loads get higher, their benefits also get bigger. That is to say, those end-users who need to buy more electricity are offered much lower electricity prices.

3.4 ELECTRICITY TRADING

It means purchasing electricity without taking into account who the suppliers and end-users are. On these days, ,in the liberalized structure trading a similar approach and practice have been adopted as a result of which consumers are able to choose and change their suppliers according to benefits the providers best meet up their needs and expectations.

According to Penados, 2008 pp. 13, some major modifications are necessary in the concept of electricity consumption in public opinion because electricity is not a merchandize in the eyes of ordinary people. They think electricity is not something to buy or sell but it is a service which must be provided by government. According to this new trend electricity is a kind of commodity to be traded.

In other words, if we want to explain the lexical mean of "commodity" as it is conveyed in Collins Cobuild English Language Dictionary 1987 p. 278,

> *Merchandise, product. A commodity is something that is sold for Money, such as food, clothing or machinery. EG the best land is reserved for such commodities as coffee, cotton and bananas. Labour can be traded just like other commodities.*

Trading electricity can be classified under two headings such as organized and non-organized. Non-organized trading (Over the Counter) means that such kind of trading has no certain formats, rules or regulations but it only depends on bilateral, verbal promises. On the other hand, organized trading is known as a redesigned market governed by spot markets which are often regulated as Power Exchanges and Power Pools. In the redesigned markets buying and selling transactions and devised situations to run are established according to certain market rules but in the prices which occur in spot markets constitute an essential allusion or citation for monetary and trading between two groups or people culture and in some other kinds of markets.

3.4.1 Electricity Power Exchanges and Power Pools

When the liberalization was first created, Power sectors needed to be organized in order to regulate the market at wholesale level at the beginning. That is to say, as soon as the liberalization process commenced, the European electricity industry was forced to undergo a considerable amount of reorganization governed by integrating some new techniques, and modifications within the content of the present framework for redesigning the operation system of electricity dispatch businesses as well as some political commitments and more which caused some essential changes within the structure of Wholesale electricity market. Afterwards, these two major sorts of electricity markets have appeared, such as power pools and power exchanges.

There has been the business of buying and selling electricity ever since those firms of utilities were formed for the first time soon after Edison invented the electric light bulb and later managed to set up a system of distribution of electricity in New Jersey in New-York in 1879. Nevertheless, two important differences between buying and selling electricity before and after the introduction of relaxation of electricity market actualized. The first step carried out was the organizing or re-devising for trading but the second one was that consumers would be free to prefer the electricity suppliers. This was encouraged by the separation between production and transmission sections of electricity. Finally, both the generation and dispatch of electricity supply activities were liberated to enhance competition and efficiency in the field of electricity generation and distribution activities.

The most significant trends related to relaxation of electricity market nowadays are those parties who can operate on two separate markets. As they used to perform their duties and functions traditionally; nowadays, transactions regarding to purchasing electricity based on bilateral negotiations and agreements on the Over-the-Counter (OTC), where huge amounts of electricity buying and selling transactions are still being actualized. Besides, in Organized Day-Ahead Markets which are named, Spot Markets. To clarify the concept of Spot Market, the following sentences will make it easier for us to understand the issue. It is widely known that the market clearing price means the spot price. In fact, the spot electricity market is another term for a day-ahead market because in such kind of electricity trading, affairs terminate the day before delivery.

There are two sorts of organized market or spot markets such as Power Pools and Power Exchanges.

According to (Penados, 2008 pp. 13-15 and also Boisseleau, 2004) the main dissimilarities between the two trading models are explained and defined by making use of two criteria which are defined as initiative and participation. It means that power pools are the consequences of a public plan and the participation is compulsory. It implies that all sorts of electricity power must be bought and sold from the same source. On the other hand, Power Exchanges are encouraged to be established on the basis of private sector and it is not obligatory to join in the system.

What is more, According to Weron, 2006, pp.4, it is a widely accepted practice that a power exchange is included into the private market by gathering those parties such as electricity generators, distributors as well as other business people who are engaged in electricity sector to provide electricity power for their prospective customers. Several countries such as Germany, Holland, France and so on established an institution to deal with electricity businesses for Europe.

In order to make it clear, the sample of the pool adopted in Europe which was introduced in England and in the Western part of England pools were included between 1990 and 2001. Another institution namely OPCOM pool was founded in Romanian between 2000 and 2005. The last but not the least, power Exchange model which is the most widely used institution in Europe can be illustrated as Nord Pool example in Scandinavia countries in 1993 which is followed by Omel in Spain in 1998 and the third one is APX established in Netherlands in 1999.

3.4.1.1 The England and Wales electricity market

Liberalization of electricity power markets was initialed in Europe after the UK Government Act was enacted in their Parliament in 1989. Until 1990, the electricity market in England and Wales was a monopol. As soon as the reform was introduced a few electricity supplying companies were able to operate in the business of generation and supply of electricity but before that all of the generating and supplying assets were owned by the Central Electricity Generating Board (CEGB).

3.4.1.2 The Nordic market

Nord Pool was known as Norwegian Electricity Market until 1992.But soon after Sweden (1996), Finland (1998) and Denmark (2000) joined into the Norwegian Electricity market it was renamed as Nord Pool. It was the first International Power Exchange market in the world.

3.4.1.3 Northern America

Liberalization of Electricity Generation and Dispatch in Northern America was introduced in the late 1990s.

3.5 THE CHARACTERISTICS OF THE ELECTRICITY LOADS AND PRICES

Electricity market have a few characteristics which can be conveyed as highly inflexible demand, frequently repeated interaction and clearly visible prices. As a result of this, it is suitable for the tasks of research and exercise of market power. A robust framework should be set up to define and quantify the real scale of market power.

Electricity is a very unique commodity due to various reasons. Because electricity is much more essential than those other kinds of commodities which their price spikes may result in heavy-tailed distributions of returns as well as very expensive price changes. Both demand and supply of electricity highly depend on weather conditions.

Electricity demand varies depending on weather conditions throughout different durations of a year. For instance, due to using air-conditioning (A/C) appliances too much on hot summer days makes it necessary to maintain comfortable conditions in both domestic and industrial areas separated for human beings if people are capable of paying their utility bills without setting any limits. (Al-Zayer and Al-Ibrahim 1996, pp.1)

Seasonality reflects the mean-reverting nature of spot prices as well as the loads of electricity at the daily, weekly, monthly and annual timetables, but they are not influenced by the hourly basis.

That is why, the precise and correct analysis of these characteristics has a vital importance in order to understand and design efficient and effective models of electricity loads and prices.

The principle characteristics of electricity markets may be expressed as follows:

a. It is not possible to store the regulated- alternative current (A/C) electricity.
b. There must be simultaneous balance of supply and demand controlled by the system operator.
c. Both demand and supply scales are highly inflexible.
d. Costs of investment, generation and distribution may exhibit a wide range of volatility at certain times.
e. There may be capacity constraints in transmission of electricity which are likely to affect the electricity network as a market.

Some innovations introduced through liberalization

f. Consumer attitudes have changed as a consequence of much greater flexibility on the demand side.
g. New contract forms have been devised due to price competition, change of supplier, price information systems, risk hedging facilities as well as different focus points of costumers.
h. Some new players have joined in the electricity markets such as Brokers, traders, clearing companies, retail chains, petroluem companies, financial analysts, international energy companies.
i. Finally, due to introduction of new systems, actors and business methods, some new organizational forms, such as co-operative and outsourcing arrangements, concern models, horizontal and vertical intergration to end-consumers, separation and unbundling of competitive and monopoly functions.

3.5.1 Price Spikes

Electricity markets exhibit various unique features. The most commonly mentioned character of electricity markets is the Price Spikes. Price Spikes are also known as “Jumps” which means sudden high volatility in the spot prices of electricity market owing to various factors. The system price may arise dramatically suddenly and may also go back to the previous rate of prices in a very short time.

These nonpermanent price spikes affect the firms in the electricity markets considerably, especially when the firms are not ready to deal with these risks promtly and properly. The price of electricity is exposed to sudden price changes more than other assets and merchandise.

According to Weron, 2006, pp. 26, price spikes are likely to change depending on several factors, such as peak hours, working days, holidays as well as seasons.

As the time horizon goes up and more data are collected the spikes become smaller and smaller clearly. Therefore, the impact of price spikes is often neutralized in the data for the averages of weekly or monthly variations. The spikes normally last for a very short time because prices of electricity go back to a normal rate after severe weather conditions are over. Price spikes may necessitate buy insurance policy for protection against sudden electricity prices movements although they occur very rarely.

The matter to be discussed in this respect is that load fluctuations do not always result in price spikes in some cases because electricity prices are determined according to several nonpermanent factors. Some technical constraints underline the market should be kept in mind in order to comprehend this phenomenon. Both the supply and demand levels should be considered throughly by taking all of their direct and indirect effects into account. Causes of extreme spikes result from unpredictable attitudes of both suppliers and electricity consumers in cases when sudden severe weather conditions occur or when some unforeseeable difficulties affect the costs of electricity generation on behalf of electricity producers due to shortage of and lack of natural energy resources to keep their power plants running. The main reason why price spikes generally occur in the electricity market is that the attitudes of both suppliers and electricity customers and consumers can not be foreseen. This causes ambiguity; therefore, both parties do not know how to react to the new situation and they cannot perform their duties and responsibilities as usual.

3.5.2 Seasonality

Weather conditions change every season naturally but in some seasons severe weather conditions are experienced due to sudden volatility in regional climate. As a result of this, the amount of electricity demand displays seasonal fluctuations because varying conditions of climate, such as temperature and for how many hours daylight is available mostly cause unexpected shiftings. As it is known, depending on their global locations, the climate of some countries exhibits very high seasonal variations in the supply side of those countries.

Electricity demand is much higher in winter than in summer in some countries. These electricity demand levels go up and down depending on the climate zones and climate types of those countries. The electricity demand levels mostly arise in summer seasons because the weather is very hot in summer. On the other hand, in countries where severe winter weather conditions are dominant, the electricity demand levels go up their peak levels although demand for electricity goes down considerable in summer time. Another reason why electricity demand and supply change according to seasons is that the amount of electricity generation in hydro units is highly depended on the amount of precipitation and snow melting rates. This causes rapid fluctuations in the amount of available water to keep the hydro power plant running. Besides, demand for electricity is inclined to fluctuate during the day as the temperature goes up and down because of human activity. Electricity demand levels change during the day and at night because the rates of domestic and commercial consumption of electricity rise during the day but decrease at night since the level of human activity goes down to its minimum level. In both seasons, there is often a considerable amount of surge in demand in the morning because people wake up and start using electrical appliances such as kettles, toasters and power showers whereas this abrupt surge increases much faster over a shorter period of time in winter. (Gavin 2014 pp. 73-74)

Demand for electricity rises to its peak levels from 6:00 am to 8:00 am but it begins to stabilize at around 9:00 am because most people live in their homes and afterwards in offices and shops. Therefore, office electrical equipment such as computers and some machines are utilized gradually.

A second surge takes place later in the day from 3:30 pm to 5:30 pm in the winter season since school children leave their schools and return home and finally the working day comes to an end.

When children and their parents go back home, they turn on several home appliances, such as cookers, televisions, home computers and kettles. After dinner demand for electricity falls and drops off when people go to bed. This evening surge is not evident in summer because people return home when there is still sunlight. Consequently, they stay out in parks or in their gardens until late in the evening so they do not consume as much electricity as they use when they prefer warm beverages or food in winter.

Moreover, air conditioning units in shops and offices are turned off in the evenings in summer which also lowers domestic electricity consumption in the evenings in summer.

According to Rubia, 2001, pp. 1-2, daily electricity demand and daily prices quoted in electricity power markets are often exposed to high rate of changes related to seasonal patterns at different times. Both modeling and forecasting probable electricity load demand for short periods of time especially an interesting issue business people, because of the character of electricity it is not possible to store.

In brief, electricity demand and supply as well as daily spot prices of electricity markets exhibit highly volatile attitude which contain strong seasonal climate patterns related to different times of the day, weeks, months and seasons of a year. Thus, the modeling and forecasting the amount of future demand for electricity are especially important point for market partners to take into account because it is not feasible to store electricity to meet electricity load demands later on.

3.5.3 Seasonal Decompositions

As seasonal decompositions cause great deviations in calculating the data to forecast future demand and supply levels which affect correctness of calculations, the seasonality in the data are removed. The content of the data should be checked throughly to make sure there are no data related to seasonal decompositions left with in the content of the general final data to be dealt with. For this reason, techniques for modeling or removing must be chosen. There are mainly 5 techniques to be utilized to remove the seasonality in the data: Differencing, Mean or Median Week, Moving Average Technique, Annual Seasonality and Spectral Decomposition, Rolling Volatility Technique.

3.5.4 Mean Reversion

In finance, mean reversion is an assumption that price of a stock is likely to change the average price of electricity over time. When the current market price is much less than the average price, the stock is much more attractive for consumers to buy because consumers know that the price of commodity will rise sooner or later. But naturally market price is expected to go down when the current market price is much higher than the average price. That is to say, variations in standard prices are often likely to change into normal levels in time.

Spot prices are likely to change depending on the sort of commodity to be purchased. There are various factors which accelerate mean reversion depending on many factors including the commodity itself as well as the delivery provisions related to the commodity. All of those factors including the commodity itself must be analyzed completely. When it comes to electricity markets, it is a widely used practice to watch abrupt price spikes to regulate them according to recent changes and former prices. For example, prices of natural gas, the rate of mean reversion is rather gradual, but the fluctuations for long run purchase deals are generally much less than the fluctuations for the short term ones. On the other hand, the proportion of mean reversion in oil markets is considered to be much longer periods so it may last months, or even years, for the prices of electricity to go back to their normal mean rates. (Weron, 2006, pp 49-50)

3.6 MODELING AND FORECASTING ELECTRICITY DEMAND LOADS

Energy of electricity may be utilized as a kind of merchandise to trade in a competitive market price. In other words, electricity is traded at current prices just like other assets.

Consequently, amounts of risk shared by electricity power producers, electricity traders and as well as buyers of utilities have increased considerably. For that reason, a great deal of statistical analysis and conscious estimations and forecast studies are necessary to regulate and manage a company which is engaged in today’s irregular electricity markets. Not only price fluctuations but also volatilities both in demand and supply of electricity result in various risks to be dealt with long before such hazardous deviations cause destructive effects on all parties involved in the businesses of electricity production, distribution, trade and consumption.

Even those who have long-term contracts cannot escape from negative effects of the electricity market because electricity generators and distributors must make a profit to supply electricity consumers with their services in reasonable prices in the future. That is to say, if electricity producers and distributors cannot make enough money to guarantee their services regularly, sooner or later, they go bankrupt so it is not possible for them to pursue their businesses. Moreover, actual demand for electricity may not meet the levels of previous estimations foreseen earlier times when contracts were signed because the businesses of electricity production, distribution and trade are widely vulnarable business fields especially at high fluctuation times. Furthermore, the phenomenon of deregulation has not developed the risky situation at all and it necessitates estimation and forecasting studies for all partners of the active electricity market.

After the introduction of liberalization in electricity markets, electricity businesses were somehow reorganized. Thus, monopolies which are engaged in utility services used to make short-term estimations to make sure that the sustainability and reliability of long-term demand and supply forecasts are in line with the basis of calculations for taking decisions on how to invest money in order to create more potential for electricity production. However, the situation has changed dramatically because of new regulations and actors who got involved in businesses of electricity. This created a highly competitive electricity market.

On the other hand, there have been various factors which affect expenses of over-contract agreement and under-contract agreement and then trading electricity power on balancing market. They result into much unexpected augmentation that they are likely to result in huge financial sufferings of the utility. As a result of this, it has been quite significant to minimize the volume of risks to avoid from making a loss. Besides, electricity demand forecasting has turn out to be one of the major issues to be dealt with immediately to secure integral procedures in designing and operating of electricity production plans, energy providers, operators as well as other market partners.

Due to the importance of this matter, rates of fine to be imposed for forecast errors have been increased to make sure that the rate of errors will reduced to very little levels to by a small percentage.

Electricity demand forecasting also enforces utility partners to make accurate predictions for both volumes and locations over different durations of time for correct planning. Since it is not possible to pursue businesses in all walks of life without electricity supply, the basic quantity of interest in the field of electricity is typically considered according to electricity load on hourly basis. Nevertheless, electricity demand forecasting is also deeply related to the procedures of hourly, daily, weekly and monthly prediction values of the electricity demand and peak electricity demand in the interconnected system. Estimations and predictions made for different time periods are quite essential for different transactions in a firm.

Even the characters of such forecasts are not the same for all partners who are engaged in electricity businesses. For instance, it is possible to guess the very next day load with a few percentage errors; however, it is not possible to guess peak load for the coming winter with the same accuracy. That is why, it is much more feasible to predict the normal winter weather conditions to estimate the level of peak load. This forecast would substitute for peak day standard weather conditions for a definite area in winter.

The duration of prediction is often classified under 3 headings such as, short term electricity demand forecasting, medium term electricity demand forecasting and long term electricity demand forecasting in terms of future planning in order to continue electricity demand forecasting studies in details.

Although active researches on prediction of electricity demand procedures date back to old times, it is still a challenging duty to perform.

In the first place, the electricity demand time sequence display seasonality such as daily, weekly and annual time scales. Another reason why such calculations are necessary is that there are a lot of exogenous variables such as weather conditions and social events.

A wide variety of methods and ideas have been introduced to perform tasks for load forecasting, at different levels of achievement. Those methods can be classified under two large headings:

i. Statistical approaches, such as similar-day (or naive), exponential smoothing, regression and time series methods.

ii. Artificial intelligence-based (or non-parametric) techniques, such as neural networks, fuzzy logic, expert systems and support vector machines.(Weron, 2006, pp 68)

The amount of electricity energy consumption is growing rapidly due to the increasing effect of environmental and human activity. Thus, the pattern of electricity demand gets much more complex and unpredictable. For example, both the number and variety of electric appliances used all around the world have been increasing dramatically because most of them are environmentally related so they increase both cyclic variation and noise on the demand side. Although a lot of forecasting methods have been devised and introduced, none of them can be adopted to perform tasks efficiently and effectively in all cases, especially when so many factors must be considered during the forecasting procedures. Consequently, the matter here is not just adopting a common method to reach a proper forecast. That is to say, different cases need different methods to obtain satisfactory forecasting outcomes. That is why, such research studies must be performed by utilizing specially designed or assigned methods to get the most accurate forecasting results. Electrical power plants installed in any country prefer often tend to create or adopt the most suitable method for their cases.

According to Pedregal and Young, 2002 pp. 91, There are a lot of areas where quickly-sampled data are available for instance on the basis of hourly, daily, weekly time periods and so on. Two major problems are likely to arise in this type of data so some measures must be taken to avoid from probable mistakes. In the first place, in order to succeed in providing an adequate representation of data the length of time series must be long enough to make correct estimations such as data based on monthly specimen. Secondly, both the amount as well as the complexity of the models of attitudes existing in the content of the data are very significant for realistic calculations, especially while dealing with the parameters which are necessary to actualize an acceptable illustration of such time series would be too many if the methods devised for less quickly-sampled time series were utilized without changing. Therefore, it is necessary to generate some simplifying suppositions and transactions to succeed in obtaining some reasonable outcomes.

3.6.1 Factors Affecting Load Patterns

Electricity load patterns are usually affected by different factors in various ways. Those who deal with jobs related to electricity matters must be aware of those factors their patterns as well as their causes and effects because they have to forecast problems early enough to take the necessary measures to avoid losses in their fields of businesses. These three factors should be considered throughly and applied properly to achieve accurate forecasting results. Initially, the first factor that must be applied effectively is the numerical efficiency of those employed algorithms. The second factor is that those data to be analyzed have to be in good quality to reach accurate results. Thirdly, it is essential to have all sorts of skills and competence to include significant exogenous elements into expected models.

Several variables, including time elements, information about weather conditions, prices of electricity, social gatherings and prospective customer groups fulfill short term load forecasting (STLF) as required. If those obtained inputs to be utilized in our models for making predictions are weak, it will be quite difficult or even impossible to carry out forecasting activities properly and effectively no matter how accurate the model is. In short, three principle factors affect the modeling procedures during the implementation of forecasting action.

While performing tasks related to duration of time, it is essential to be aware of the following points. On one hand, several elements must be considered in details such as time elements, information about weather conditions as well as groups of those prospective customers for short term operations. On the other hand, information about weather conditions in the past, number of consumers in different groups, those apparatus in the area as well as their natural properties including age, data related to economic situation and population of the zone and their forecasts data of appliances sales together with some other factors are taken into account in order to fulfill medium and long term forecasts. Time factors are composed of the hours of the day, days of the week and months of the year because electricity current loads display significant variations depending on those above mentioned fractions of time. For instance, on week days on Mondays and on Fridays which are being adjacent to weekends may have different load patterns structure in comparison to those days from Tuesday to Thursday, especially during the summer. Holidays exhibit a wide range of fluctuations which makes it even more difficult to forecast electricity loads during that time owing to their relative infrequent occurrence. Moreover, weather conditions affect electricity load demands depending on seasons of the year. For that reason, previously forecasted weather parameters are essential factors to make predictions related to short term electricity loads. Different weather variables must be considered to fulfill effective load forecasting tasks because temperature and damp are also the most widely utilized load forecasters.

3.6.1.1 Time factors

Time factors which influence electricity loads may contain any time of the whole year, the hour of the day, the day of the week, and so on. Load profiles display various forms depending on seasons, weekdays, weekends and different times of a day. Electricity loads often occur quite inconsistently from Monday to Friday as well as at weekends because the amount of electricity supply and demand may change considerably due to various reasons and effects.

Due to its highest effect on consumer load, time becomes the most significant factor in load forecasting. It has been discovered that the electricity demand curve here has "time of the day" feature according to observations fulfilled at various grid stations to determine the shapes of the load curves of load forecasting. It reflects similar variations for " the day of the week", "week of the month" and "the month of season" property basis. This conveys that electricity demand curve displays recurrent variations in nature.

3.6.1.2 Economic factors

Nowadays electricity has become a daily need for people, which turned electricity into a commodity. Therefore, economy of countries also affect consumptions of electricity that causes the economic factor turn out to be the most significant one both short term and long term electricity demand prediction tasks. For instance, the daily electricity demand curve shapes of developed countries exhibit quite contrasting patterns in comparison to the daily electricity consumption curves of those under-developed countries. Owing to huge industrial activities in developed countries, it has been observed that electricity consumption rates rise dramatically. This causes their daily electricity consumption curves which increase up to their highest peak levels from 11:00 am to 4:00 pm. On the other hand, peak levels of electricity consumption rate curves go up after 6:00 pm in under-developed countries. That is why, electricity load forecasting patterns display big variations according to economic growth levels of countries. This makes it necessary for us to consider economic conditions of a country while fulfilling load forecasting activities. Another effect on the usage of electricity is people's buying potential as well as the price of electricity. Therefore, higher cost of electricity bills result in lower domestic electricity consumption. For instance, most people in Pakistan cannot afford to pay utility bills for using air conditioner because price of electricity affect the daily electricity consumption load curves accordingly. (Fahad and Arbab, 2014 pp.305-306)

3.6.1.3 Weather conditions

Weather conditions also affect both demand and supply of electricity levels. Besides, weather conditions display the most influential exogenous variables except for time factors. Different weather variables can be taken into account and considered throughly but among them only the factors of temperature and humidity are the most widely adopted to be used as load predictors.

Among various factors affecting load forecasting task, weather emerges as the most significant dependent variable. The impact of weather is the most substantial for consumers who use electricity at home and for agricultural purposes; however, it can also change the electricity demand profile of electricity consumers who are engaged in industrial businesses. For that reason, related weather forecast data and some other factors are taken into account while creating electricity demand forecasting models in order to foresee the probable future load because operational costs are often a priority to minimize expenses. Weather factor is often regarded as the tipping point which is likely to result in unreliability in the interconnected electricity distribution system by reducing adequate provision of energy. Unforeseeable sea breeze followed by afternoon Thunderstorms appear to be some of those environmental elements which are likely to decrease temperature and thus leading to overestimated electricity demand forecast. As a result of this, more electricity is produced than actually needed. Temperature changes can also modify the conductivity of transmission lines. Therefore, the overall transmission potential of electricity wiring lines is affected somehow. High temperature rates cannot only increase the resistance of the electricity distribution wiring lines, but it also change the reactance of electricity lines owing to temperature created enlargement of the length of electricity wiring lines in that area. The weather factor includes the following phenomenon:

1. Temperature
2. Humidity
3. Precipitation
4. Wind Speed
5. Cloud cover and amount of light

Now it is time to define and explain the most important one of these factors and their impact on load forecasting tasks.

3.6.1.3.1 Temperature

According those results obtained by (Paravan, et al pp. 4; Fahad and Arbab 2014 pp.305-306) there is a big favorable positive relationship between temperature and electricity demands in the season of summer; however, there is a negative relationship between temperature and electricity load actualization rates in winter. This reveals that temperature will cause to increase electricity load; however, it will cause decrease in both daily average load and in peak demand. In winter, just the opposite occurs, so electricity load will increase according to the amount of decrease in temperature for per degree. Therefore, as it is seen here, there is a reverse interaction between temperature and electricity demand consumption rates in winter seasons.

3.6.2 Statistical Methods

As it was mentioned above earlier, electricity load forecasting tasks have gained great importance gradually in highly competitive electricity markets nowadays because the risks of supply and demand in electricity markets exhibit high rates of fluctuation due to various hazards for both buying and selling. That is why real time balancing market prices have gone up so much because such risks are likely to result in huge financial loses for both parties. This forces energy generation firms to take some radical measures to minimize their volume of risks in a short period of time. Due to many variables in the field of electricity generation, distribution and actualization of their prospective targets in highly competitive market, it is not possible to design the best single model to deal with such risks safely.

According to (Pedregal and Young, 2002, pp. 91),

$$Yi = Ti + Wi + Di + ei \, , \tag{3.1}$$

where Yi is the amount of electricity demand consumed during a four hour period of time; Ti is a trend element; Wi is a weekly element; Di is a daily element; and ei is the residuals (error element).

Nevertheless, one of the following methods below can be adopted to create protection against probable risks in electricity market.

a. Similar-Day Method
b. Exponential Smoothing
c. Regression Methods
d. Autoregressive Model
e. Autoregressive Moving Average Model
f. Autoregressive Integrated Moving Average Model

3.6.2.1 Similar-day method

Among many factors which affect electricity load generation, distribution and transactions, there are some differences and similarities. Similar historical day data method considers all aspects of similarities to figure out favorable solutions for probable problems by examining all of these factors in details. This method tries to forecast electricity load by choosing similar data that belong to similar days and afterwards, a weighted average is derived from these similarities.

This approach has been devised to search for data belonging to the past for those days which contain similar properties for the previously forecasted day. Those similar properties are likely to include various periods of time, such as day of the week, day of a year or even weather phenomenon. The similar-day method can be utilized to create some unique modeling for special duration of time components such as holiday. After that, the research studies are conducted on the basis of data which belong to the past within one, two or three years. Thus, the electricity demand of similar, the forecast may consist of a linear amalgamation or a regression transaction which may contain some similar days. (Weron, 2006, pp.79)

3.6.2.2 Exponential smoothing

Exponential smoothing method is one of the most prominent forecasting strategies to estimate reliable findings to deal with seasonal effects of the weather regarding to electricity generation, distribution and trade businesses. According to (Pedregal and Young 2002), Exponential Smoothing (ES) methods were first suggested by Holt (1957) and Winters (1960) a long time ago whereas its variations are still widely used due to their huge success and practical utility .

This method was devised by Holt-Winters to forecast seasonal time series owing to its power and are convenient if there is only one seasonal clear periods especially when similarities of demand are convenient pattern in the time cycle series. The weights of earlier observations are much more inefficient than the newer ones. (Jalil et al. 2013 pp. 1540-1541)

3.6.2.3 Regression methods

Matter, 2004 pp.297-298 explained the nature of regression method his book as follows dependent variables are often affected by some variables such as income, temperature, expenses and so on during the application of regression analysis approach. On the other hand, they are also influenced by some other variables which have several important features or in nominal proportion, in nature such as religion, sex, color, nationality and so on.

As explained in the book by Pedregal and Young 2002, pp. 86-89, The Dynamic Linear Regression (DLR) model has become the standard linear regression model after being generalized so as to enable researchers to modify regression parameters available depending on necessitates in time. After considering many confusing parameters, it can be formulated as follows for simplicity and accuracy as in the case of single unknown time variable parameters in the DLR case simplifies to

$$yt = utbt + et \,, \tag{3.2}$$

where *bt* is the Time Variable Parameter and *ut* is the regression variable. This can also be considered output *yt* is interrelated to input *ut* by the time variable *bt* as illustrated in the content of the formula.

More information is compiled about the correlation between independent elements likely to change and dependent elements likely to change when multiple regression method is utilized. Multiple regression methods are often adopted and implemented to estimate the correlation between independent and dependent elements likely to change. That is to say, the major concern of the multiple regression method is directed on the correlations between a dependent element likely to change and more independent elements likely to change. Multiple regression analysis help us to understand how a typical value of a dependent value or criterion value vary when even one of the values are different in although the other independent values are kept permanent in a fixed situation.

Moreover, electricity load forecasting methods are often utilized to design models related to relationship of electricity load and some other factors weather, type of the day, class of customer and so on. This model conveys the load a kind of linear duty of one or more explanatory elements likely to change and also an error term:

The explanatory variable may be as simple as a maximum daily temperature datum or a few complex tasks of some simple variables like squared difference between those minimum and maximum daily temperature variations. In the classical of the multiple regression methods, it is assumed that the relationship between variable displays linear nature.

3.6.2.4 Autoregressive model

Autoregressive Models (AR) are supposed to be a stochastic process which is composed of a weighted sum of the previous value and a white noise error. The simplest AR model is the first-order AR(1).

3.6.2.5 Autoregressive moving average model

ARMA (Autoregressive Moving Average Model) is also a stochastic process composed of some of AR (Autoregressive Models) and MA (Moving Average) models. An ARMA process displays a stationary nature.

3.6.2.6 Autoregressive integrated moving average model

ARIMA (Autoregressive Integrated Moving Average Model) is the same as ARMA (Autoregressive Moving Average Model) except for its being stationary. An ARIMA process is composed of the addition of AR (Autoregressive Model) and MA (Moving-Average Model) components. These models are adapted to time series data either to comprehend the data better or to foresee prospective points of view in the series. They are practiced in some situations where data reveal proof of non-stationary nature, where the first step of differencing (related to the "integrated" section of the model) can be implemented to extract the non-stationary.

3.7 CHALLENGES FOR DISTRIBUTORS

One of the latest difficulties which appeared during the last decades originates from deregulation and liberalization of electricity loads generation, distribution and marketing. It created highly competitive fields of businesses due to extreme volatility. As a result of this new situation, both producers and wholesale consumers are exposed to huge risks owing to price movements which are likely to exceed levels much beyond than those firms can afford because fluctuations in the field of electricity generation, distribution and marketing can cause much more losses than other assets. That is why, Price forecasting has become an essential task in order to supply energy companies with reliable data while those firms are trying to make effective decisions and develop new strategies to deal with harmful effects of those price fluctuations. Solutions suggested within this regard may be classified in terms of setting some new methods both for, the durations of adopting new horizons as well as improving modern methodology to apply to this highly competitive field of business. Generally, durations of price forecasting may be divided into three periods such as short term price forecasting, medium term price forecasting and long term price forecasting; however, there is not any unanimously accepted principles related to matters in this new case of load forecasting steps. As it is widely accepted and put into practice, the main objective of utilizing long term price forecasting is to analyze and plan the prospective investment profitability which is an essential step in order to determine future cites or fuel sources of power plants. Lead times are often measured in years here but mid-term or monthly time horizons are usually chosen put into practice for risk management, pricing derivatives and balance sheet calculations.

4. PROBLEM DEFINITION

As it has been explained in the literature survey section, it has been observed that there are many unknown risks in this new field of businesses after the introduction of liberalization. Various statistical model and optimization tools have been invented either to avoid or to reduce destructive effects of those new challenges in the field of electricity distribution which has a significant role in risk management within this context. Here, in the content of this research study, it has been intended to clarify some probable risks and prospective profits of electricity distributors. The following real data analysis and electricity loads as well as temperature findings for eleven cities in Turkey related to the period of time from 2008 to 2014 has been discussed, considered and their outputs have been adopted both to forecast and to make comparisons while conducting my research on the year of 2015. 1000 profit scenarios have been created for each month of the year 2015 in order to enable electricity distributors to foresee their probable electricity load demands as well as their prospective rates of profit and loss. As a result of this, electricity distributors will be able to see their positions in the competitive electricity market much more clearly. After creating 1000 profit scenarios, their cases of profit and loss will be seen clearly by utilizing future contracts with the help of related optimization tools. Before going into details of the subject matter, it is necessary to say a few words on risk management.

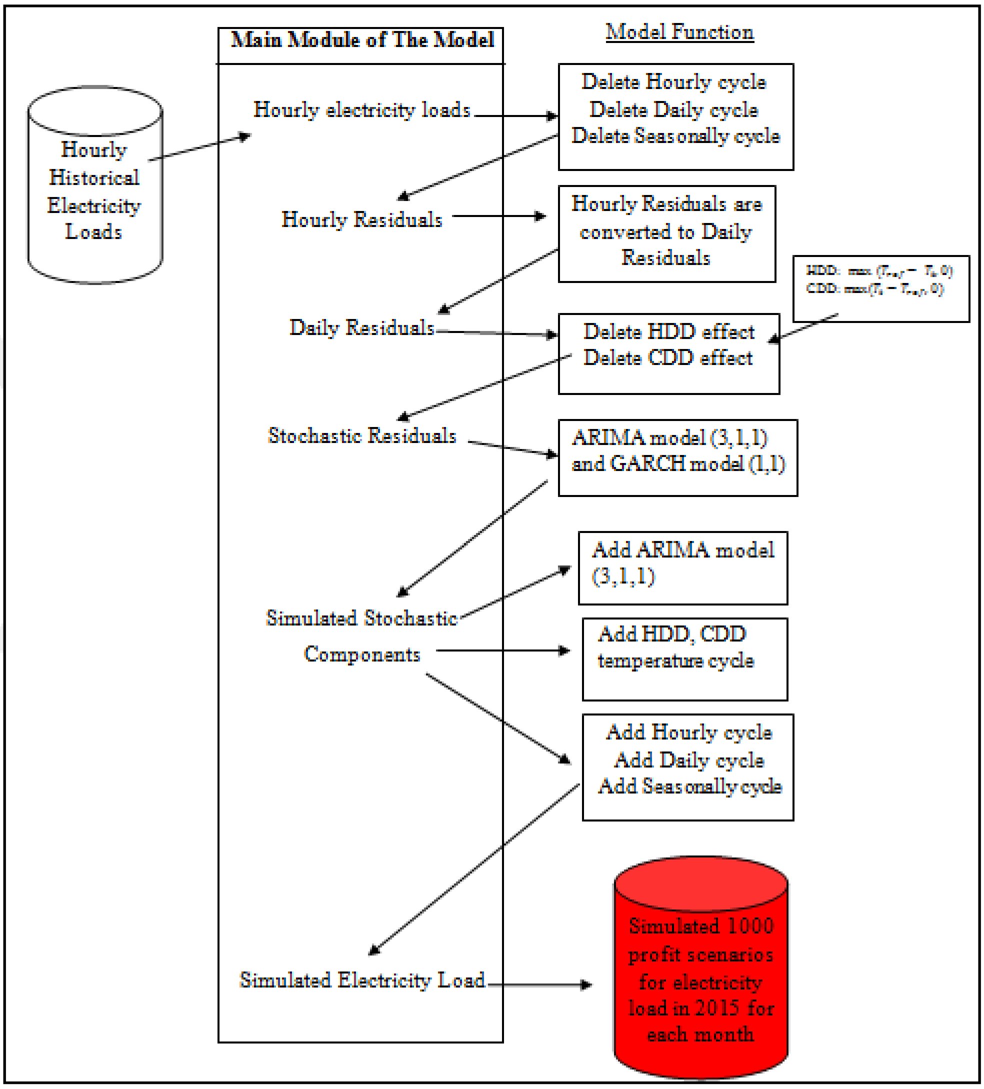
4.1 RISK MANAGEMENT

Risk management in all walks of life necessitates take into account of all probable prospective hazardous acts, events, activities which are likely to threaten objectives to be actualized. Risk management in the fields of electricity generation and dispatch enforces us to bear the following issues in mind. Initially, the capacity of power plant should be flexible in order to meet immediate electricity demand simultaneously because electricity needs must be satisfied as soon as they occur. That is to say, electricity consumers can not queue for electricity as it is not possible to store electricity by any means effectively nowadays. Electricity power plants vary according to their sources of energy to activate electricity generators such as hydraulic, coal, windmill, fuel oil, natural gas, diesel, solar and nuclear. Except for solar energy and windmill energy, all of the other sources of energy pollute the environment and they are not renewable energy sources. That is to say, we have to pay for them continuously to keep those power plants running. On the other hand, solar energy and windmill energy are both free and renewable energy sources. Therefore, the number of solar power plants and windmill power plants must be increased as soon as possible so that the risk of cost will be reduced as much as possible in the near future. Although there is sunshine in Germany only for 65 days a year at most, Germany generates 86 percentage of its electricity demand in solar power plants. On the other hand, there is sunshine almost 300 days a year in Turkey but Turkey is still encouraged to invest money in natural gas power plants and nuclear power plants. Risk management is an essential issue to be considered in all walks of life as well as for participants who are engaged in the deregulated electricity market because of their important price and amount risks that they may undergo in some unfortunate cases. This is because the confusing structure of the wholesale electricity market may result in very expensive price changes at times when consumers' demands go up to top levels as a consequence of electricity supply shortages. Such particular characteristics of prices risks often rely on some physical fundamentals of the electricity market when the mixture of different electricity generation plants as well as the relationship between demand and current weather patterns which affect the environment at that time. Those unpredictable Price Spikes and the steps of price likely to occur will be dealt with in another part separately.

4.2 PHASES OF FORECAST AND SIMULATION

Here is the simplest explanation of those tasks performed in the phase of forecast and simulation procedures illustrated within the following diagram. (See Figure 4.1)

Figure 4.1: Overview of the electricity load demand forecast and simulation model



According to Migon and Alves 2012 pp. 579-580, it is known for a long time that electricity load has a huge amount of components possible to guess beforehand owing to its very powerful attitude related to hourly, daily, weekly and yearly time bases, together with changes based on the weather effects. All of those models devised so far contain constituents that reveal trends, seasons at various rates, dummies to be considered on the basis of time elements such as weekends, holidays and some other special days, as well as a few short-term dynamics beside weather regression impacts, together with nonlinear functions for cooling and heating effects.

Before going into more details, steps of Linear Regression analysis and assumptions have been examined as seen briefly below:

Multiple Linear Regression analysis method is used, if two variables which are linked with each other and also cause to change one of them, then, the other one is also affected by its systematic variation. The formula to calculate those variations is expressed as follows:

Generally Regression Equation

$$Y_i = \beta_0 + \beta_1 X_i + \beta_2 X_i + \varepsilon_i \quad i = 1, \ldots \ldots, n \tag{4.1}$$

Here, Y_i is a linear combination of the parameters, ε_i is an error term and X_i are independent variables.

As it is time to explain those regression assumptions in general, the following arguments can be stated:

1. Variables must be distributed normally

Multiple regression analysis supposed that variables display normal distribution but Non-normally distributed variables, highly skewed or kurtotic variables, or variables with substantial outliers and so on are likely to spoil relationships between variables and the accuracy of significant test results.

2. Assumption of linearity

   If the connection between independent variables and the dependent variable is non-linear, the outputs of the regression analysis will decrease in accordance with the rules of true connection between and among them.

3. No autocorrelation between the data
4. Variance of residuals has to be constant.

As it can be seen in the diagram above, regression method has been utilized to remove the effects of trend and seasonality on hourly electricity load demands with the help of dummy variables. Afterwards, what are left in our hands are hourly residuals which have been converted into daily residuals.

According to (Valor et al 2001 pp. 1414), their previous studies reveal that temperature is usually the most important weather variable which affects electricity demands because conditions affect electricity loads, consumption, distribution, price and production dramatically. The regression method has been repeated a second time to delete the effects of temperature factors (HDD, CDD) from daily residuals. Our temperature data is composed to population weighted temperature of eleven cities in Turkey.

During my research studies in this field it has been observed that the mean daily outdoor temperature has often been utilized almost in all research papers because this factor is the best temporal variation of temperature during the course of a day. That is why it is necessary to calculate those daily temperature changes by considering the factor of population weighted temperature as it is stated in (Valor et al., 2001 pp. 1415) to fulfill the requires of an academic research properly.

The degree-day method concentrates on the reasons of climatic sensitivity of energy consumption (Sailor and Munoz 1997, pp.991-992)

According to the former studies by (Valor et al. 2001 p 1418-1419) it was demonstrated that various statistical models may be improved by making use of two different independent variables as well as some initial variables such as temperature, relative dampness and so on. Some other derived variables including heating degree-days (HDD), cooling degree-days (CDD) are accounted for as it was mentioned above.

Most models reveal that the major weather variable is the outdoor temperature in HDD and CDD form. The variation of electricity load demand together with temperature display a non-linear character owing to the usage of electrical apparatus utilized for keeping our workplaces and homes warm in winter and devices used to keep our living medium cool enough on hot days in summer. However, the electricity load demand is inflexible to the temperature variations when the current temperature is around 18℃, so the following formulas are utilized to calculate HDD and CDD

For HDD : $HDD_t = max(T_{ref} - T_t , 0)$ and for CDD : $CDD_t = max (T_t - T_{ref} , 0)$ where T_{ref} is a reference temperature which is 18 ℃ for the experiment.

After applying the daily regression model, Durbin Watson has been implemented and it has been observed that there is an autocorrelation between our residuals. Thus, Box-Jenkins ARMA models have been utilized to remove that relationship between our residuals.

Autocorrelation conveys the relationship between those consecutive residual values. According to Meko 2015, a autocorrelation means correlation of time ranges with their own past and future values. It is sometimes called “lagged correlation” or “serial correlation”, both of them reveals the correlation between components of those ranges of numbers arranged on the basis of time.

According to Pedregal et al pp. 72-73, ARIMA model is one of the available methods to be used to generate hourly forecast of the demand for electricity distribution companies. For that reason, ARMA or ARIMA models have been adopted.

Before using ARMA or ARIMA model, it is better to examine some points regarding this issue.

In reference to NIST/SEMATECH e-Handbook of Statistical Methods website

Autoregressive (AR) Model

Modeling time series can be dealt with by adapting a number of approaches. Autoregressive (AR) model is one of the most common approaches for modeling univeriate time series.

$$X_t = \delta + \emptyset_1 X_{t-1} + \emptyset_2 X_{t-2} + \ldots\ldots + \emptyset_p X_{t-p} + A_t \tag{4.2}$$

Where X_t is the time series, A_t is white noise and

$$\delta = \left(1 - \sum_{i=1}^{p} \emptyset_i\right)\mu \tag{4.3}$$

With μ denoting the process mean. An autoregressive model is simply a linear regression of the current value of the series against one or more prior values of the series.The value of p is called the order of the AR model.

Moving Average (MA) Model

This model is another common method for modeling univeriate time series model.

$$X_t = \left(\mu + A_t - \theta_1 A_{t-1} + \theta_2 A_{t-2} \ldots \ldots \theta_q A_{t-q}\right) \tag{4.4}$$

Where X_t is the time series, μ is the mean of the series, A_{t-i} are white noise terms and $\theta_1 \ldots \theta_q$ are the parameters of the model. The value of q is called the order of the MA model.

Box-Jenkins Models

Facing very complicated data patterns such as a combination of a trend, seasonal, cyclical and random volatility appear, Box-Jenkins models must be adopted.

A mixture of the AR and MA models constitute the Box-Jenkins ARMA model.

$$X_t = \delta + \emptyset_1 X_{t-1} + \emptyset_2 X_{t-2} + \ldots\ldots + \emptyset_p X_{t-1} + A_t - \theta_1 A_{t-1} + \theta_2 A_{t-2} \ldots\ldots \theta_q A_{t-q} \quad (4.5)$$

where X_t is the time series, μ is the mean of the series, A_t is white noise terms, $\theta_1, \ldots \theta_q$ are the parameters of the model and

$$\delta = \left(1 - \sum_{i=1}^{p} \varnothing_i\right)\mu \quad (4.6)$$

According to NIST/SEMATECH e-Handbook of Statistical Methods website Box-Jenkins models are implemented in three stages.

1. Recognition

Makridakis and Hibon [no date] pp. 4,5 cites the concept of immobility as follows:

Stationary:

According to The Box-Jenkins method short and seasonal (long) differencing to accomplish stationary in the mean, and logarithmic or power transformation to realize stationary in the variance. Time series is assumed as stationary according to the Box-Jenkins model. The lexical meaning of Stationary is immobile or it is something which is not moving at all. Therefore, Box-Jenkins models suggest differencing one or more times to accomplish stationary if the time series are not stationary. In this case, ARMA model turn into ARIMA (Integrated) model if time series are processed by applying differencing method.

Seasonality:

The Box-Jenkins approach suggest that multiplicative seasonal models coupled with long-term differencing, in the case the series are seasonal if it is necessary, to realize stationary in the mean. There is a difficulty in application of such methods because there is practically never enough data available to determine the suitable level of the seasonal ARMA model with any reasonable degree of confidence.

At the recognition step of the model, our aim is to determine seasonality, if there is any, and to recognize the order of the seasonal autoregressive behavior and seasonal moving average terms. This duration of time is clear so it is enough to use a single seasonality term for many series/ranges.

After the concepts of stationary and seasonality have been stated, the next phase to follow is to recognize the order p and q of the autoregressive and moving average terms consecutively.

The first instruments to be used to perform these tasks are the autocorrelation plot and the partial autocorrelation plot. When the order is clear, the sample autocorrelation plot and the sample partial autocorrelation plot are contrasted to the abstract attitudes of those plots.

2. The Establishment of the Initial Model

To combine the components of ARIMA model as an integrated model an initial model must be established first and afterwards following models should be designed consecutively which necessitates to make a decision on degrees of AR and MA components

Order of ARMA Model is discovered by examining the autocorrelations and partial autocorrelations of the stationary series. While the estimating the Model's Parameters of this model, this is the simplest step of the Box-Jenkins approach where the non-linear optimization procedure, based on the approach of steepest descent (Marquardt 1963 pp. 431-441), has been adopted to calculate the parameter values of p and/or q (and their seasonal equivalent P and/or Q) (Makridakis and Hibon [no date] pp. 4, 5)

3. Diagnostic Control

The most accurate and widely used beneficial models are chosen by utilizing AIC Akaike Information Criteria) and BIC (Bayesian Information Criterion)

The Augmented Dickey-Fuller test is used in order to check unit root test to obtain our Autoregressive model. Augmented Dickey Fuller test the null hypothesis of an autoregressive integrated moving average (ARIMA) against stationary is inspected by implementing this test. Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test is also utilized to determine whether our model is stationary or not. Therefore it is clarified that our daily residuals are not stationary. Since it is compulsory for data to be stationary in Box-Jenkins models, as it has been explained above, differencing operation has been utilized and thus the model to be used has to be ARIMA. The accuracy of the model is controlled by AIC or BIC. Among various different choices of ARIMA models, ARIMA (3,1,1) has been selected because AIC and BIC values have been looked into and it has been seen that they have the lowest values.

ARCH&GARCH Model

Autoregressive Conditional Heteroskedasticity (ARCH) approaches are utilized to characterize and model the observed time ranges in econometrics. They are adopted when there is a suspicion that the error terms will have a unique size and variance at any point in a series. This model is a theorized generalized autoregressive conditional heteroskedasticity (GARCH), if an autoregressive moving average model (ARMA model) is supposed to be the error variance, the Bollerslev (1986) model. As a result of seeing that our residuals have variances, GARCH (1,1) model has been selected to remove that effect.

After finding out seasonal and trend components, they are removed from our electricity demand data and afterwards, forecasting for the electricity demand in 2015 has been estimated. These procedures are followed to devise prospective risk analysis for electricity distributors. Various risks occur in almost all walks of life due to some uncertainties, fluctuations and some unexpected hazardous events. Risk analysis is necessary to predict prospective risks much earlier and to take all sorts of necessary precautions in time to avoid high rates of losses. While performing the duties of risk analysis step by step, first probable risks are identified clearly and afterwards the reasons why such risks are arise are discovered; therefore, possible effects of the adverse outcomes are estimated. Finally, efficient number of experiments is performed to find out how to solve those uncertainties, volatilities and risks here as in other fields of science experiments are carried out to avoid too risky and expensive real world experiences of real life.

At this stage of the practice of our research, ARIMA model, Daily Regress model and Hourly Regress model are put into practice in their reverse form to forecast probable electricity load for the year 2015. The data obtained as a consequence of all those operations have been simulated for each month of the year 2015 to actualize 1000 probable demand scenarios for electricity distributors. Later on, probable profit cases have been generated by using bilateral contracts and market contracts in order to prepare for the optimization model. Here it has been assumed that the total value of bilateral and market contracts equal to those values for demand scenarios. Eleven different cases of profitability for each month of the year 2015 have been observed. These eleven different cases have been actualized by considering the bilateral contracts as well as by increasing the values of demand scenarios at the amount of their average rates.

Expected Return values, VaR, Conditional VaR, Variance, Standard deviations have been looked into for each different 11 case for each month of the year 2015.

In short, Expected Value represents those prospective average values obtained as result of constant random experiments in which all of those probable possibilities are modified at each repetition although they are repeated many times.

If it is necessary to explain prospective portfolio risk measures, most investors are interested in results of which actualized far behind of expectations because if results are much more satisfactory than what they expect bring them much more profit. In other words, investors want to make as much profit as possible but they do not want to lose any money. Portfolio variance and other dispersion measures cannot display this fact correctly. As Markowitz (1959) pointed out this shortcoming of his model, afterwards he suggested another precaution to repair poor sides of his method so he recommended a risk measure as well as its semi-variance, as an alternative way of assessing portfolio risk. The most important role of Variance and Standard Deviation in accordance with the portfolio selection step emerge here as suggested by Markowitz(1959) more than 60 years ago, the portfolio variance (or, equivalently, standard deviation) is the most famous dispersion measure to get rid of risks. (Dessislava A. Pachamanova and Frank J. Fabozzi, 2010 pp 277-278)

4.2.1 Portfolio Risk Measures

VALUE-AT-RISK (VaR)

Due to possibility of huge risks of losing money, it is essential to foresee probable hazardous occurrences likely to cause huge losses for investors. VaR help portfolio experts to devise methods how to avoid devastating effects of risks likely to occur on behalf of investors. The risk assessment formula namely VaR is utilized to discover those portfolios which contain the highest risks and profits for investors in general. To exemplify, if we have 1000 scenarios in hand arranged in a range of 0,95 probability level, ((1000 – [0.05 · 1000] + 1) = 951), in this case, the 951^{st} profit scenario which displays the highest rate of risk is selected as the VaR element. In order words, the 49^{th} scenario which bears the lowest value of profit is selected as the VaR element. (Pachamanova and Fabozzi 2010 pp. 283,289,290)

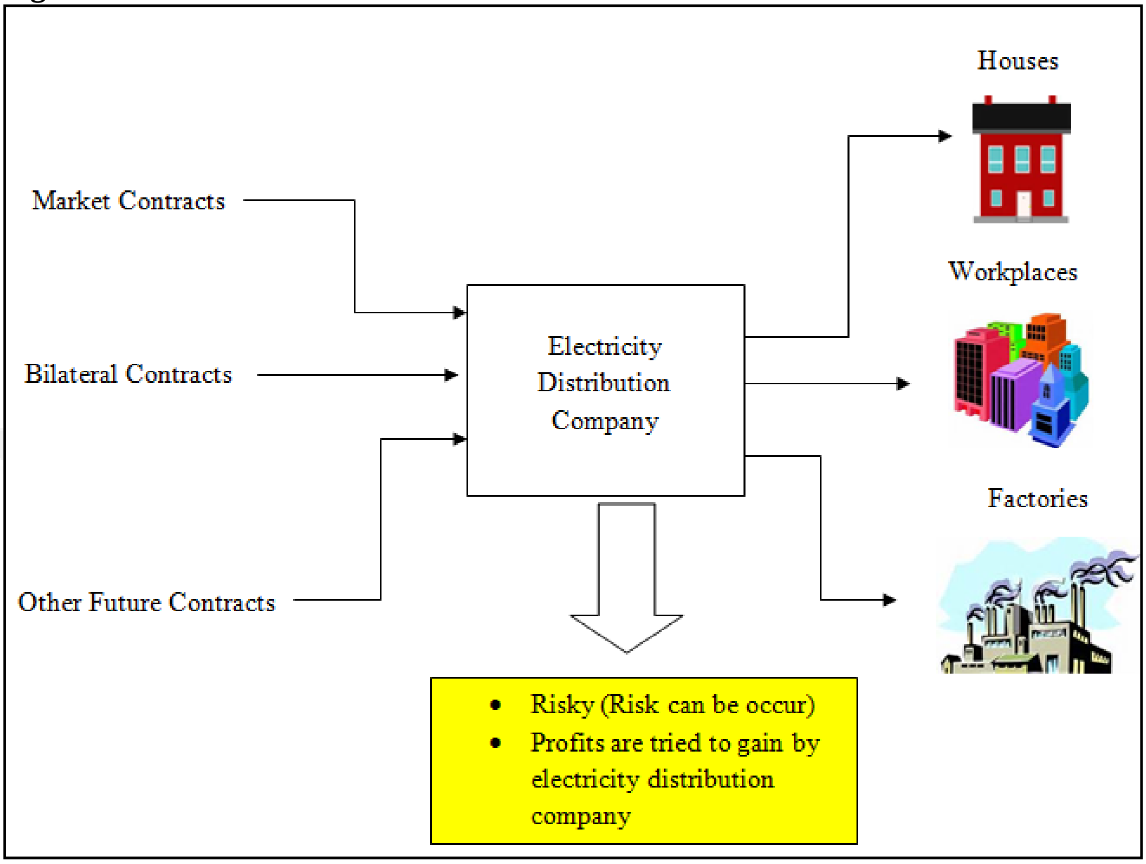
Conditional value-at-risk (CVaR)

VaR deals with only the highest loss rate but CVaR element enquires what happens on average if the amount of losses goes beyond $100(1 - \varepsilon)\%$ VaR.

As mentioned above, the findings obtained as a result of calculation on the basis of 1000 scenarios, the average of all those 49 scenarios which have the lowest values are taken into account, and thus their average value is displayed as CVaR. (Pachamanova and Fabozzi 2010 pp 301-302)

4.3 THE PHASE OF OPTIMIZATION

Figure 4.2: Overview at Distributors



As it can be observed in the figure above, electricity load distributors can dispatch those electricity loads to houses, workplaces and factories with the help of their market contracts, bilateral contracts and some other contract types. They are likely to face many risks while pursuing their jobs and transactions and of course electricity distributors must make a profit to maintain their businesses and services. Various statistical methods and optimization instruments are utilized to minimize their risks but maximize their profits.

At this stage, it is necessary to employ some new techniques to help electricity load distributors while paving the way for their objectives. Here, hedging and portfolio optimization methods have been adopted among those risk management techniques in order to generate models which can enable us to reduce probable risks but to increase prospective profits by making use of future contacts as it was mentioned in the literature section earlier. These are the contracts used consecutively; Bilateral contracts, Peak contracts, Off-peak contracts, Weather Derivative contracts. These issues have been dealt with in details under the heading of articles on optimization.

Markowitz's mean-variance optimization model has been selected among many risk management techniques in order to provide electricity distributors with the highest rate of profit but the lowest rate of risk. Here it has been intended to create models which will allow them to maximize their profit by ignoring risk (variance) factor for the first model. This time maximum profit or expected return has been ignored and thus minimum risk model has been put into practice as the second model. Since it is necessary to benefit from many different models, a wide variety models have been actualized by taking both expected return model and variance model into account.

Here, while summarizing the utilization of formulas, the needed inputs are revealed for mean-variance optimization model, which are the expected return for each asset, the variance of each asset as well as the co-variances between those assets. If the returns of the assets comply with a normal distribution, the total distribution of a portfolio may be defined by means of the mean and variance only.

Therefore, here the expected return for a definite portfolio, which contains *N* assets may be formulated as follow:

$$E(r_p) = \sum_{i=1}^{N} x_i r_i \tag{4.7}$$

Here *N* reveals the number of assets which are included in the portfolio, x_i expresses the weight percentage of ith asset in portfolio and r_i means expected return of ith asset.

The variance for a definite portfolio may be formulated as seen below:

$$(\sigma_p^2) = \sum_{i=1}^{N} \sum_{j=1}^{N} x_i x_j \sigma_{ij} \tag{4.8}$$

σ_{ij} is the covariance value between the returns on the ith asset and jth asset. The covariance σ_{ij} quantifies the number of returns on two assets which are likely to interact with each other.

As Gökgöz 2011 pp.260 cited that the fundamental mean-variance optimization model contains the minimization of the variance of the portfolio under three main constraints.

$$\min(\sigma_p^2) = \sum_{i=1}^{N}\sum_{j=1}^{N} x_i x_j \sigma_{ij} \quad (4.9)$$

Subject to

$$\sum_{i=1}^{N} x_i r_i = r_e \quad (4.10)$$

The first constraint is the expected return of the portfolio which has to be equal to target return.

$$\sum_{i=1}^{N} x_i = 1 \quad (4.11)$$

Secondly, the sum of the weight percentages of financial assets included in the portfolio must be equal to 1.

$$x_i \geq 0, \forall \mathrm{x_i} \in [1,2,\ldots,\mathrm{N}] \quad (4.12)$$

Finally, the concept of non-negativity condition for the weight percentages of assets is defined. In order to produce a method in balances, a general method of explaining preferences of a decision maker are discovered and supplied for the usage of a utility function. According to a concept of the utility theory which was first suggested by D. Bernoulli and G. Cramer a general method was introduced but later on Von Neumann and Morgenstern developed that general theory. (Liu 2006 pp.1513) According to their theory, the value of utility function is named as utility value which is widely preferred by the owners of those portfolios with higher utility values. Utility of a portfolio is assets from a function which combines the expected return and risk choices of a decision maker into a simple relation in the mean variance optimization model.

Here it is assumed that investors are risk averse. That is, they prefer higher expected return but lower risk. Therefore, here the most widely used utility function in financial literature appears as follows expressed as in two formulas:

$$U = E(r) - \frac{1}{2}\mathrm{A}\sigma_{\mathrm{p}}^2 \quad (4.1)$$

5. REAL DATA ANALYSIS

5.1 DATA

During this literature research study hourly electricity load demands for Turkey from January 1^{st} , 2008 to October 31^{th} , 2014 have been taken into account. After studying all sectors such as residential, commercial and industrial are included in the subject matter. 59868 sample electricity load patterns on the basis of hourly consumption as well as and 2496 daily sample electricity load patterns have been studied on in general.

This study reveals that the highest average electricity loads occur at noon. Besides, average electricity loads go up (above 75000) in the afternoon from 1 pm to 3 pm. Nevertheless, the lowest average electricity loads go down (above 10000) in the morning from 5 am to 7 am because during this period of time both domestic and industrial activities lower substantially.

The necessary data related to weather and temperature have been obtained from Bloomberg Financial Center at Bahçeşehir University and The temperature data of eleven cities (namely Adana, Ankara, Antalya, Diyarbakır, İstanbul, İzmir, Konya, Kars, Malatya, Niğde, Trabzon) in Turkey from 01.01.2008 to 31.10.2014 have been taken into account.

The weighted average of eleven cities together with their population have been taken into account as the subject matter of my research for temperature variations.

There is dense interaction between electricity loads and the weather effects including their time basis such as hourly, daily, weekly and yearly. For that reason dummy variables are utilized on the basis of time elements such as weekends, holidays and some other special days. Besides, their cooling (CDD) and heating (HDD) temperature effects are taken into account.

According to experiments conducted on this issue so far temperature has two clearly defined effects on electricity load as it is stated above. In the first place, the daily electricity load reacts considerably to the changes of temperature.

In brief, in most articles, models reveal the major weather variable as the outdoor temperature in HDD and CDD form. The variation of electricity load demand displays a non-linear character together with temperature. However, the electricity load demand is inflexible to the temperature variations when the current temperature is around 18℃, so the following formulas are utilized to calculate HDD and CDD

For HDD : HDD_t = $max(T_{ref}$ - T_t , 0) and for CDD : CDD_t = max (T_t - T_{ref} , 0) where T_{ref} is a reference temperature which is 18 ℃ for the experiment.

5.2 TREND AND SEASONALITY

Multiple linear regression and ARIMA models are generally utilized in Matlab to determine trend and seasonality factors. The function of multiple linear regression approach is utilized to analyze the effect of exogenous variables such as CDD, HDD and seasonal variables that capture on the basis of 'hour of the day', 'day of the week', 'holidays' and 'month of the year' impact. After that, the importance of the contrasting autoregressive attitude and dynamic arrangement are controlled with the help of ARIMA models in Matlab.

To start with, it is essential to handle powerful trend for long-term in hourly electricity load demand. This trend was observed by (Valor et al. 2001 p. 1414) and it was related to social, economic and population elements. The basic method for extracting trend in time series is differencing.

Dummy variables are utilized to calculate seasonal effects by exhibiting all days in a week. Six dummy variables such as Tuesday, Wednesday, Thursday, Friday, Saturday, Sunday except Monday are used. Here, Monday is accepted as the base variable. Dummy variables are entered manually for Holidays. Similarly, three dummy variables such as Spring, Summer, Winter are adopted to represent all seasons of a year except for Autumn because Fall is regarded as the base variable. And last of all, eleven dummy variables are taken into account to represent all hours of the day such as 02.00-03.00; 04.00-05.00 ;06.00-07.00; 08.00-09.00; 10.00-11.00; 12.00-13.00; 14.00-15.00;16.00-17.00; 18.00-19.00; 20.00-21.00; 22.00-23.00. Here, 00.00-01.00 is the base variable.

Our main concern in the analysis of the daily seasonality and in the impacts of other dynamic arrangements on electricity demand-temperature relationship is to make them compatible with those previous studies performed by (Valor et al.2001 pp 1413-1421) who revealed important seasonal daily constituents in the electricity load demand ranges.

During this study, linear least-squares regression methods have been utilized. It has been supposed that there is a highlighting linear connection between the dependent variable such as electricity consumption and the climatic independent variables of interest. (Sailor and Munoz1997 pp. 990)

During the steps of calculation to obtain accurate figures the hourly electricity loads must be regressed in order to remove both seasonal and trend components initially. (see Table 5.1)

Table 5.1 : Results in Linear Regression Model for Hourly Electricity Load Demand with Matlab

Variables	Coefficient	Coefficient Intervals	
Base	22.651,61	(22.533,65	22.769,57)
Tuesday	685,06	(587,84	782,27)
Wednesday	714,28	(617,20	811,35)
Thursday	838,10	(740,95	935,25)
Friday	623,39	(526,44	720,33)
Saturday	-462,07	(-559,10	-365,03)
Sunday	-2.873,04	(-2.969,90	-2.776,17)
Holidays	-5.219,26	(-5.370,48	-5.068,03)
Winter	-275,42	(-347,60	-203,24)
Spring	2.295,18	(2.222,93	2.367,42)
Summer	1.299,02	(1.225,45	1.372,60)
Hours 02-03	-1.832,19	(-1.957,01	-1.707,36)
Hours 04-05	-2.347,61	(-2.472,43	-2.222,78)
Hours 06-07	-1.883,44	(-2.008,26	-1.758,62)
Hours 08-09	2.933,00	(2.808,17	3.057,82)
Hours 10-11	5.257,20	(5.132,38	5.382,02)
Hours 12-13	4.646,82	(4.522,02	4.771,62)
Hours 14-15	4.854,46	(4.729,67	4.979,25)
Hours 16-17	4.588,67	(4.463,88	4.713,45)
Hours 18-19	4.041,18	(3.916,39	4.165,97)
Hours 20-21	3.888,92	(3.764,13	4.013,71)
Hours 22-23	3.198,06	(3.073,27	3.322,84)
R^2	F statistic	p Value	ErrorVariance
0,53	3.222,88	0	10.111.215,44

Consequently, hourly residuals are obtained. After that those hourly residuals are converted into daily residuals because earlier studies revealed that mean daily temperature is better displayed by making use of the variation of temperature during the course of a day.

Outdoor temperature is converted into HDD and CDD forms. According to the formulas below:

For HDD: HDD_t = $max(TI_{ref}$ - T_t , 0) and for CDD: CDD_t = max (T_t - TI_{ref} , 0). HDD, CDD temperature and daily residuals are also regressed in order to examine the relationship between HDD, CDD and electricity load (as shown in table 5.2)

Table 5.2 : Results in Linear Regression between Daily Residuals and HDD,CDD with Matlab

Variables	Coefficient	Coefficient Intervals	
Base	-1.176,89	(-1.406,72 -947,05)	
HDD	138,00	(109,35 166,65)	
CDD	223,22	(184,72 261,71)	
R^2	F statistic	p Value	Error Variance
0,05	69,45	0	8.077.271,39

5.3 AUTOREGRESSIVE AND DYNAMIC EFFECTS

Durbin Watson test was conducted after daily regression analysis had been completed. This test is applied to see if there is an autocorrelation between residuals.
In Durbin Watson test

$$d= \frac{\sum_{t=2}^{T}(e_t - e_{t-1})^2}{\sum_{t=1}^{T}(e_t^2)} \qquad (0<d<4) \tag{5.1}$$

where d: Durbin Watson value
e: residuals
t: time
Durbin Watson value of "d" always changes between zero to four. For example, when "d=2", it means that there is not any autocorrelation.
Our time series data have been calculated as d= 0,1066 because when d value is smaller than two (d<2), it is assumed that there is a positive autocorrelation between residuals which means our variance is much smaller than we expected. As a result of this, the value of t test is much bigger than expected. In other words, the value of R^2 always

displays a different value than it is supposed. Since the value of F test is also much bigger than expected. In conclusion, t and F tests lose their credibility. After these derivatives it is understood that our regression data demonstrate autocorrelation behavior which necessitates ARMA or ARIMA model to make much better forecast in this respect.

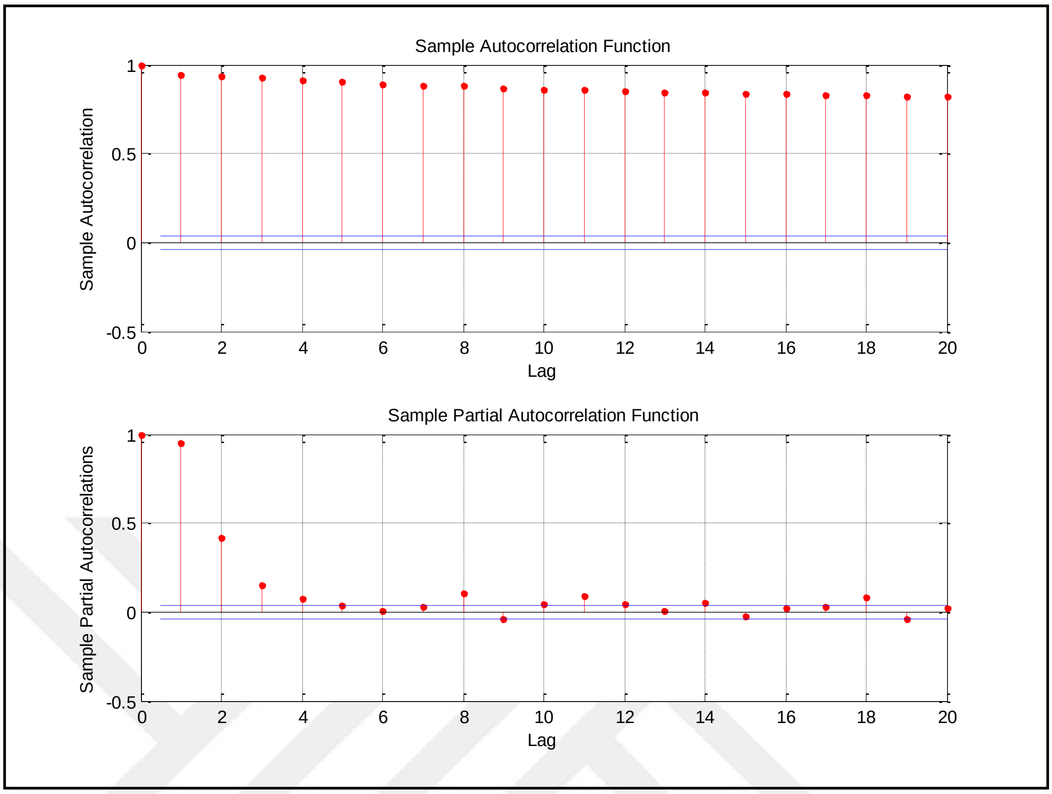
5.4 UNIT ROOT TEST AND STATIONARY

The Augmented Dickey-Fuller and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) tests are utilized to determine whether our model is stationary or not. Therefore it is clarified that our daily residuals are not stationary.

Since our residuals have an autocorrelation between them in our model, ARMA or ARIMA model have to be adopted to fulfill procedures to break the existing autocorrelation between them. That is why, ACF and PACF correlograms are analyzed with the help of Matlab.

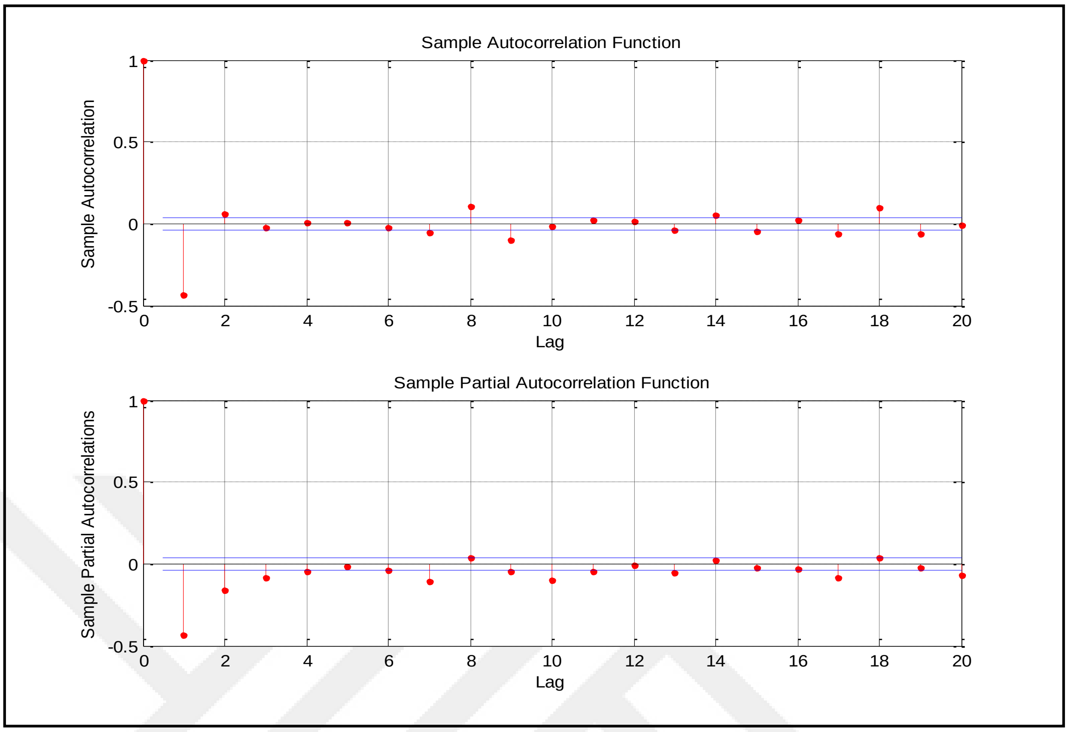
Our correlograms have been displayed in as they are seen before applying differencing operation.(See Figure 5.1)

Figure 5.1 : ACF and PACF Correlogram before Differencing



As it is seen in the graph above our model exhibits a non-stationary nature. Therefore, differencing operation must be applied here. After applying differencing operation once, our model turns into the shape seen below. (See Figure 5.2)

Figure 5.2 : ACF and PACF Correlogram after Differencing



As it can be seen in the graph above, the first correlogram exhibits much bigger correlations at lags 1,2; however second correlogram displays bigger correlations at lags 1,2,3.

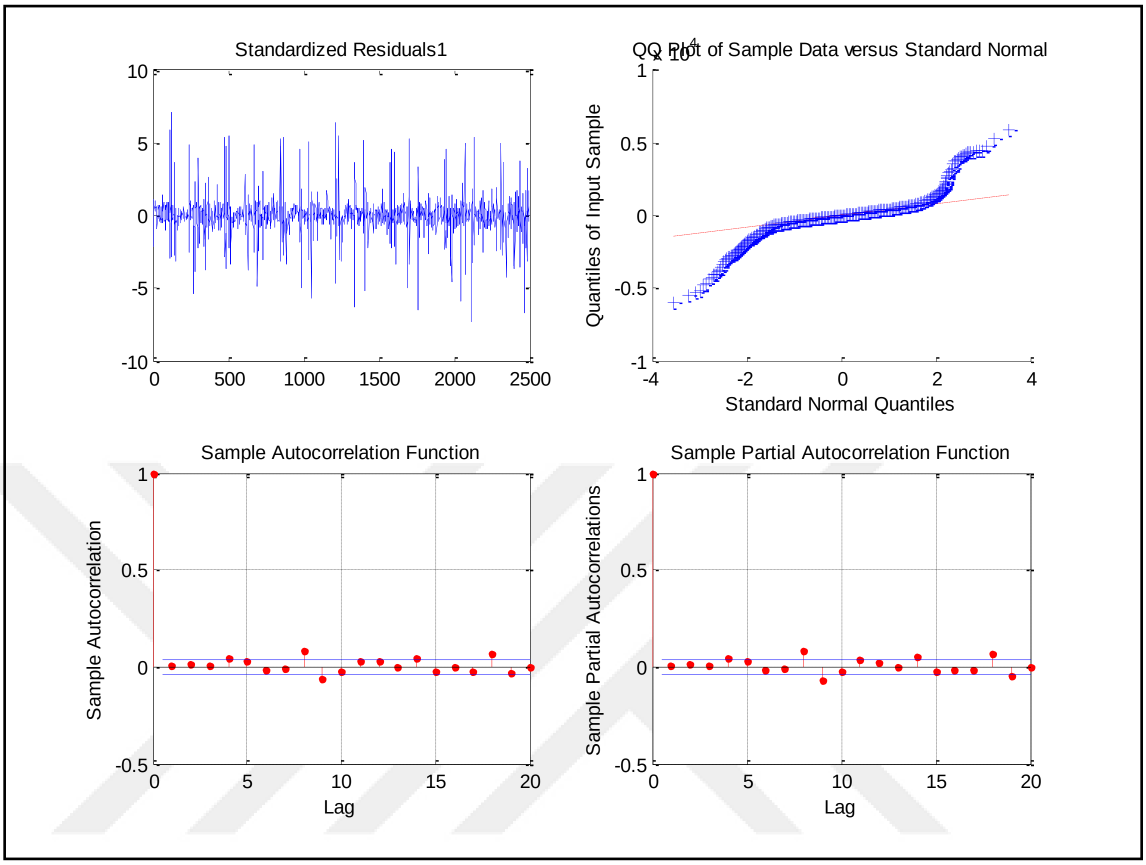
Therefore, our ARIMA models (p,D,q) appear as follows :

(1,1,1); (1,1,2); (2,1,1); (2,1,2); (3,1,1); (3,1,2)

1. Diagnostic Control

The accuracy of the model is controlled by AIC (Akaike Information Criteria) or BIC (Bayesian Information Criterion) after fulfilling the requirements of the estimated AR, MA or ARMA model of a time series. Therefore, the model that gives the lowest AIC or BIC value has been selected. The ARIMA (3,1,1) model has been preferred in our research study because it enables us to obtain the lowest AIC and BIC values. (See Figure 5.3)

Figure 5.3: ACF, PACF Results and Normality Graph after Choosing ARIMA (3,1,1) Model

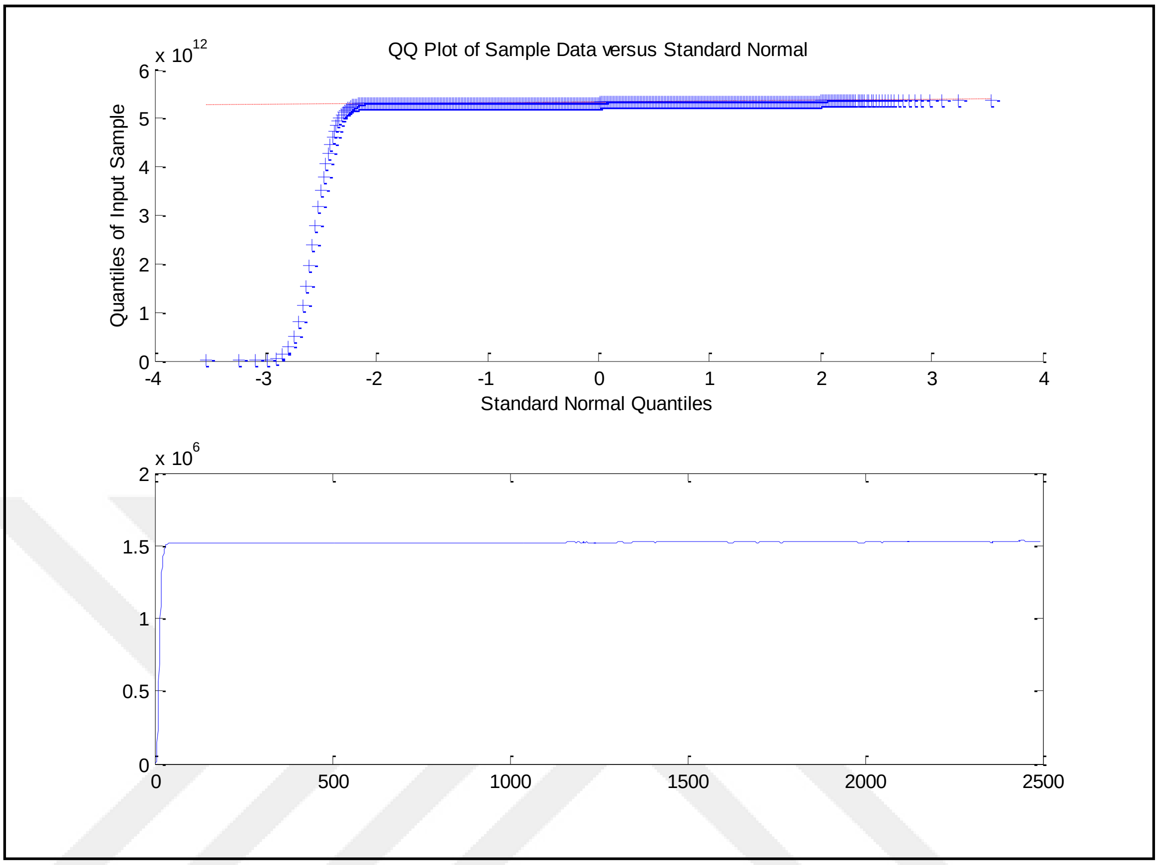


Standardized Residuals correlogram displays high levels of fluctuation clustering in series. Therefore, big movements follow big changes in logarithmic returns and small logarithmic returns follow small changes.

GARCH Model

Assuming that residuals affect each other, GARCH model was adopted to reduce the number of mistakes to reach more accurate results. After the square of residuals are taken, (1,1) GARCH model was selected because it is the most widely used practice (See Figure 5.4)

Figure 5.4 : Normality Graphs after Choosing GARCH(1,1) Model



5.5 APPLICATION OF FORECASTING AND SIMULATION

While ARIMA model, Daily Regress model and Hourly Regress model are put into practice in their reverse application. Here, it is intended to create 1000 scenarios for each month in 2015 and; thus, it will be possible to foresee probable profit-loss cases for electricity load distributors.

If it is necessary to go into details in this subject matter, the ARIMA (3, 1, 1) model has been simulated for 31 days because there are 31 days in January. The number of days to be taken into account depends on the number of days of each month. As random HDD, CDD temperature values are needed to create 1000 prospective scenarios for daily regression model. First, these random HDD, CDD temperature values are actualized and then they are multiplied by their coefficient values. Afterwards, dummy variable values are multiplied by their coefficient values for the hourly regression model. Finally, the values of ARIMA, Daily regression model and Hourly regression model are added altogether. And this is repeated 1000 times in order to create 1000 different scenarios for one month in 2015. Therefore, those 1000 scenarios which were created earlier for January can be easily adapted to the other eleven months of a year by taking the number of days of each month separately into account as well as varying temperatures of each month accordingly.

To exemplify our finding for January;

The average values of the temperatures actualized in January from 2008 to 2014 have been taken to find the variance of the temperature data. After that, a graph has been devised to determine whether the temperature data display a normal distribution or not. (See Figure 5.5 and Figure 5.6)

Figure 5.5 : Histogram of January Temperature Data Displaying a Normal Distribution (To Exemplify Winter Season)

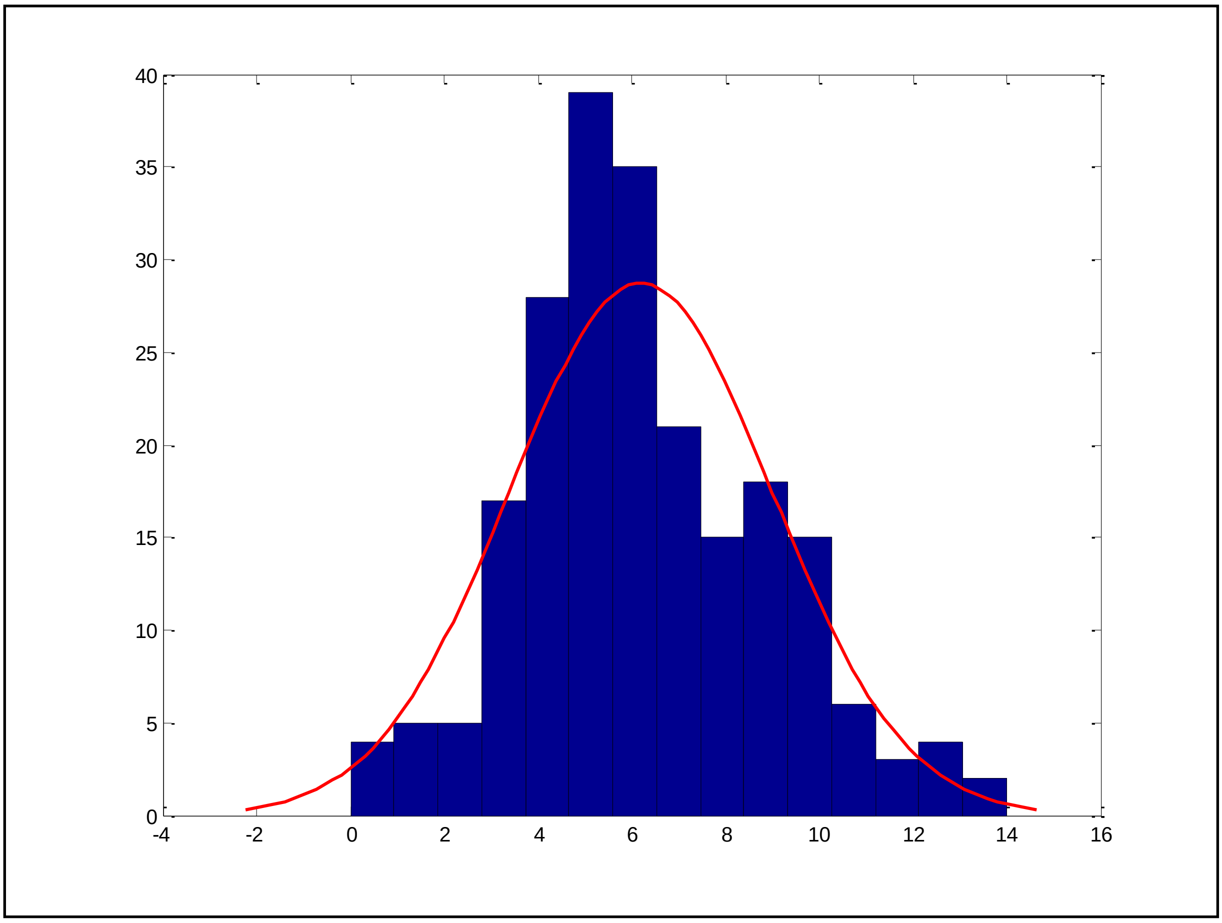
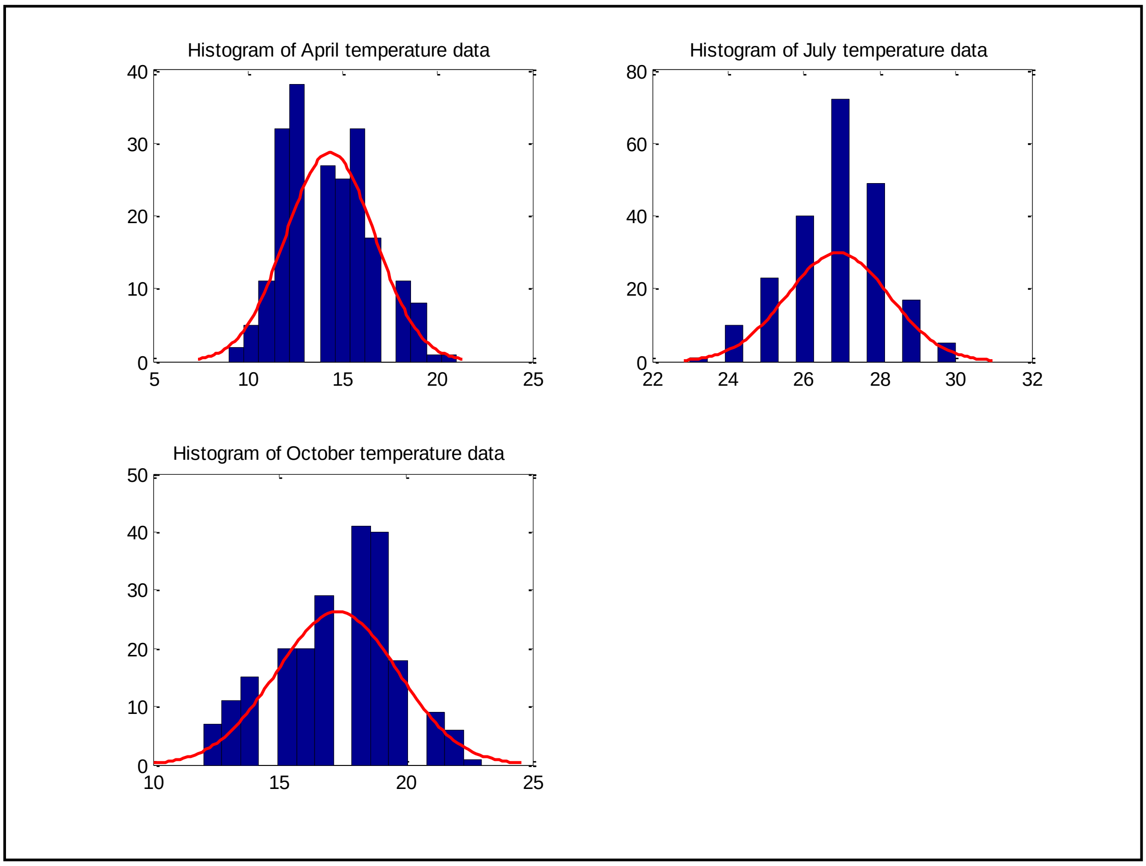


Figure 5.6 : Temperature Data Histograms for Each Seasons



As it is mentioned earlier, the random daily temperature data have been created for 31 days for January 2015 and so Random HDD, CDD temperature values have been obtained for each day separately.

The following formulas are used to maintain the necessary procedures to be done for forecasting as follows:

CDD : max(18+randomtemperaturedata);

HDD : max(-18+randomtemperaturedata);

The reason why the value of 18 C^0 is selected here for formulas is that as it is mentioned previously it is an inflexible value for temperature rates. The value numbers found for random HDD, CDD are multiplied by their coefficients as calculated for the daily regression model. After that, the ARIMA model (3,1,1) has been simulated for one month for January in this case. Additionally, those eleven dummy variables created on the basis of hourly, daily, seasonally regression model are multiplied by the values of the coefficient that was calculated the hourly monthly, seasonally model.Lastly those rates obtained for the random daily temperature model, random ARIMA model and random Hourly Monthly, Seasonally model are added together. As a result, the following data have been obtained as 744 (31 days * 24 hours). The same procedures are repeated for 1000 different scenarios in Matlab. After that, calculations are performed to find out the amount of profit likely to be gained

Basically

$$Profit_{1:12} = (f_1 * x_1) - ((f_2 * x_2) + (f_3 * x_3)) \tag{5.2}$$

Parameters are

$$f_1 = Sale\ Price$$
$$f_2 = Bilateral\ Contract\ Price$$
$$f_3 = Market\ Contract\ Price$$

Variables are

$$x_1 = Demand\ Variables$$
$$x_2 = Bilateral\ Contract\ Variables$$
$$x_3 = Market\ \ Contract\ Price$$

And

$$x_1 = x_2 + x_3 \tag{5.3}$$

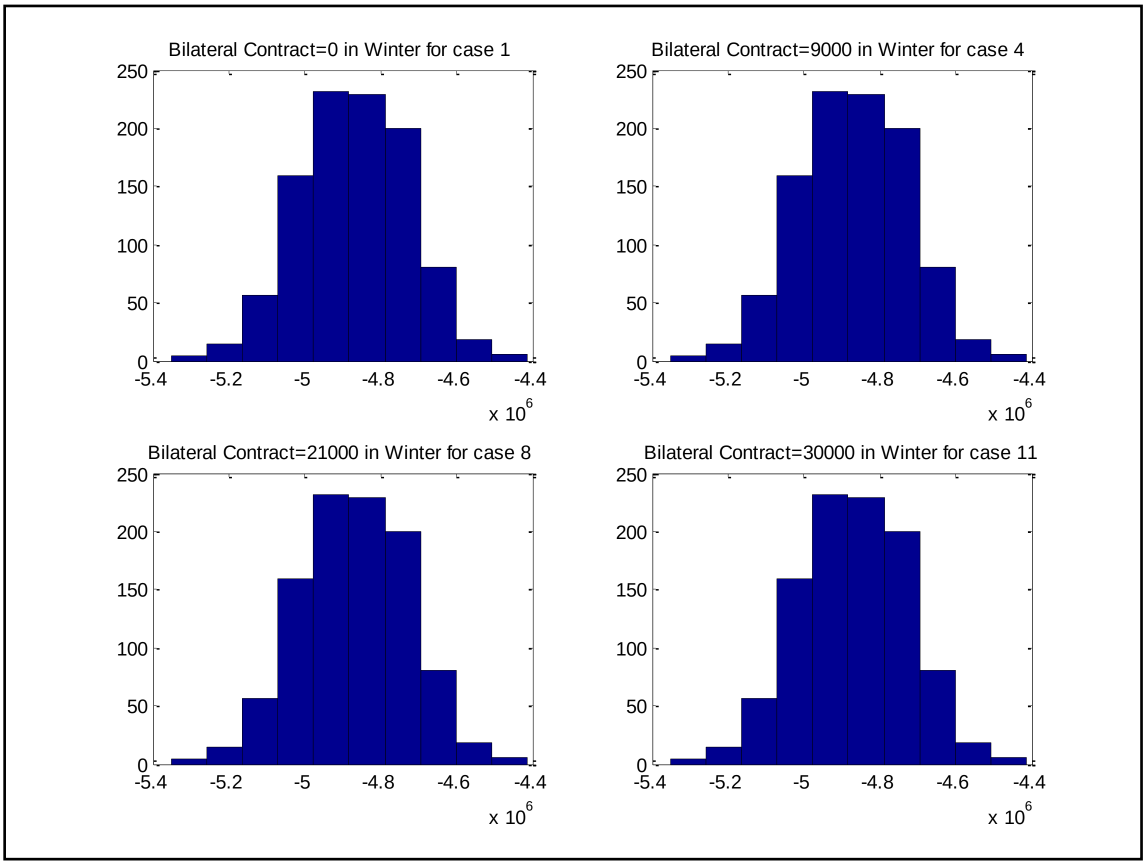
because contracts are provided for as the number of demands offered.

As a result of our calculations, 1000 Demand Variables were obtained and those demand variables constituted our scenarios for each month of 2015. Demand variable amount should be equal to Bilateral contract variable plus Market contract variable amount. Market contract prices are assumed as hourly data which are collected from ENERJİ PİYASALARI İŞLETME A.Ş . for each month of 2015, for January from 01.01.2015 to 31.01.2015. Bilateral contract prices are derived from the average of monthly market contract prices. Sale prices of electricity loads are different for each month but they are collected from the same institution ENERJİ

PİYASALARI İŞLETME A.Ş. Sale prices are always regarded as a constant value for the duration of one month.

In order to see the prospective amount of profit for each month, eleven different cases are created to obtain bilateral contract variable by contemplating on the mean of demand because the proportion of profit vary due to different factors and each bilateral contract as seen within the content of the following histogram for each month. (See figure 5.7)

Figure 5.7 : Histograms for Case 1,4,8,11 in January a month for Winter



(For other seasons see Appendix 1 : Figure 1, Appendix 2 : Figure 2, Appendix 3: Figure 3)

In addition to this, Profits, VaR, conditional VaR, E(x), Variance and Standard Deviation have been examined by considering 11 different cases one by one. (See Table 5.3) Last of all, Profits, VaR, conditional VaR, E(x), Variance, Standard Deviation have been examined whenever the contract variable increased at the rate of one percent. (See Table 5.4)

Table 5.3 : Expected Value E(x), Variance, Standard Deviation, Value at Risk (VaR), Conditional Value at Risk (CVaR) in January for 11 Different Cases

Profits	E(x)	Variance	STD	VaR	Conditional VaR
1	48.515.786,70	1.984.096.285.128,14	1.408.579,53	46.301.719,33	45.693.734,61
2	48.515.864,88	1.983.654.686.784,58	1.408.422,77	46.288.693,15	45.693.135,90
3	48.515.943,06	1.983.272.422.649,08	1.408.287,05	46.275.666,97	45.692.537,18
4	48.516.021,24	1.982.949.492.741,64	1.408.172,39	46.269.348,82	45.691.938,46
5	48.516.099,42	1.982.685.897.045,33	1.408.078,80	46.272.426,66	45.691.339,75
6	48.516.177,60	1.982.481.635.556,07	1.408.006,26	46.284.088,54	45.690.741,03
7	48.516.255,78	1.982.336.708.288,19	1.407.954,80	46.295.113,05	45.690.129,57
8	48.516.333,97	1.982.251.115.224,79	1.407.924,40	46.289.247,89	45.689.180,31
9	48.516.412,15	1.982.224.856.374,07	1.407.915,07	46.297.846,47	45.688.231,06
10	48.516.490,33	1.982.257.931.736,02	1.407.926,82	46.306.720,47	45.687.281,80
11	48.516.568,51	1.982.350.341.318,85	1.407.959,64	46.315.594,47	45.686.332,55

Table 5.4 : Expected Value E(x), Variance, Standard Deviation, Value at Risk (VaR), Conditional Value at Risk (CVaR) when bilateral contract price was increased one percent in January for 11 Different Cases

Profits	E(x)	Variance	STD	VaR	Conditional VaR
1	48.518.314,19	1.976.807.271.467,61	1.405.989,78	46.338.238,21	45.702.765,78
2	48.513.369,66	1.975.718.881.926,93	1.405.602,68	46.331.654,98	45.698.274,76
3	48.508.425,12	1.974.696.550.421,55	1.405.238,97	46.323.659,10	45.693.783,74
4	48.503.480,58	1.973.740.276.946,34	1.404.898,67	46.314.377,00	45.689.292,71
5	48.498.536,05	1.972.850.061.497,20	1.404.581,81	46.305.094,90	45.684.801,69
6	48.493.591,51	1.972.025.904.078,75	1.404.288,40	46.295.812,79	45.680.310,67
7	48.488.646,97	1.971.267.804.716,12	1.404.018,45	46.286.530,69	45.675.819,65
8	48.483.702,44	1.970.575.763.360,06	1.403.771,98	46.282.024,16	45.671.231,16
9	48.478.757,90	1.969.949.780.048,55	1.403.548,99	46.277.952,39	45.666.633,81
10	48.473.813,37	1.969.389.854.769,25	1.403.349,51	46.273.880,62	45.662.036,45
11	48.468.868,83	1.968.895.987.517,56	1.403.173,54	46.269.808,85	45.657.439,09

(For other seasons see Appendix 4: Table 1, Appendix 5: Table 2, Appendix 6: Table 3)

5.6 PRACTICE OF PORTFOLIO OPTIMIZATION

In this study, some practices of mean variance optimization model for the following steps are included by adapting several current formulas to my survey:

Parameters

$S = number\ of\ scneario$ (1000)

Variables

$x_1 = \ Number\ of\ Bilateral\ contracts\ bought$

$x_2 = Number\ of\ Peak\ contracts\ bought$

$x_3 = Number\ of\ Offpeak\ contracts\ bought$

$x_4 = Number\ of\ HDD\ weather\ derivatives\ contracts\ bought\ (long)$

$x_5 = Number\ of\ HDD\ weather\ derivatives\ contracts\ sold\ (short)$

$x_6 = Number\ of\ CDD\ weather\ derivatives\ contracts\ bought\ (long)$

$x_7 = Number\ of\ CDD\ weather\ derivatives\ contracts\ sold\ (short)$

$cost^s(x_1, x_2, x_3, x_4, x_5, x_6, x_7)$

$$\text{F(x)=E} [\ Cost^s\ ] = \frac{1}{1000} \sum_{s=1}^{1000} Cost^s \tag{5.4}$$

$$\text{G(x)=} \sqrt{\sigma^2\ [Cost^s\ ]} = \sqrt{\frac{1}{1000} \sum_{s=1}^{1000} (Cost^s - \ E[Cost^s])^2} \tag{5.5}$$

Objective function

$$\text{Min}\alpha\text{F(x)} + \ ((1 - \ \alpha)\text{G(x)}) \tag{5.6}$$

Subject to

$$0 \leq x_i \leq 30000 \ \epsilon\ [1,2,\ldots,7] \tag{5.7}$$

MODELS	α	1-α
EXPECTED COST	0	1
STANDARD DEVIATION	1	0
2	0.999	0.001
3	0.99	0.01
4	0.9	0.1
5	0.8	0.2
6	0.7	0.3
7	0.6	0.4
8	0.5	0.5
9	0.4	0.6
10	0.3	0.7
11	0.2	0.8
12	0.1	0.9
13	0.01	0.99
14	0.001	0.999
15	0.0001	0.9999

Although this issue has been explained earlier, if it is necessary to explain it again by clarifying queries related to the rule which suggests that the investor should maximize their excepted returns for their investment in the future, this rule must be considered throughly all over again. The next step to be followed in this regard is that the investor should consider the expected return as an advantageous thing and variance of return a disadvantageous thing. Relationships between beliefs and choice of portfolio must be demonstrated or explained by concrete shapes and figures relying on the expected return-variance of returns method mathematically. Regarding to the method which allude to varying funds among all those securities which yield the investor maximum expected return. As it is widely known that those investors who invest larger amounts of capital in a certain field of business will often obtain approximately similar return to what they hope to gain. Those portfolios attach to maximum rate of expected return are not in correlation with minimum rate of variance. In short, there is a proportion at which the investor may acquire an expected return either by undertaking a variance or reduce a variance by waiving an expected return.

5.7 OPTIMIZATION RESULT

Within the consideration of the mean-variance optimization method, 7 types of contracts or securities are utilized to discover models which are likely to supply us with minimum risks but maximum profits for electricity load distributors. Here, our objective is to select the most convenient model among 1000 portfolio in one month on behalf of investors (electricity loads distributors). This model has been applied for three seasons, such as Winter, Spring, Summer. (See Tables 5.5 , 5.6, 5.7)

Table 5.5 : For Winter Amounts of 7 Contract Variables Actualized in 17 Models and Values for each Expected Return and Variance

They are illustrated in different colors as follows Red: Least costly objective, Yellow: Least risky objective

MODELS	x1	x2	x3	x4	x5	x6	x7	EXPECTED COST	STANDARD DEVIATION
EXPECTED COST	0	30.000	30.000	30.000	30.000	0	0	3.619.773.336,72	106.301.823,46
STANDARDDEVIATION	19.409,88	8.788,39	10.153,80	0	30.000	0	0	3.637.642.048,48	105.999.239,85
2	18.604,28	9.937,69	11.364,19	0	30.000	0	0	3.636.872.694,72	106.000.476,72
3	0	28.328,23	29.691,33	0	30.000	0	0	3.619.986.339,78	105.999.382,36
4	0	28.501,11	30.000	0	30.000	0	0	3.619.959.899,30	106.000.505,29
5	0	28.859,74	30.000	1,99	30.000	0	0	3.619.952.552,49	106.001.841,95
6	0	29.331,16	30.000	0	30.000	0	0	3.619.942.918,99	106.005.085,16
7	0	29.954,99	30.000	0	30.000	0	0	3.619.930.157,12	106.012.071,84
8	0	30.000	30.000	0,02	30.000	0	0	3.619.929.236,31	106.012.693,69
9	0	30.000	30.000	0,06	30.000	0	0	3.619.929.236,10	106.012.694,06
10	0	30.000	30.000	30.000	30.000	0	0	3.619.773.336,72	106.301.823,46
11	0	30.000	30.000	30.000	30.000	0	0	3.619.773.336,72	106.301.823,46
12	0	30.000	30.000	30.000	30.000	0	0	3.619.773.336,72	106.301.823,46
13	0	30.000	30.000	30.000	30.000	0	0	3.619.773.336,72	106.301.823,46
14	0	30.000	30.000	30.000	30.000	0	0	3.619.773.336,72	106.301.823,46
15	0	30.000	30.000	30.000	30.000	0	0	3.619.773.336,72	106.301.823,46

As seen in the table above, 17 objective models are created and therefore, necessary calculations are performed by giving some assumed weighted values to expected return and variance. Our first objective model has been designated to obtain maximum rate of profit by neglecting risks so variance model has been accepted as zero. During the process of this application only excepted return model has been implemented. Our second model has been devised by accepting the value of expected return as zero but the rate of value one was attributed to variance model. On the other hand, in our other objective models some weighted values are assigned to expected return and variance. The total of those weighted values assigned to expected return and variance equals to one. Therefore, 7 contract variables are produced for each 17 objective models.

Optimal expected return and variance are calculated for each 17 objective model by utilizing values of 7 contract variables. As a result, those models having the lowest cost and risk are illustrated on the table in different colors. The model that electricity load distributor should choose depends on his preferences to his risk aversion behavior as well as his choices regarding to the rate of risk he is ready to take and rate of profit he would like to make.

Values obtained as a result of calculations for other seasons such as Spring and Summer by utilizing Matlab optimization tool and they are illustrated within in the content of the tables below:

Table 5.6 : For Spring Amounts of 7 Contract Variables Actualized in 17 Models and Values for each Expected Return and Variance

They are illustrated in different colors as follows Red: Least costly objective, Yellow: Least risky objective

MODELS	x1	x2	x3	x4	x5	x6	x7	EXPECTED COST	STANDARD DEVIATION
EXPECTED COST	0	0	0	0	0	0	0	1.899.259.593,79	63.525.203,33
STANDARDDEVIATION	16.969,46	7.618,65	9.282,64	0,50	30.000	30.000	0	1.903.586.450,98	59.597.780,83
2	15.684,15	8.866,89	10.567,74	0	30.000	30.000	5,84	1.903.542.391,59	59.597.781,01
3	0	24.347,64	26.245,96	0	30.000	30.000	33,03	1.903.041.663,65	59.597.958,58
4	0	22.026,41	25.937,02	164,48	30.000	3.239,11	0	1.902.649.772,78	59.628.255,27
5	0	18.903,88	26.052,70	12,71	30.000	9.635,73	1.365,68	1.902.196.925,05	59.709.146,71
6	0,40	14.806,21	25.896,50	0,72	30.000	960,86	2.147,16	1.901.572.921,38	59.917.615,93
7	28,19	8.991,47	25.783,89	0,25	30.000	11.032,94	7.240,47	1.900.724.869,47	60.390.013,85
8	2,29	772,06	26.311,44	18,38	30.000	5.594,45	30.000	1.899.457.947,99	61.430.800,61
9	0	0	0	0	0	0	0	1.899.259.593,79	63.525.203,33
10	0	0	0	0	0	0	0	1.899.259.593,79	63.525.203,33
11	0	0	0	0	0	0	0	1.899.259.593,79	63.525.203,33
12	0	0	0	0	0	0	0	1.899.259.593,79	63.525.203,33
13	0	0	0	0	0	0	0	1.899.259.593,79	63.525.203,33
14	0	0	0	0	0	0	0	1.899.259.593,79	63.525.203,33
15	0	0	0	0	0	0	0	1.899.259.593,79	63.525.203,33

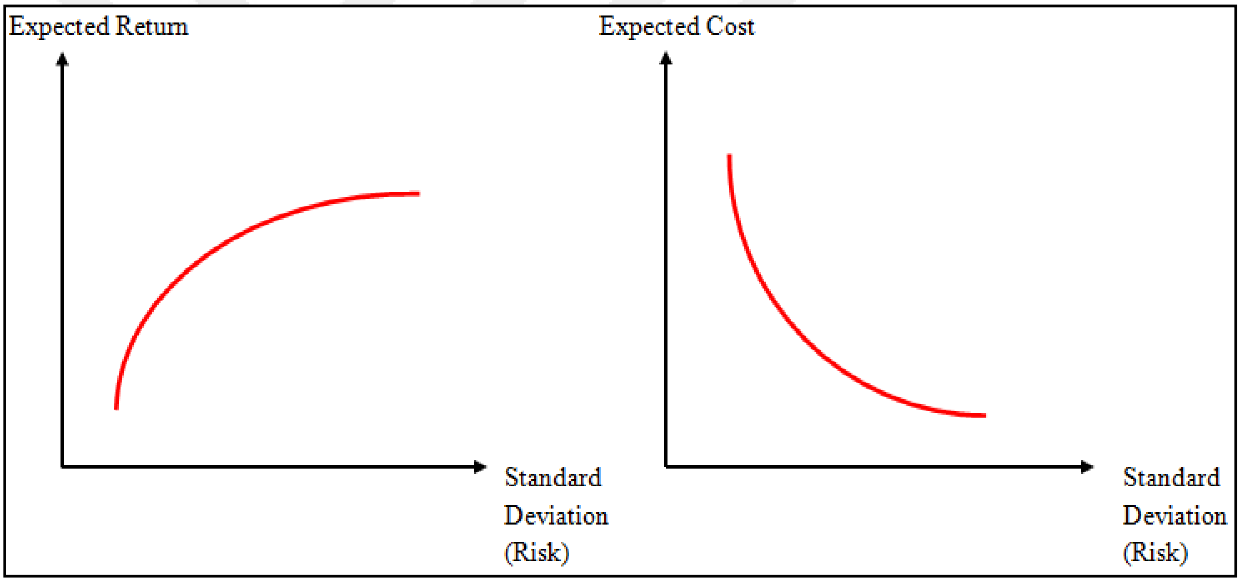
Table 5.7 : For Summer Amounts of 7 Contract Variables Actualized in 17 Models and Values for each Expected Return and Variance

They are illustrated in different colors as follows Red: Least costly objective, Yellow: Least risky objective

MODELS	x1	x2	x3	x4	x5	x6	x7	EXPECTED COST	STANDARD DEVIATION
EXPECTED COST	0,03	0	30.000	0	0	30.000	1,64	2.936.766.677,39	82.251.771,43
STANDARDDEVIATION	19.128,45	7.129,05	11.987,18	0	0	0	30.000	2.944.007.334,50	79.270.700,09
2	1.117,28	25.121,52	30.000	0	0	0	30.000	2.940.762.176,27	79.270.701,52
3	1.133,81	24.934,74	30.000	0	0	0	30.000	2.940.736.213,28	79.270.845,64
4	1.314,45	22.864,43	30.000	0	0	0,01	30.000	2.940.448.048,22	79.288.312,38
5	1.565,89	20.007,91	30.000	0	0	0,05	30.000	2.940.050.764,99	79.360.086,91
6	1.895,93	16.320,77	30.000	0	0	1,05	30.000	2.939.538.728,29	79.533.895,88
7	2.324,48	11.363,75	30.000	0	0	0,01	30.000	2.938.848.212,80	79.912.217,59
8	2.913,41	4.283,15	30.000	0	0	1.540,75	30.000	2.937.853.523,45	80.743.654,94
9	402,87	0	30.000	0	0	30.000	30.000	2.936.766.914,86	82.051.419,05
10	0	0,10	30.000	0	0	1,04	30.000	2.936.799.100,92	82.027.527,45
11	0,52	0,00	30.000	0	0	30.000	30.000	2.936.700.198,82	82.137.455,03
12	39,69	382,63	30.000	0	0	30.000	30.000	2.936.766.684,28	82.050.940,56
13	0	0,01	30.000	0	0	30.000	14,23	2.936.766.646,44	82.251.727,46
14	0	0	30.000	0	0	30.000	3,36	2.936.766.669,35	82.251.771,27
15	0,03	0	30.000	0	0	30.000	1,64	2.936.766.677,39	82.251.771,43

An optimal portfolio is the one which yields the highest rate of benefit over the efficient frontier for an investor. The optimal portfolio takes place at the intersection point of the efficient frontier and benefit curve. Since the behavior of electricity distributor has not been within the content of this quantitative research study, the choice of optimal portfolio has been left for the distributor. Expected profit and risk factors are displayed in the graph above. This efficient frontier curve is illustrated like this as seen in the graph below. Since our topic is expected cost and risk, the efficient frontier curve is modified like this as seen graph. (See Figure 5.8)

Figure 5.8 : Efficient frontier curve between expected return (profit) and standard deviation (risk) and efficient frontier curve between expected cost and standard deviation (risk)



Our optimization models' graphs for 3 seasons are illustrated below. (See figures 5.9, 5.10, 5.11)

Figure 5.9 : Efficient frontier curve for winter

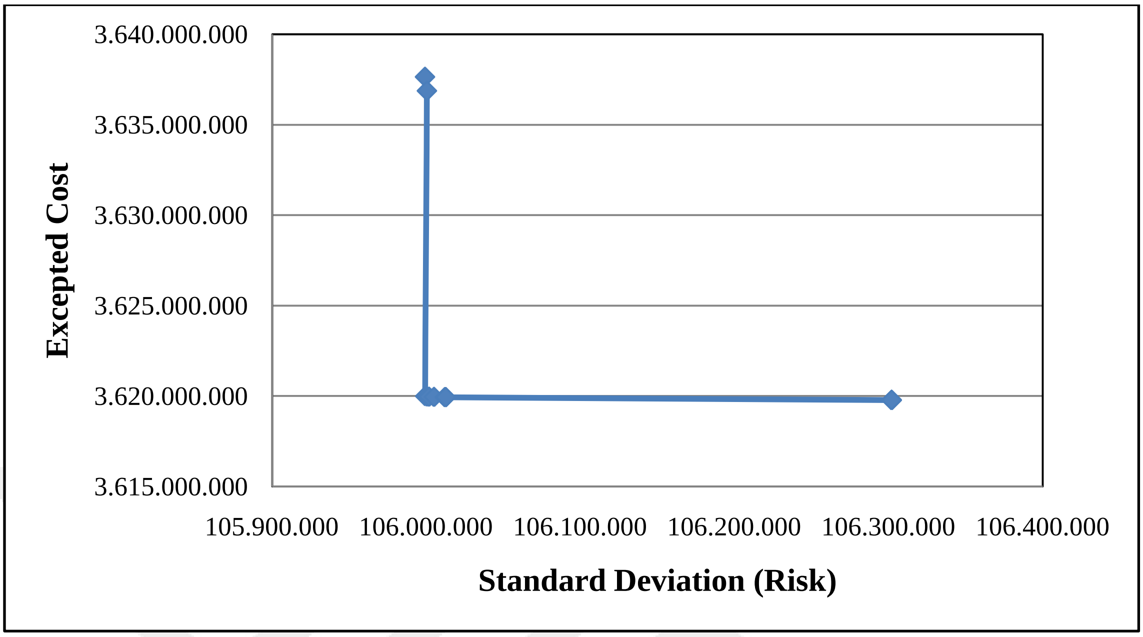


Figure 5.10 : Efficient frontier curve for spring

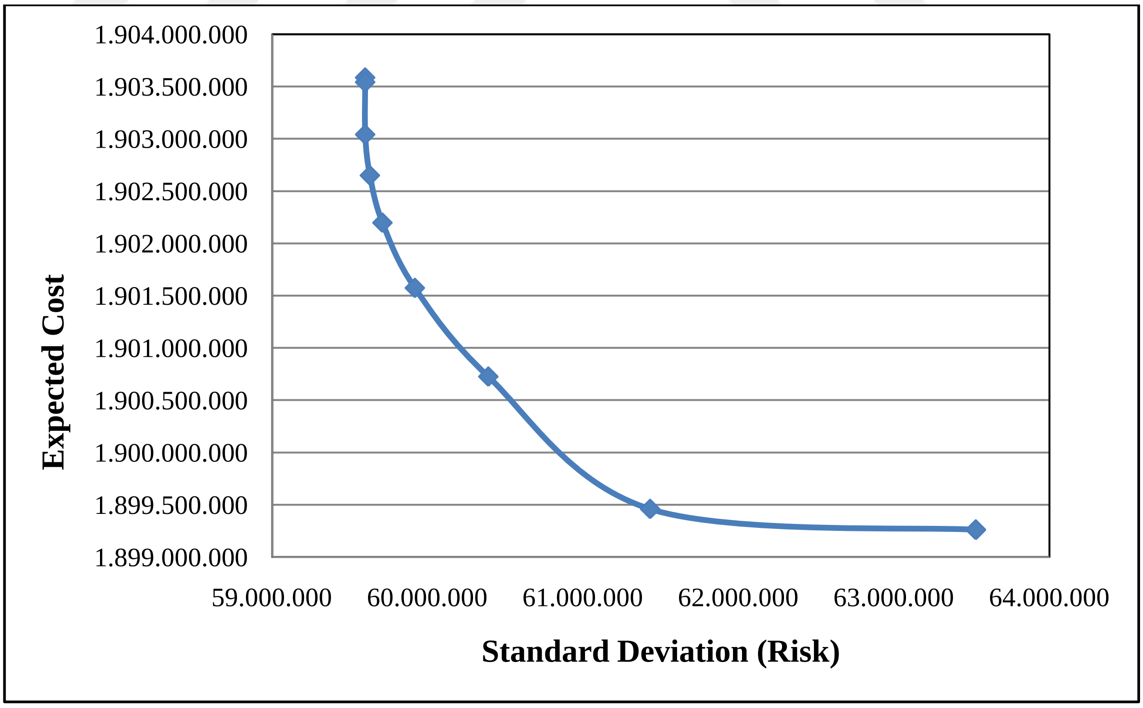
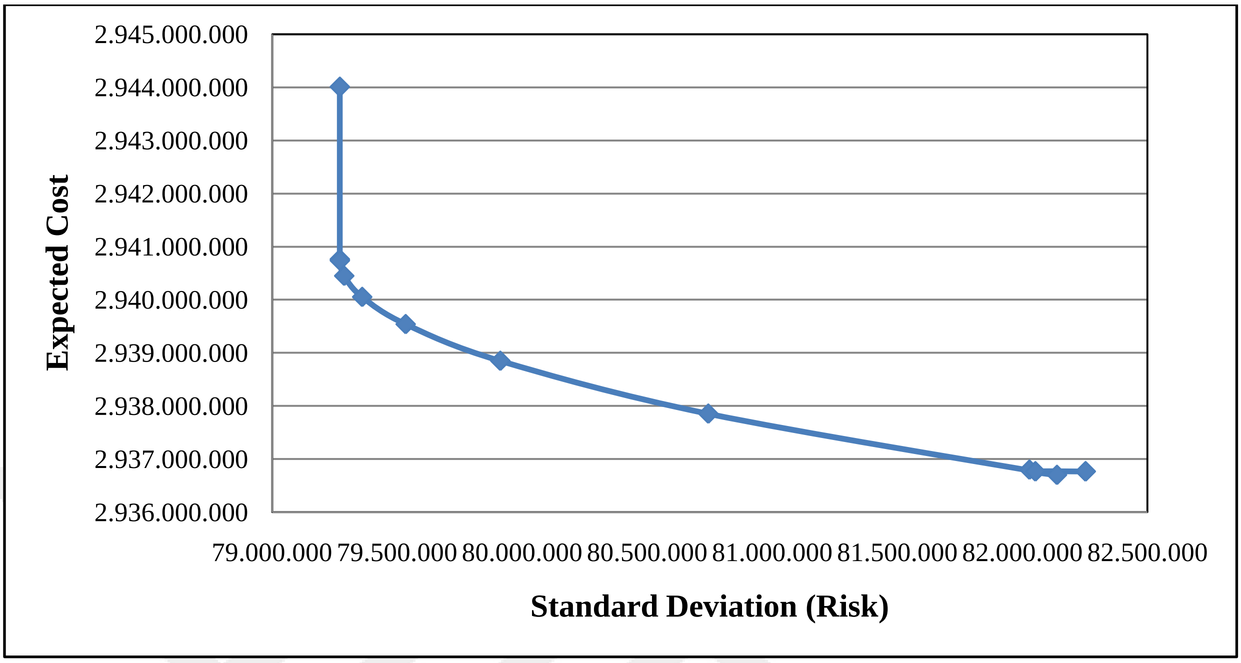


Figure 5.11 : Efficient frontier curve for summer



As seen in the figures above, the rate risk decreases as long as the cost goes down. That is to say, as long as the rate of profit increases, the rate of risk is reduced.

6. CONCLUSION

In this quantitative research study, a wide range of reference books, articles and websites have been examined in details to compile essential data for my study.

To start with, electricity markets are studied within the context of wholesale level together with electricity trading applications globally in order to comprehend the structure and operation of current electricity markets. It has been observed that electricity generation and distribution businesses are generally liberalized worldwide by abolishing monopolies in electricity market. After liberalization of electricity market, some new institutions are established to substitute for electricity generation and distribution monopolies. A few examples of liberalized electricity market structures are provided here to exemplify how those electricity markets are organized in different parts of the world.

Moreover, characteristics of electricity loads, prices and modeling and forecasting of electricity load demand are searched for by taking into account of their several advantageous and disadvantageous practices and statistical methods.

What is more, many real data analysis have been studied and compared with each other to come up with the most convenient models to be chosen to adopt for practice in my study.

Furthermore, risk and profit analysis have been conducted for electricity load distributors in order to find out the most effective and profitable models by making use of several current financial instruments to utilize in Turkey.

Finally, seventeen models are generated for electricity load distributors to choose the most convenient one for their own objectives and preferences.

In conclusion, many both comprehensive and concise quantitative research studies should be conducted on various challenges that electricity loads distribution companies have been experiencing ever since new forms of tasks, jobs and transactions became a common practice among distributors in a wide range of areas and regions to enable them forecast probable risks and prospective profit rates in all aspects of their businesses. Much wider span of time durations should be adopted while performing forecasts in order to reach more accurate quantitative research values. Here, only temperature factor has been taken into account but some other weather factors such as humidity, rate of precipitation can be included in the modeling part of the surveys. Some other hedging instruments such as options, swap contracts should be included in the content of future studies as well as future contracts. Besides, studies with in this respect may deal with both small and big electricity load distribution companies operating in different regions and locations.

REFERENCES

Books

Collins cobuild english language dictionary 1987, Collins ELT Harpers Collins Publishers 77-85 Fulham Palace Road London W6 8JB; pp. 278

Matter,F. 2004. *Gujarati: Basic Econometrics*, Fourth Edition pp. 297-298

Pedregal, D. J.; Young, P.C., 2002, *Statistical Approaches to Modeling and Forecasting Time Series* 2002, 2004 Blackwell Publishing Ltd pp. 72-91

Weron,R.2006. *Modeling and forecasting electricity loads and prices a statistical approach* John Wiley & Sons Ltd. pp. 1-178

Periodical

Ali, M. & Iqbal, M. J. & Sharif, M. , 2013. *Relationship between extreme temperature and electricity demand in Pakistan ,* Pakistan

Al-zayer, J.; Al-ibrahim A.A. , 1996, *Modelling the impact of Temperature on Electricity Consumption in the Eastern Province of Saudi A*rabia Journal of Forecasting, Vol. 15, pp. 98-99,105 97-106

Asadoorian, M.; Eckaus, R. and Schlosser, C n.d.; *Modeling climate feedbacks to electricity demand: The case of China,* Energy Economics, 30, **4**, pp. 1577-1602

Bessec,M.;Fouquau, J. 2007. *The non-linear link between electricity consumption and temperature in Europe: A threshold panel approach* .pp. 2705-2721

Bianco, V. & Manca, O. & Nardini, S. ,2009. *Electricity consumption forecasting in italy using linear regression models,*Roma,(Italy)

Boisseleau, F. 2004. *The role of power exchanges for the creation of a single european electricity market: market design and market regulation.* PhD Thesis, University of Paris IX Dauphine, Delft University, pp. 728-732

Bruhns,A.; Deurveilher,G. and Roy SJ.2015. *A Non-Linear Regression Model For Mid-term Load Forecasting and Improvements in Seasonality* Electricité de France Clamart, France pp. 1-8

Cancelo JR, Espasa A. and Grafe R. 2008.*Forecasting the electricity load from one day to one week ahead for the spanish system operator.* International Journal of Forecasting; 24. pp.59–83.

Cochran, S.; Mansur, I. and Odusami, B. 2015, *Equity market implied volatility and energy prices: A double threshold GARCH approach,* Energy Economics, 50, pp. 264-272,

Cottet R, Smith M.2003 *Bayesian modeling and forecasting of intraday electricity load.* Journal of the American Statistical Association.**98.** pp.839–849.

Crowley, C. & Joutz Frederick L. ,2003. *Hourly electricity loads: temperature elasticities and climate change*, Washington, D.C.

Dordonnat V, Koopman SJ, Ooms M, Dessertaine A. and Cottet J.2008. *An hourly periodic state space model for modelling French national electricity load*. International Journal of Forecasting. 24. pp. 566–587.

Fahad,M.U.; Arbab,N.2014. Factor *Affecting Short Term Load Forecasting*.Journal of Clean Energy Technologies, Vol. 2, No. **4**, pp. 305-306

Giannakopoulos, C. and Psiloglou, B.E. , 2006, *Trends in energy load demand for Athens, Greece : weather and non-weather related factors,* National Observatory of Athens, Institute of Environmental Research & Sustainable Development, Climate Research Vol: 31, Athens, Greece, pp. 97-108

Gökgöz,F.; Atmaca, M.T. 2011. *Financial optimization in the Turkish electricity market: Markowitz'smean-variance approach* Ankara University, Faculty of Political Sciences, Department of Management, Ankara, Turkey. pp. 359-360

Gökgöz F. 2009. *Mean variance optimization via factor models in the emerging markets: evidence on the Istanbul stock exchange*. Investment Management and Financial Innovations 6**(3**). Pp.43–53.

Harvey, A.C. 1989. *Forecasting Structural Time Series Models and the Kalman Filter*. Cambridge: Cambridge University Press pp. 91

Henley, A.; Peirson, J.1998 *Residential energy demand and the interaction of price and temperature: British experimental evidence.* Energy Economics, 20**, (2),** pp. 157–171

Howden, S.M. and Crimp, S. [no date], *Effects of climate and climate change on electricity demand in Australia,* Australia, pp. 655-660

Jalil,N.A.A.; Ahmad,M.H. and Mohamed,N.2013.*Electricity load demand forecasting using exponential smoothing methods.* Department of Mathematics, Faculty of Sciences, pp. 1540-1543

Kaye RJ, Outhred HR and Bannister CH.1990. *Forward contracts for the operation of an electricity industry under spot pricing*. IEEE Transactions on Power Systems pp. 1

Lam,J.C.; Tang,H.L. and Li, D.H.W.2008. *Seasonal variations in residential and commercial sector electricity consumption in Hong Kong* Building Energy Research Group, Department of Building and Construction, City University of Hong Kong, China Energy **33** . pp. 513–523

Liu M, Wu FF. 2006a. *Managing price risk in a multimarket environment.* IEEE Transactions on Power Systems pp.1513

Liu M, Wu FF, Ni Y.2006b. *A survey on risk management in electricity markets.* IEEE, Power Engineering Society General Meeting. pp. 1–6.

Makridakis, S. and Hibon, S. [no date], *ARMA models and the Box-Jenkins methodology,* Printed at INSEAD, Fontainebleau, France, pp. 1-19

Markowitz,H.M. 1952 *Portfolio selection*, j.Fin., vol. 7, no. 1, pp 77-80

Marquardt, D. W.1963. *An Algorithm for Least-Squares Estimation of Nonlinear Parameters* Journal of the Society for Industrial and Applied Mathematics, Vol. 11, **No. 2.** pp. 431-441

Migon,H.S.; Alves,L.C.2012 *Multivariate dynamic regression: modeling and forecasting for intraday electricity load* pp. 579-580

Mirasgedisa, S. & Sarafidisa, Y. & Georgopouloua, E.& Lalasa, D.P. & Moschovitsb, M.& Karagiannisb, F. & Papakonstantinoub D. , 2006. *Models for mid-term electricity demand forecasting incorporating weather influences,* Energy **31**, Athens,(Greece), pp. 208–227

Mohamed,Z.; Bodger, P.2005. *Forecasting electricity consumption in New Zealand using economic and demographic variables.* Department of Electrical and Computer Engineering, University of Canterbury, P.O. Box 4800, Christchurch, New Zealand Energy 30. pp. 1833–1843

Pachamanova,D. A.; Fabozzi, F.J.2010. *Simulation and Optimization in Finance: Modeling with MATLAB, @RISK, or VBA.*pp. 277-302

Paravan, D.; Debs,A.; Hansen,C.; Becker,D.;Hirsch,P. and Golob,R. *Influence of temperature on short-term load forecasting using the EPRI-ANNSTLF.* pp.4

Pardo, A. & Meneua, V.& Valor , E.,2002. *Temperature and seasonality influences on spanish electricity load*, Energy Economics **24** (Valencia), Spain pp. 55-70

Peirson, J. and Henley, A., 1994, Electricity load and temperature: issues in dynamic specification, Energy Economics, Volume **16**, Issue 4, pp. 235-243

Penados, C. V., 2008. *Role of the physical power exchange in the electricity wholesale market*, Pontificia Comillas University Madrid, pp.13-29

Petrick, S.; Rehdanz, K. and Tol, R.S. J. 2010 *The impact of temperature changes on residential energy consumption* Kiel working paper, No. 1618 pp. 3-4

Pezzulli, S.; Frederic, P.; Majithia, S.; Sabbagh, S.; Black, E.; Sutton, R. and Stephenson, D. 2006, *The seasonal forecast of electricity demand: a hierarchical Bayesian model with climatological weather generator*, Applied Stochastic Models In Business & Industry, **22, 2**, pp. 113-125

Quayle, R. G. and Diaz, H.F. 1979. *Heating degree day applied to residential heating energy consumption.* National Climatic Center, NOAA, Ashville, pp. 241-246

Rubia,A.2001. *Testing for weekly seasonal unit roots in daily electrıcıty demand: evidence from deregulated markets* University of Alicante. Departamento de Economía Financiera. Carretera de San Vicente, s/n. 03080 San Vicente del Raspeig (Alicante) pp. 1-2

Sailor,D. J. ; Muñoz, J. R. , 1997, *Sensitivity of electricity and natural gas consumption to climate in the U.S.A methodology and results for eight states.* Energy **22,** pp.987–998

Sheble GB.1999. Decision *analysis tools for GENCO dispatchers.* IEEE Transactions on Power Systems. pp. 1-3

Tanlapco E, Lawarree J, and Liu CC. 2002. *Hedging with futures contracts in a deregulated electricity industry*. IEEE Transactions on Power Systems. pp. 1-2

Taylor JW.2003. *Short-term electricity demand forecasting using double seasonal exponential smoothing.* Journal of Operational Research Society **54**. pp.799–805.

Tol, R.S.J. 2009 *The economic effects of climate change*. American Economic Association pp. 29-30

Torro, H. & Meneu, V. & Valor, E.,2001. *Single factor stochastic models with seasonality applied to underlying weather derivatives variables,* WP-EC 2001-22. Valencia (Spain)

Valor, E. & Meneu, V. & Caselles, V., 2001, *Daily air temperature and electricity load in spain,* American Meteorological Society volume 40, pp. 1413-1421

Vehvilainen I, Keppo J. 2003. *Managing electricity market price risk.* European Journal of Operational Research. pp. 2

Zarnikau, J.,2003. *Consumer demand for 'green power' and energy efficiency.* Energy Policy, 31, (**15**),pp. 1661–1672

Zeng, L., 1999. *Weather derivatives and weather insurance: concept, application and analysis,* Risk Analysis and Technologies, E.W. Blanch Company, American Meteological Society, Minneapolis, Minnesota Vol. **81** No.9, pp. 2075-2082

Other Publications

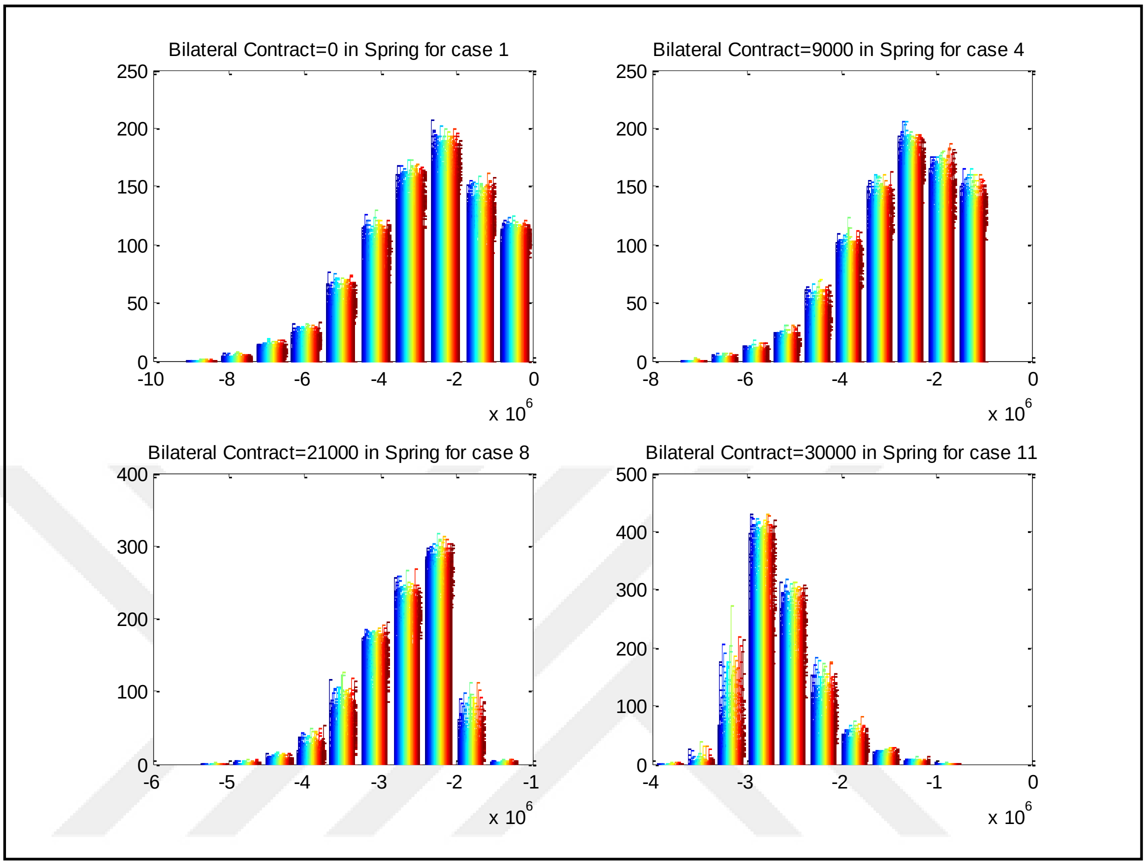
Gavin 2014 Seasonal variations in electricity demand pp. 73-74 https://www.gov.uk/government/uploads/system/uploads/attachment_data/file/295225/Seasonal_variations_in_electricity_demand.pdf [accessed 27 December 2015]

Meko,D. 2015 *http://www.ltrr.arizona.edu/~dmeko/geos585a.html#cLesson3* [accessed 27 December 2015]

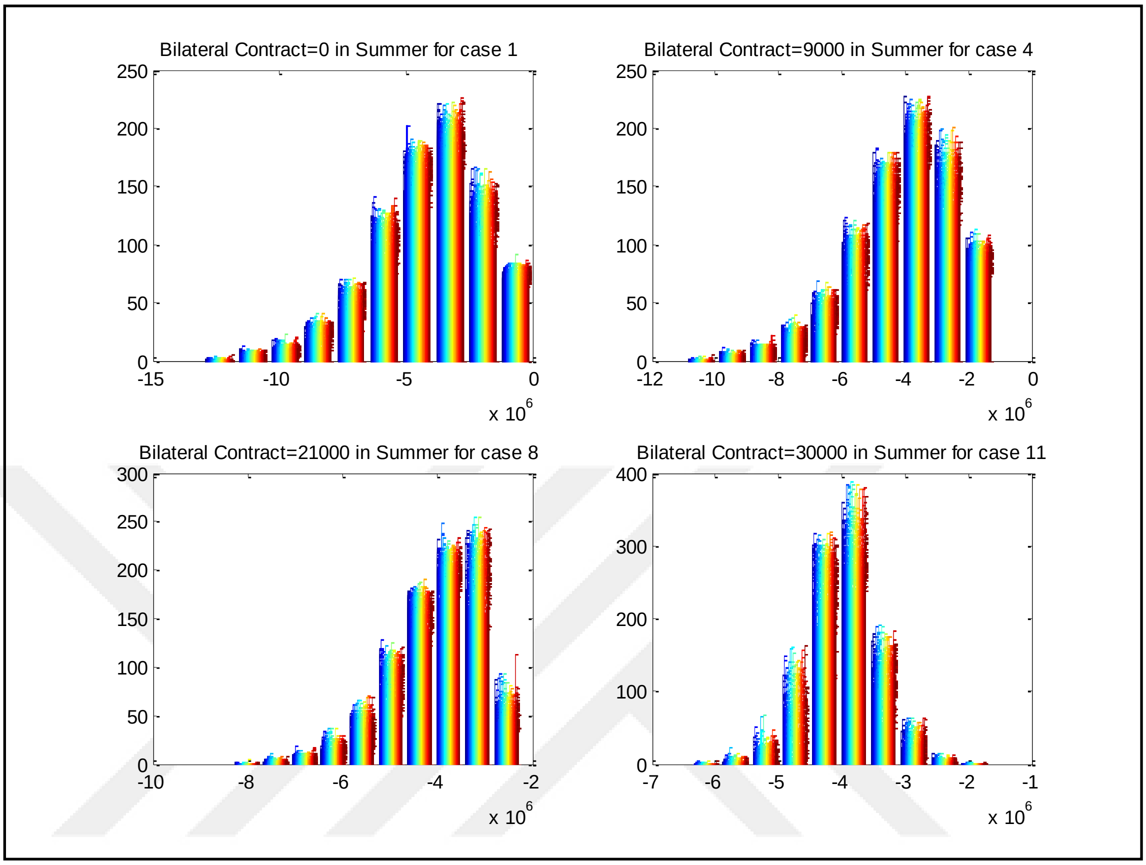
NIST/SEMATECH e-Handbook of Statistical Methods website 2015 http://www.itl.nist.gov/div898/handbook/ [accessed 27 December 2015]

APPENDICES

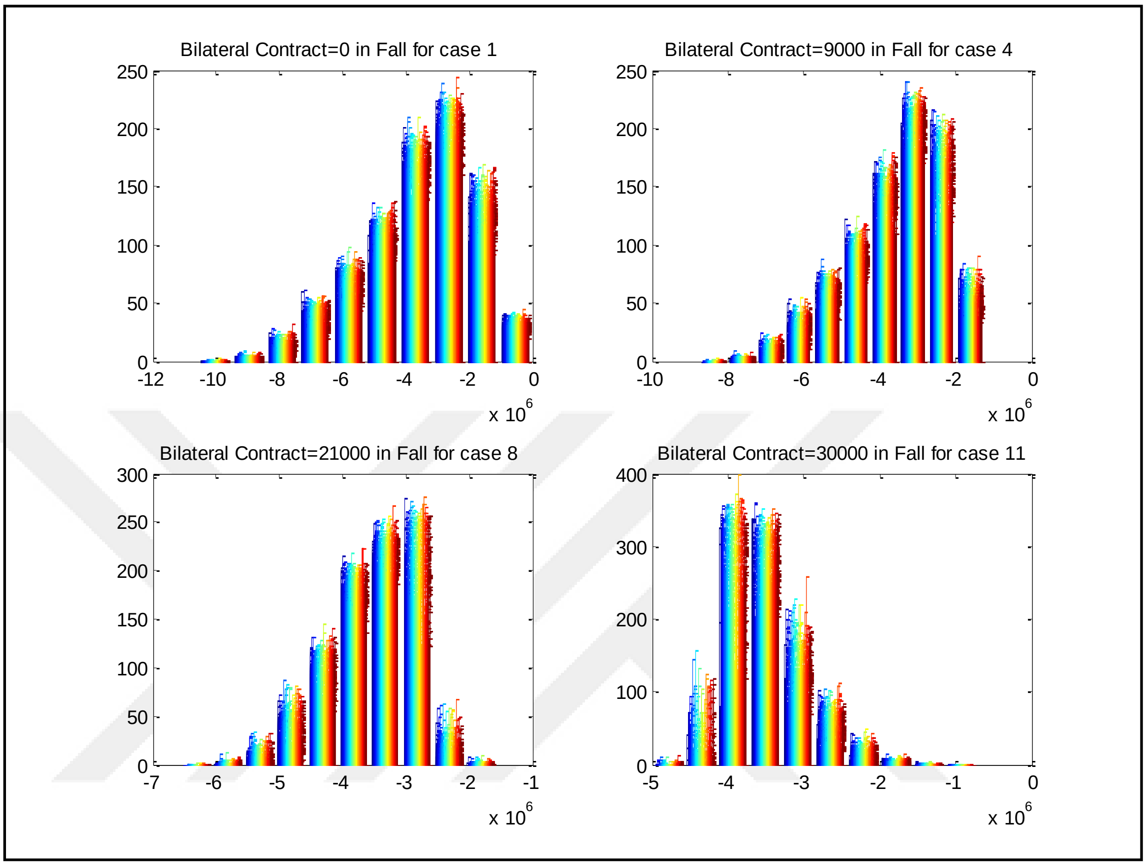
APPENDIX 1: Figure 1 Histograms for Case 1, 4, 8, 11 in April a month for Spring



APPENDIX 2 : Figure 2 Histograms for Case 1, 4, 8, 11 in July a month for Summer



APPENDIX 3 : Figure 3 Histograms for Case 1, 4, 8, 11 in October a month for Fall



APPENDIX 4 : TABLE 1 Expected Value E(x), Variance, Standard Deviation, Value at Risk (VaR), Conditional Value at Risk (CVaR) in April for 11 Different Cases

Profits	E(x)	Variance	STD	VaR	Conditional VaR
1	45.555.379,24	2.256.720.698.344,68	1.502.238,56	43.123.363,04	42.445.393,57
2	45.555.445,84	2.256.330.601.171,92	1.502.108,72	43.121.969,66	42.445.331,37
3	45.555.512,45	2.255.965.311.886,73	1.501.987,12	43.120.576,29	42.445.269,17
4	45.555.579,05	2.255.624.830.492,19	1.501.873,77	43.119.182,91	42.445.206,97
5	45.555.645,66	2.255.309.156.979,57	1.501.768,68	43.117.789,53	42.445.144,77
6	45.555.712,26	2.255.018.291.352,73	1.501.671,83	43.116.396,16	42.445.082,57
7	45.555.778,87	2.254.752.233.622,17	1.501.583,24	43.115.002,78	42.445.020,37
8	45.555.845,47	2.254.510.983.774,05	1.501.502,91	43.115.146,10	42.444.958,17
9	45.555.912,08	2.254.294.541.812,98	1.501.430,83	43.116.791,49	42.444.895,97
10	45.555.978,68	2.254.102.907.749,99	1.501.367,01	43.118.436,89	42.444.833,77
11	45.556.045,29	2.253.936.081.558,94	1.501.311,45	43.120.082,28	42.444.771,57

APPENDIX 5 : TABLE 2 Expected Value E(x), Variance, Standard Deviation, Value at Risk (VaR), Conditional Value at Risk (CVaR) in July for 11 Different Cases

Profits	E(x)	Variance	STD	VaR	Conditional VaR
1	51.562.401,66	2.057.382.383.873,28	1.434.357,83	49.279.820,17	48.673.603,75
2	51.562.397,83	2.056.778.872.581,38	1.434.147,44	49.280.853,98	48.673.207,80
3	51.562.394,00	2.056.215.529.643,69	1.433.951,02	49.287.770,49	48.672.811,86
4	51.562.390,17	2.055.692.355.058,67	1.433.768,58	49.291.775,69	48.672.345,39
5	51.562.386,34	2.055.209.348.855,03	1.433.600,14	49.283.955,43	48.671.613,06
6	51.562.382,51	2.054.766.510.995,86	1.433.445,68	49.284.989,25	48.670.880,73
7	51.562.378,68	2.054.363.841.500,64	1.433.305,22	49.286.023,07	48.670.148,40
8	51.562.374,85	2.054.001.340.357,06	1.433.178,75	49.287.056,88	48.669.416,07
9	51.562.371,02	2.053.679.007.583,58	1.433.066,30	49.288.090,70	48.668.683,73
10	51.562.367,19	2.053.396.843.165,85	1.432.967,84	49.289.124,52	48.667.951,40
11	51.562.363,36	2.053.154.847.115,15	1.432.883,40	49.288.359,33	48.667.141,55

APPENDIX 6 : TABLE 3 Expected Value E(x), Variance, Standard Deviation, Value at Risk (VaR), Conditional Value at Risk (CVaR) in October for 11 Different Cases

Profits	E(x)	Variance	STD	VaR	Conditional VaR
1	44.484.619,01	1.973.451.021.269,68	1.404.795,72	42.135.010,18	41.563.317,76
2	44.484.506,30	1.973.340.899.001,46	1.404.756,53	42.132.187,89	41.562.973,11
3	44.484.393,60	1.973.273.718.910,46	1.404.732,61	42.130.503,86	41.562.605,22
4	44.484.280,90	1.973.249.480.979,24	1.404.723,99	42.128.819,82	41.562.237,34
5	44.484.168,19	1.973.268.185.204,71	1.404.730,65	42.127.135,78	41.561.869,46
6	44.484.055,49	1.973.329.831.601,76	1.404.752,59	42.125.451,74	41.561.501,58
7	44.483.942,78	1.973.434.420.161,67	1.404.789,81	42.123.767,70	41.561.133,70
8	44.483.830,08	1.973.581.950.873,65	1.404.842,32	42.122.083,66	41.560.765,82
9	44.483.717,38	1.973.772.423.760,29	1.404.910,11	42.120.399,62	41.560.397,94
10	44.483.604,67	1.974.005.838.809,52	1.404.993,18	42.118.715,58	41.560.030,05
11	44.483.491,97	1.974.282.196.008,02	1.405.091,53	42.117.031,54	41.559.662,17