SMART GRID APPLICATIONS AND TECHNOLOGIES IN DISTRIBUTION SYSTEMS

A THESIS SUBMITTED TO
THE GRADUATE SCHOOL OF NATURAL AND APPLIED SCIENCES
OF
MIDDLE EAST TECHNICAL UNIVERSITY

BY

KÜBRA PEHLIVANOĞLU GÜRBÜZ

IN PARTIAL FULFILLMENT OF THE REQUIREMENTS
FOR
THE DEGREE OF MASTER OF SCIENCE
IN
ELECTRICAL AND ELECTRONIC ENGINEERING

JANUARY 2019

Approval of the thesis:

SMART GRID APPLICATIONS AND TECHNOLOGIES IN DISTRIBUTION SYSTEMS

submitted by **KÜBRA PEHLIVANOĞLU GÜRBÜZ** in partial fulfillment of the requirements for the degree of **Master of Science in Electrical and Electronic Engineering Department, Middle East Technical University** by,

Prof. Dr. Halil Kalıpçılar
Dean, Graduate School of **Natural and Applied Sciences** _____

Prof. Dr. Tolga Çiloğlu
Head of Department, **Electrical and Electronic Eng.** _____

Prof. Dr. Osman Sevaioğlu
Supervisor, **Electrical and Electronic Eng., METU** _____

Examining Committee Members:

Prof. Dr. M. Cengiz Taplamacıoğlu
Electrical and Electronics Engineering, Gazi University _____

Prof. Dr. Osman Sevaioğlu
Electrical and Electronic Eng., METU _____

Assoc. Prof. Dr. Murat Göl
Electrical and Electronics Engineering, METU _____

Prof. Dr. Ömer Usta
Electrical Engineering, ITU _____

Assist. Prof. Dr. Süleyman Sungur Tezcan
Electrical Electronics Engineering, Gazi University _____

Date: 22.01.2019

I hereby declare that all information in this document has been obtained and presented in accordance with academic rules and ethical conduct. I also declare that, as required by these rules and conduct, I have fully cited and referenced all material and results that are not original to this work.

Name, Surname: Kübra Pehlivanoğlu Gürbüz

Signature:

ABSTRACT

SMART GRID APPLICATIONS AND TECHNOLOGIES IN DISTRIBUTION SYSTEMS

Pehlivanoğlu Gürbüz, Kübra
Master of Science, Electrical and Electronic Engineering
Supervisor: Prof. Dr. Osman Sevaioğlu

January 2019, 126 pages

Smart grid control purposes to rise the percentage of energy production through alternative energy sources like renewable resources and to make consumers to be comprehended in grid actively, is realising importance day by day. Further to that it can help us employment opportunities and improving growth in addition to keep the power on at minimum cost to prosumers, while the participation is elucidated and enabled new products, service and markets, accommodating all generation and storage options and provided the power quality for the range of requires in the 21st century economy by smart grid control. Some methods which are able to ensure the detection, isolation forecast have been developed for load forecasting in Smart Grid Control applications which In scientific research a lot of methods have been proposed to overcome load fluctuations. The purpose of this thesis is to specify the requirement of Smart Grid Technologies in load forecasting. Our objective is to build an accurate load forecasting model in Smart Grid Control for generating reasonable forecasting using previous decades load consumption data with Artificial Neural Network (ANN). The proposed smart grid load forecasting methodology provides an applicable option for developing the perfect balance among reliability, availability, efficiency and cost for Turkey. Present state of the system was simulated in MATLAB ANN tool and 11 years of data was used on distribution lines. In the scope of this thesis, some critical

parameters are prescribed as effective parameters for load forecasting. It is seen that the system presented in this study is open to improvements and suggestions to make the system to be able to work confidentially.

Keywords: Smart Grid Control, Load Forecasting, Artificial Neural Network

ÖZ

DAĞITIM SİSTEMLERİNDE AKILLI ŞEBEKE UYGULAMALARI VE TEKNOLOJİLERİ

Pehlivanoğlu Gürbüz, Kübra
Yüksek Lisans, Elektrik ve Elektronik Mühendisliği
Tez Danışmanı: Prof. Dr. Osman Sevaioğlu

Ocak 2019, 126 sayfa

Akıllı şebeke kontrolü, yenilenebilir enerji kaynakları gibi alternatif enerji kaynakları aracılığıyla enerji üretiminin yüzdesini arttırmak ve tüketicilerin şebekede aktif olarak kavranmasını sağlamak için her geçen gün önemini ortaya koymaktadır. Bunun yanı sıra, 21. yüzyıl ekonomisinde akıllı şebeke kontrolü tüketicilere en az maliyetle güç tüketimi, enerji üretim ve depolama seçeneklerini barındıran yeni ürün, hizmet ve pazarlara katılımını etkin hale getirmiş, güç kalitesinin artırılmasını sağlamış ve ek olarak istihdamın artırarak büyümenin devamlılığını sağlamaktadır. Bilimsel araştırmalarda, yük dalgalanmalarının üstesinden gelmek için birçok yöntem önerilerek Akıllı Şebeke Kontrol uygulamalarında yük tahmini için tespit ve izolasyon tahminlerini sağlayabilecek bazı yöntemler geliştirilmiştir. Bu çalışmanın amacı akıllı şebekler teknolojisi ile yük tahmininde bulunmak. Bu kapsamda hedefimiz Yapay Sinir Ağı (YSA) ile önceki yıllardaki yük tüketim verilerini kullanarak makul tahminler üretmek için Akıllı Şebeke Kontrolünde doğru bir yük tahmin modeli oluşturmaktır. Önerilen akıllı şebeke yükü tahmin metodolojisi, Türkiye için güvenilirlik, kullanılabilirlik, verimlilik ve maliyet arasında mükemmel dengeyi geliştirmek için geçerli bir seçenek sunmaktadır. Sistemin mevcut durumu MATLAB ANN aracında simüle edilmiş ve dağıtım hatlarında 11 yıllık veriler kullanılmıştır. Bu çalışma kapsamında bazı kritik parametreler yük tahminin performansı etkileyen

parametreler olarak öngörülmüştür. Çalışmanın sonucunda görülmüştür ki, ilgili tez kapsamında sunulan sistem enerji iletim şebekesinin güvenilir çalışabilmesi sağlamaktadır.

Anahtar Kelimeler: Akıllı Şebeke Kontrolü, Yük Tahmini, Yapay Sinir Ağları

To My Father

ACKNOWLEDGMENTS

First of all, I would like to thank to my supervisor, Prof. Dr. Osman Sevaioğlu for his guidance and recommendations throughout this study.

It is hard to describe how much I am deeply grateful with my father, my mother and my sister. Their support has always been with me not only for this study but also for my whole life. I would not be able to complete this thesis without their emboldening. Throughout my whole life, they always believe me that I can success.

I would like to express my thanks to Assoc. Prof. Dr. Yılser Devrim, Hüseyin Devrim and TEKSİS İleri Teknolojiler, for their motivation and encouragements in my personal and business life.

Special thanks to Atilla Gürbüz for his unquestioning support and precious guidelines. I owe a debt of gratitude to Celal Yılmaz for his ideas and advices during modeling processes.

I would like to give thanks to my dear friends, Sevim Köleli, Mahmure Arı and Gizem Nur Bulanık for their friendship and moral support.

I am also very grateful to Sinan Kul for his support and understanding in my business life.

I would also like to thank to my beloved friends Eyşan Ekici and Damla Kaya who gave me their awesome fellowship endless support during the hard times of this study.

The last word goes for Mehmet, love of my life. He has given me the extra strength and motivation to get things done.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF ABBREVIATIONS

AAM	Advanced Asset Management
AC	Alternating Current
ADA	Advanced Distribution Automation
ADO	Advanced Distribution Operation
AMI	Advanced Metering Infrastructure
ANN	Artificial Neural Network
ATO	Advanced Transmission Operation
ARIMA	Autoregressive Integrated Moving Average
B&S	Balancing and Settlement
BOO	Build-Own-Operate
BOT	Build-Operate-Transfer
BP	Back-propagation
BSR	Balancing and Settlement Regulation
CPP	Critical Peak Pricing
DA	Distribution Automation
DC	Direct Current
DER	Distributed Energy Resource
DoE	American Department of Energy
DTS	Distribution Transformers Substation
EMRA	Energy Market Regulatory Authority

EPDK	Republic of Turkey Energy Market Regulatory Authority
EPIAS	Energy Exchange Istanbul (ing. EXIST)
EUAS	Public Generation Company
GDP	Gross Domestic Product
GWh	Gigawatt Hour
HAN	Home Area Network
HEMS	Home Energy Management System
HV	High Voltage
IED	Intelligent Electronic Device
kTOE	Kilotonne of Oil Equivalent
LM	Levenberg-Marquardt
LTLF	Long-Term Load Forecasting
LV	Low Voltage
MFSC	Market Financial Settlement Centre (PMUM in Turkish)
MTLF	Medium-Term Load Forecasting
MV	Medium Voltage
PLC	Power Line Communication
PMU	Phasor Measurement Units
PSO	Particle Swarm Optimization
RES	Renewable Energy Source
SG	Smart Grid
STLF	Short-Term Load Forecasting

TCC	Time Current Characteristic
TEAS	Turkish Electricity Generation Transmission Company
TEDAS	Turkish Electricity Distribution Company
TEIAS	Public Transmission Company (Turkish Electricity Transmission Company)
TEK	Turkish Electricity Authority
TETAS	Public Wholesale Company
TOOR	Transfer of Operating Rights
TOU	Time of Use
VHV	Very High Voltage
WAMACS	Wide Area Measurement and Control Systems

LIST OF SYMBOLS

Symbol	Definition
A	Output of network
g	Differentiable monotonic function
W	Connection weight of jth neuron to i^{th} layer neuron
α	Input of the neuron
t	Target value
ε	Random error
X	Design matrix in Regression Method
β	p coefficient values
a(t)	Random shock component of ARIMA model
$\emptyset(B)$	Autoregression function
B	Backward shift operator
$v(t)$	Rate of change in PSO model
mean(se)	Mean value of the difference between the simulation output
max(test target)	Maximum value of the test target

CHAPTER 1

INTRODUCTION

Energy is an important factor in terms of economic, social and environmental subjects of sustainable development (Midilli, Ay, Dincer, & Rosen, 2005; Rosen & Dincer, 1997). World energy consumption density trend is an substantial indicator of the complete subscription of primary and end-use energy consumption in heating-cooling, electric and transportation sectors. Primary energy is harvested directly from the natural resources. In order to transform the form of the primary energy, energy conversion technology is required. On the other hand, end-use energy is the energy directly utilised from the consumer.

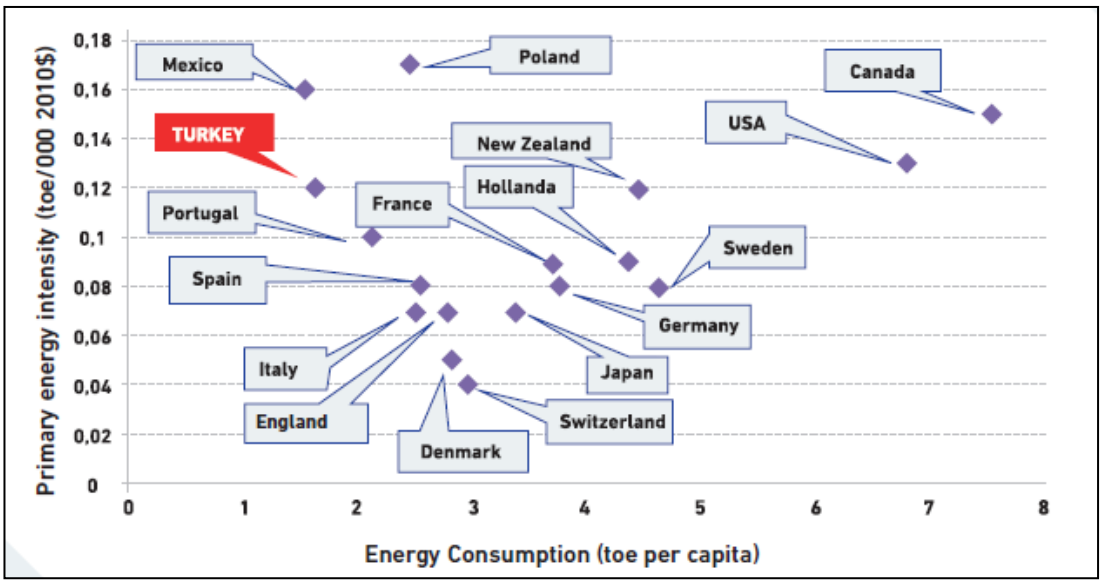

Figure 1-1. Comparison of countries by primary energy intensity ("National Energy Efficieny Action Plan (NEEAP)," 2018)

Figure 1-1 shows primary energy intensity of Turkey in the World. The energy savings potential has an important place despite energy consumption per capita is lower among developed countries. The energy consumption of Turkey is rised by 70% unit when

GDP of Turkey grown between the years 2005 and 2014. For the same GDP increment, the energy consumption of France is 1.1 unit, Germany 0.7 unit, Japan 3.3 unit and lastly UK is 2.0 unit in that period.

The biggest part of the energy source uses in industrial and domestic applications comes from the conventional fuels like petroleum, coal and natural gas comprehensively. Total Primary Energy Supply (TPES) in Turkey by source is given Figure 1-2 which excludes electricity and heat trade between 1990-2016.

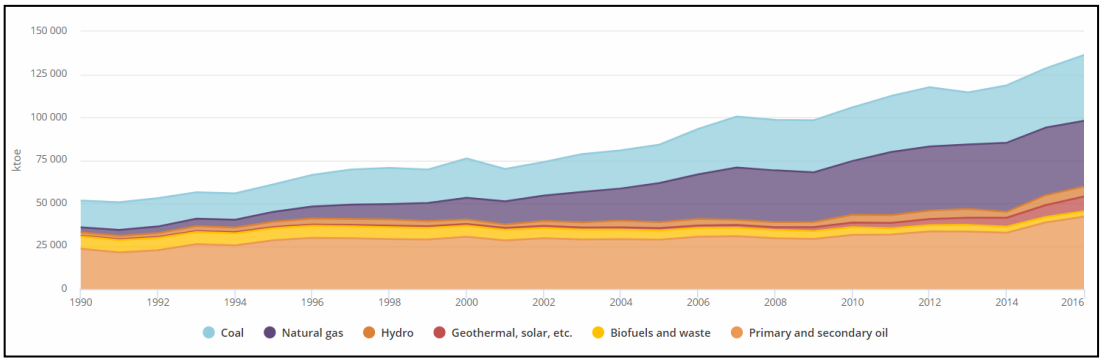

Figure 1-2. TPES by source ("Total Primary Energy Supply (TPES)," 2017)

The most basic and substantial type of the end-use energy is electrical energy. It determines economic and social development of the countries. End-use energy consumption has expanded rapidly with the country's growth in recent years. Turkey's final electricity consumption sector has about 98000 GWh of end-use electrical energy consumption in 2000, it has been growing up to about 215000 GWh in 2015 (Kılıç, 2006). End-use electricity consumption contains industry and buildings and services.

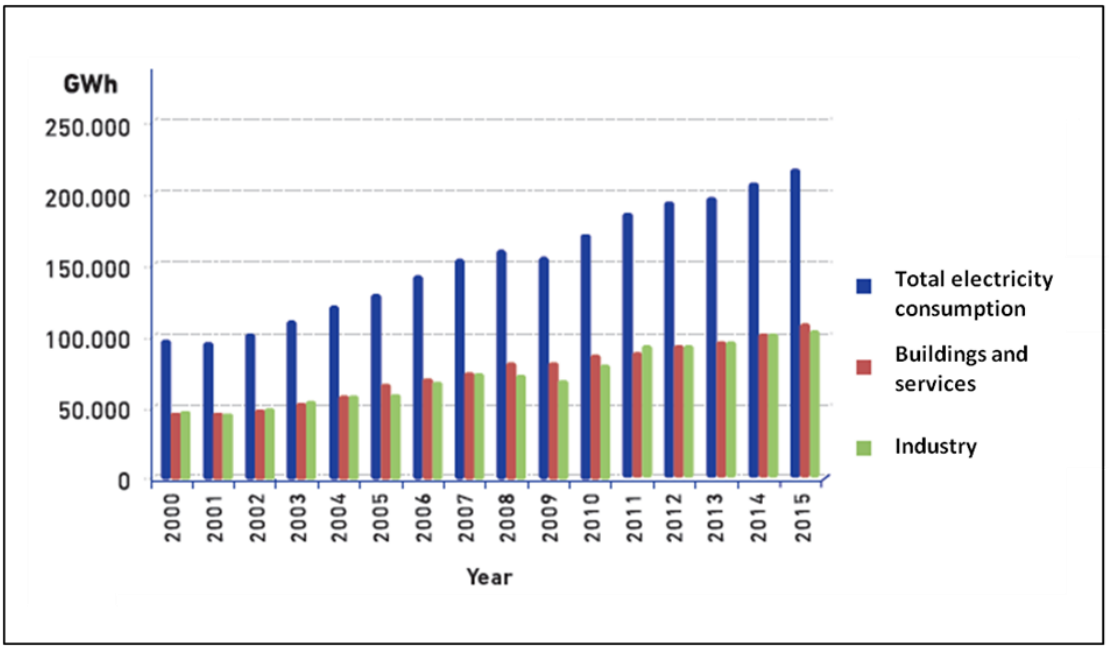

Figure 1-3. Changes in end-use electricity consumption by year ("National Energy Efficieny Action Plan (NEEAP)," 2018)

As seen from Figure 1-3 the global electricity requirement for the World especially for our country has grown, because of industrialization and urbanization. In the same breath, energy generation supplies the largest part of source of CO2 emissions (Steffen, 2018; "Summary for Policymakers," n.d.). Another important point is that Turkey is excessively needer on the import of fossil fuels like coal, oil and gas from abroad. To these respects, renewable energy solutions such as wind, sun, tidal, geothermal and biomass in an alternative way to use as energy systems worldwide (Canaria, Cabrera, & Lund, 2018; Lund, 2000). Generated electricity both from conventional fuels and renewable energy sources integrated to the electricity power grid from where it is distributed in varied areas ("Sources of energy," n.d.).

The working principle of traditional grid based on the coaction between distribution and transmission but end user is not enclose predominately. Dynamic demands on the power grid pioneer to a more responsive system, such as the lately recommended smart grid, to make certain the effective participation of consumer (A. B. M. S. Ali,

2013; Murtaza, Singh, & Prakash, 2014; U.S. Department of Energy, 2010). During the past ten years, the electrical energy generation, transmission and distribution system are had an impact upon that a new way of changes has been taken place in the power system called by name of Smart Grid (SG) (Murtaza et al., 2014).

Recently, the industry of electrical energy has been continual significant alterations which has a mind to rising the influence of RES into electric generation technology and productivity in power production, transmission and distribution systems. Stimulations in back of alterations are rapid step up in electric power requirements developing countries, unfavourable environmental effects of power production from conventional fuel and exhaustion of these generation sources. Substations reduce the high voltage to medium voltage in transmission and distribution system to transmit the energy to consumers as an end users. Since the usage of information and communication technologies (ICT) have been increasingly gone on in all spheres as is the case with power grid system, electric power transmission and distribution system are anticipated to be "smart". The characteristic of the smart grid system is summarized as below listed;

- Decreasing electricity prices for consumers by minimizing enterprise, operation and maintenance costs
- Attainment to specify and straight several inaccuracy (short circuit, loss of phase, etc.) in the grid system feeders
- Conservation encounterer cyber attacks
- Transmitting the electric power with high grade and stability
- Optimizing acquisition management
- Skill to accommodate different energy generation plants with multifarious resources (fossil-fuel based, RES)

Transmission and distribution system consists of transformers substations, voltage distribution feeders, equipments (circuit breakers, disconnector switches, fuses, potential and current transformers, etc.), conductors and cables for the most part. In

smart grid technologies, smart distribution, transmission and generation communication technologies are used in addition to these equipments. The grid system are monitored and controlled with them to ensure serviceability for energy requirement and power property indices are among significant liabilities of a distribution company.

The restrictions in the established electric power - laid out and developed in the 20th century like enhancing transmission congestions, more compact major blackouts and limited flexibility to accommodate smart ingredients such as renewable and distributed energy resources is run up rapidly (U.S. Department of Energy, 2010). The Smart Grid theme is associating a number of control technologies, consumer solutions and addresses various policy and regulatory drivers.

Smart Grid does not have any unique apparentness definition (A. B. M. S. Ali, 2013). The American Department of Energy (DoE) describes the SG as "a class of technology people are using to bring utility electricity delivery systems into the 21st century, using computer-based remote control and automation. These systems are made possible by two-way communication technology and computer processing that has been used for decades in other industries. They are beginning to be used on electricity networks, from the power plants and wind farms all the way to the consumers of electricity in homes and businesses. They offer many benefits to utilities and consumers –mostly seen in big improvements in energy efficiency on the electricity grid and in the energy users' homes and offices" (Leszczyna, 2018). Additionally, from the aforementioned definitions, the Smart Grid can be identified as the electrical power network which uses computational and other advanced level of technologies to mind out and administer the transport of electricity from all electric energy generation sources to counterbalance the varying electricity demands of customers (International Energy Agency, 2011).

In order to efficiently deliver sustainable, economic and secure electricity supplies, this brainy technology is an electricity network that can intelligently integrate the actions of all users connected to it - producers, consumers and those that do both

(Otuoze, Mustafa, & Larik, 2018; Platform, n.d.; Vijayapriya & Kothari, 2011). Figure 1-4 shows how to smart grid technologies ensure convenience (Kabalci & Kabalci, 2017). Since SG is ensuring sufficient datum supplying from substations, distributions, transmission and generations, to enhance the safety, robustness and efficacious supervise and looking out of assets and services, the intelligence of grid system's interoperation has been improved by the provision of multi-directional flow of energy and information between any two or more subsystems in the grid to attain a revolutionised energy industry (Ananda Kumar, Pandey, & Punia, 2014; Camarinha-Matos, 2016; Farhangi, 2010; Ghansah, 2012; Otuoze et al., 2018).

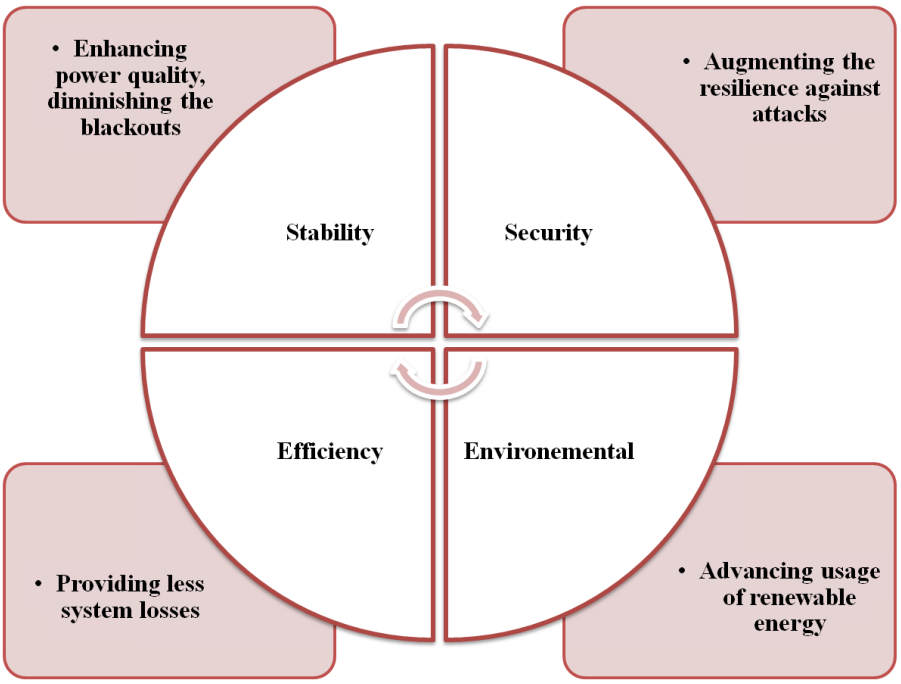

Figure 1-4. Progress subjects of smart grid control

Carrying out the target of sustainable, reliable and affordable power supplies with active end users' attendance is the concept used worldwide. Users and utilities are connected to each other by using Advanced Metering Infrastructure (AMI) that

associated with Home Energy Management System (HEMS), may be employed in order to handle the rising requirement adequately. Utilities on consumers' consumption pattern are instructed by HEMS and smart meters allowed AMI. In addition to this, convenience information of energy from the grid along with prices and incentives etc. can be obtained (Opris & Caracasian, 2013; Zafar et al., 2018; Zhou, Xu, & Ma, 2010).

Smart grid presents some advantages to provide convenience like improving quality and reliability of power delivery, facilitating deployment of distributed energy sources and renewable sources, enhancing resilience to disruption and ability of self- recovery, being more predictive maintenance, automating operation and maintenance and being wider consumer choice (Leszczyna, 2018; Publication, 2012). Usage of some of smart end-use devices rise the electrical energy consumption (More, 2014). Consequently, It is inevitable to have to forecast the load consumption for smart grid control.

On the other hand some difficulties during the implementation of smart grid control technologies are given the following (Kaushal, 2011).

- Policy and regulation
- Ability and knowledge
- Technology maturity and delivery risk
- Attainment to affordable capital
- Lack of mindfulness
- Cyber security and data privacy

Distributed generation units located at prosumer's site generate electricity in accordance to their relevant generation technology. Prosumer also has a level of consumption as fixed or variable electrical loads such as household appliances on permanent or intentional use. The information of current generation and consumption levels, pattern and magnitude of increase or decrease trends in

generation/consumption, power quality status (voltage level, current level, harmonics) are exchanged to the grid operator as a consolidated status report of prosumer site.

Local grid conditions around the prosumer site, forecasts of local consumption patterns, planned outages and maintenance activities, status of local critical loads (such as hospitals etc.) are consolidated and exchanged to respective prosumers in order to sustain relevant safety measures, optimize and manage local power flow, provide status indication of prosumer within the local grid so that the grid operator and prosumer can maintain a secure and efficient communication channel to increase efficiency, safety and benefits on both sides of the energy exchange.

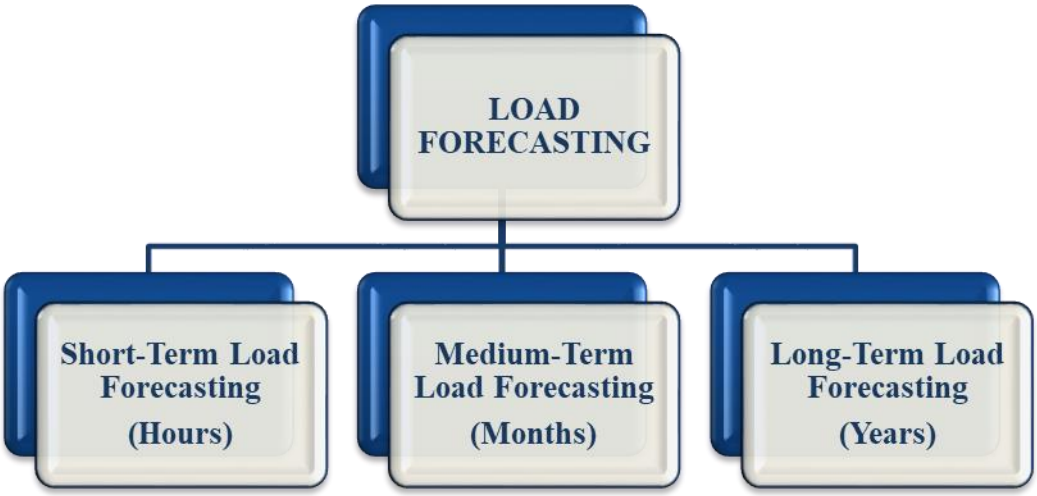

Figure 1-5. Load forecasting types

Forecasting of the electric power consumption is an essential and wholistic operation in the shaping and operation of consumers (Alfares & Nazeeruddin, 2002). Rising security of electrical energy supply and distribution system, favourable decisions for oncoming improving for future development, operating cost saving and maintenance costs saving are come by straight load forecast (Almeshaiei & Soltan, 2011). It involves the unfailingly estimation of both the consumption and position of electric load during the different periods (hours, monthly, annually) of the intended duration (Alfares & Nazeeruddin, 2002). Figure 1-5 shows that Load forecasting can be

classified according to period of time, Short-Term Load Forecasting (STLF) is maximal 1 day with 5 minute increments, Medium-Term Load Forecasting (MTLF) is 1-12 months and Long-Term Load Forecasting (LTLF) is within the range of 1 to 10 years (Srinivasan & Lee, 1995; Tayeb, Ali, & Emam, 2013). The model of the electrical power consumption forecasting is remained one of the most compelling issue (Campo & Ruiz, 1987; Christiaanse, 1971; Elhawary & Mbamalu, 1990; Hagan & Behr, 1987; King, 2007; Liu et al., 1996; Moghram & Rahman, 1989; Nagasaka & Mamun, 2004; Papalexopoulos & Hesterberg, 1989; SINGH, BISWAS, & MAHALANABIS, 1978; S. Soliman, 2010; S. A. Soliman, Persaud, El-Nagar, & El-Hawary, 1997; Toyoda, Chen, & Inoue, 1970).

There are many studies under the umbrella of electric power prediction. Studies can be split into different groups according to the methods, data analysing forms, data sets, the input variable and hourly/half-hour forecast. But, generally in review studies, they are grouped according to the methods.

The used techniques can be divided into three as statistical methods, artificial intelligence methods and hybrid methods. The most commonly used techniques are based on:

- Regression models (Feng & Ryan, 2016),
- Times series models (Dudek, 2016; Panapakidis, 2016),
- Autoregressive Integrated Moving Average models (Friedrich & Afshari, 2015),
- Artificial Neural Network models (Çevik & Çunkas, 2014; Sun et al., 2016),
- Fuzzy models (Çevik & Çunkaş, 2015; Engineering & Is, 2017),
- Support vector machine models (Abdoos, Hemmati, & Abdoos, 2015),
- Particle swarm optimization models (Mengliang, 2011),
- Genetic algorithm models (Castelli, Vanneschi, & De Felice, 2015; Hoverstad, Tidemann, Langseth, & Ozturk, 2015)
- Wavelet transform (Li, Goel, & Wang, 2016)

- ANFIS (Çevik & Çunkaş, 2015).

Among these successful techniques, ANN is one of the most forceful one to forecast the performance of electrical power systems with no recognisable parameter interrelation.

1.1. Scope of Thesis

With this thesis, the aforementioned problem will be examined. This thesis proposes a load forecasting based on the artificial neural network (ANN) for LTLF to improve the planning of operation of power grids. It aims to improve energy efficiency and rising savings, putting down peak energy demand and electric power requirement.

The starting point of this thesis, and thus the electrical energy forecasting and planning, is the study of the development of smart grid technology. The proposed model uses the measured temperature, weekend-weekday, population and historical load consumption. In this thesis, an efficient and robust modeling approach which gives good results by The Artificial neural network. Just like any other load forecasting methods, ANN method, shows excellent accuracy prediction. This study says that training can be able to identify energy demand with respect to technology functionality. Specially, the goal of this thesis is to predict oncoming execution and how smart grid control achieve energy consumption with an effective way for load forecast in Turkey.

1.2. Structure of Thesis

This study aligned a classic structure consisted by five parts as follows;

Chapter 2 gives a background of the traditional grid, Turkey's electricity market policy, main principles of smart grid technology, electricity load forecasting and artificial neural network. This section mention about the fundamental concepts that are used in the paper and presents a brief description is given of the method and a

literature review offers a representative selection of principal publications in the given category. Recent discussions on smart grid control techniques are given to be helpful to find out the improvement. Regression model details is dedicated to train the network. Within this chapter, previous existing forecasting methods are described and analysed.

Chapter 3 introduces the concept of forecasting factors and load analysis. This section describes the main elements of load forecasting model. A brief description about ANN model is given. This section also proposes a presentation the formulation and functions of the study and clarifies the methodologies to predict the load demand.

Chapter 4 is the key part of the study. This section specify basic frame of the our work and the working procedure, input data, target data and output data. The application of the predict method for load forecasting in smart grid control is studied Training methodology is determined and evaluation criteria are described.

Chapter 5 is the final part of the work. This section gives a conclusion about the study and it concludes with closing remarks. Some discussion and concluding remarks are given in this section.

CHAPTER 2

BACKGROUND AND LITERATURE REVIEW

2.1. Introduction

In this chapter traditional electric grid, smart grid technologies, electric load forecasting and Artificial Neural Network are explained shortly. Then a brief information is given about electric grid background with the weakness of system. Then recent improvements on the traditional grid and smart grid technology are given at great length. Load forecasting and Artificial Neural Network, which are the main topic of this thesis, are defined and concluded for Turkey.

2.2. Traditional Electric Grid

Better, shining, and purifier life is acquired with electricity. Thomas Edison, Charles Brush, and Werner von Siemens pioneered the industry in Direct Current (DC) systems in the 1870's and 1880s. The transmission distance power generation system to consumer for electric power is limited by stiff power losses in wires. DC electric power was produced and run out of within only a few kms (The University of Texas at Austin Energy Inittute, 2017). Factories and small downtown areas are powered by DC systems. However, it couldn't exceed 95% of commorant. DC electricity systems used Edison’s, while Alternating Current (AC) systems was promoted by Tesla and others, in direct competition with Edison. Long transmission distances was founded a solution by AC Power. In addition, it gave an answer for interconnection generation sites represented in Figure 2-1. Three-phase AC power system was improved in the fourth quarter of the 1880 but it was substantiated and distributed entire cities and regions began in the 1890s. The utilisation of the AC power system allowed the gradate for power plants, reduction the electricity unit cost, and making electricity

consistently more cost efficient and convenient to ever more consumers (The University of Texas at Austin Energy Inittute, 2017).

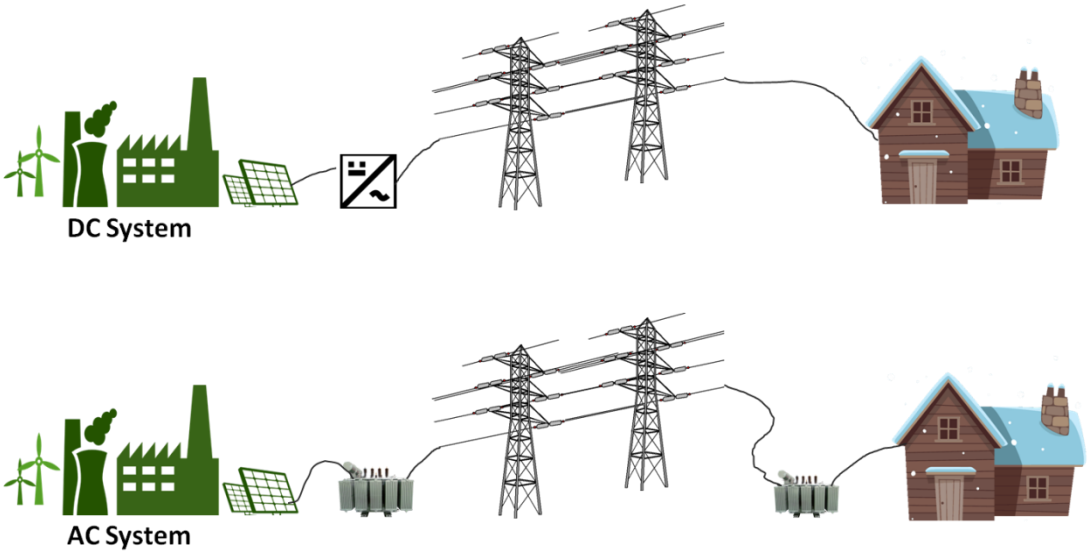

Figure 2-1. DC system and AC system

The traditional electrical grid can be divided into three parts which are generation, transmission and distribution. According to data obtained from Republic of Turkey Ministry of Energy and Natural Resources the total electricity generation is 274.407,70 GWh in Turkey shown in Table 2-1.

The generation part mainly consists of large energy power plants that transform several types of conventional energy resources into electrical energy. The majority about 32,52% of this was from natural gas. The other resources are hydropower, imported coal, lignite and coal, wind, sun, geothermal, biofuels and other thermal respectively 24,50%, 17,39%, 16,24 %, 5,65 %, 0,38%, 1,76 %, 0,86 % and 0,70 % given in Figure 2-2 ("Electricity Production in 2016 in Turkey," 2016).

Table 2-1. *Electricity energy production according sources in Turkey in 2016 ("Electricity Production in 2016 in Turkey," 2016)*

SOURCE	GENERATION (GWh)
Imported coal	47.717,90
Lignite and coal	44.555,20
Natural gas	89.227,10
Other thermal	1.926,30
Hydro	67.230,90
Wind	15.517,10
Biofuels	2.371,60
Geothermal	4.818,50
Sun	1.043,10
TOTAL	**274.407,70**

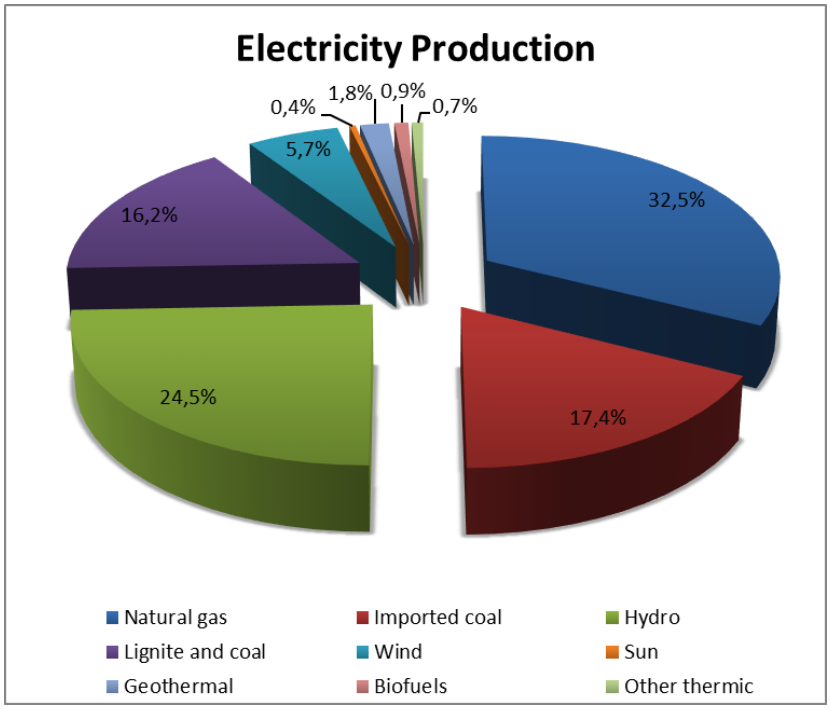

Figure 2-2. Total electricity production ("Electricity Production in 2016 in Turkey," 2016)

Energy generation from conventional fuels has some challenges. First of all it is harmful with regard to environment. Global warming emissions eventuating from energy generation are climate impacts. Furthermore, fossil fuels connect us to the abroad from the viewpoint of energy generation. To overcome these problems alternative energy sources have been well-liked due to its head start in our country. Actually, renewable energy potential in Turkey is higher than fossil fuels because of situating excellent geographical position.

Hydropower, which is one of the most common alternative electric energy source, has an essential role for energy generation in Turkey Table *2-2* gives 2016 data. Turkey's theoretical hydroelectric potential takes in consideration 67.230,9 GWh/year that is approximately 1% of the world's total hydropower potential (Atilgan & Azapagic, 2016; Gözde, 2018; “Turkey Water Report,” 2009; “Türkiye Elektrik Üretim-İletim İstatistikleri,” 2017). Furthermore, The Country's wind energy potential is considered nearly 88 GW annually. While the capacity of onshore is about 2 GW (Atilgan & Azapagic, 2016).

Turkey is one of the richest countries in the world with regard to technical solar energy capacity, with the overall potential of 1.043 GWh (Gözde, 2018). On the other hand, Like sun energy, only a fraction of the geothermal potential is considered with the capacity 4.818,5 GWh/year (Karagöl & Kavaz, 2017; “Türkiye Elektrik Üretim-İletim İstatistikleri,” 2017).

Table 2-2. *Renewable energy generation in Turkey in 2016 ("Turkey Water Report," 2009; "Türkiye Elektrik Üretim-İletim İstatistikleri," 2017)*

SOURCE	GENERATION (GWh)	PERCENTAGE (%)
Dam	48.962,1	54%
Lake and River	18.268,8	20%
Geothermal	4.818,5	5%
Biofuels	2.371,6	3%
Wind	15.517,1	17%
Sun	1.043,1	1%
TOTAL	**90.981,2**	100%

It is clear that the renewable energy capacity of Turkey is quite significant when compared to the rest of the World. However, Turkish government has a goal for 30% of the electricity power production to be considered from alternative energy resources by 2023, on the purpose of increasing the usage of alternative energy sources and decreasing energy dependence on bring into. The goal of defines 34 GW of hydro, 20 GW of wind, 5 GW of solar, 1 GW of biomass and 1 GW of geothermal power ("Türkiye ulusal yenilenebilir enerji eylem plani," 2014).

Traditional electrical grid is an interconnection that consists of the consignment of electricity from producers to customers. This structure is composed of power plants, step - up transformers, transmission lines, distribution lines, step - down transformers, power switches and consumers as illustrated in Figure 2-3 (Colak et al., 2014). The large-scale physical structure of the grid, high-voltage transmission lines are connected between tall metal towers and carry electricity over the conductors. Long-distance electricity transmission is done by high voltage electricity since it is more efficient and less expensive. The generated electricity from power plants is transmitted from transmission power lines to distribution power lines to carry electricity to

consumers. However, the high voltage is adjusted to lower voltage that is safer for the usage of homes and businesses, to deliver the customers by local distribution power lines.

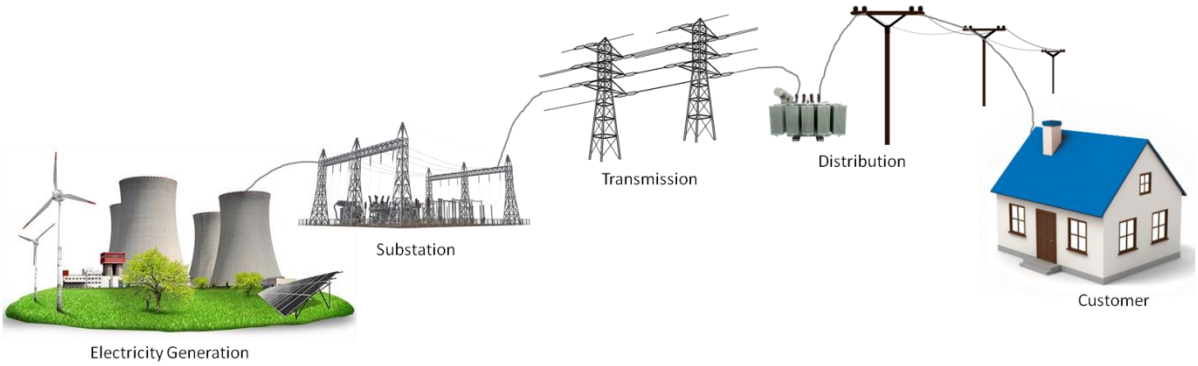

Figure 2-3. Traditional grid (Colak et al., 2014)

This system is the electric transmission and distribution grid, each component of this structure has a unique operation and has a distinctive specification. Since power stations are usually far away from consumer, the electricity has to been transported and distributed from the generation point to the customers, either personal or industrial (Mejia & Marine, 2014).

Table 2-3. *Number of existing plants in Turkey ("Türkiye Elektrik Üretim-İletim İstatistikleri," 2017)*

Type of Energy Generation Plant	Number of Energy Generation Plant
613	Hydroelectric Power Plant
288	Natural Gas Power Plant
186	Wind Energy Facility
1773	Solar Energy Plant
40	Coal Power Plant
33	Geothermal Plant
165	Other Power Plants

In Turkey, the number of hydroelectric power plant, Natural Gas Power Plant, wind energy facility, Solar Energy Plant, coal power plant, geothermal plant and other plants is 613, 288, 186, 1773, 40, 33, 1773 and 165 respectively given in the Table 2-3 ("Türkiye Elektrik Üretim-İletim İstatistikleri," 2017).

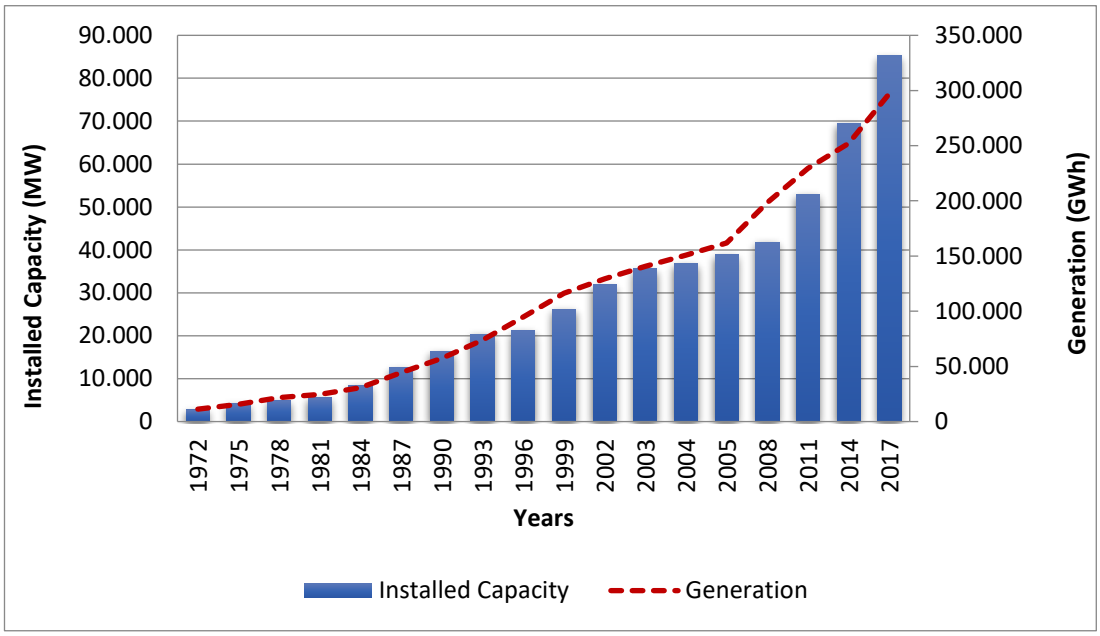

Figure 2-4. Annual development of Turkey's installed capacity and generation

The installed power capacity of Turkey reaches 85200 MW by 2017 end shown in Figure 2-4. This capacity consists of 46.284,5 MW thermal power plant, 1.063,7 MW geothermal power plant, 27.273,1 MW hydroelectric power plant, 6.516,2 MW wind energy facility and 3.420,7 MW solar energy plant. Figure 2-6 indicates the change of the installed capacity by primary energy resources between the years 2007-2017.

Gross electricity energy demand is 294,9 billion kWh and peak power demand is 47.600 MW. Since 295,5 billion kWh energy has generated, 2,7 billion kWh energy has imported to meet electric power requirement. On the other hand 3,3 billion kWh total offered electrical energy has exported. The electrical network includes very high voltage (VHV), high voltage (HV), Medium Voltage (MV) and Low Voltage (LV).

Public Transmission Company (TEİAS) has prompted a map containing the overall Turkish transmission system map shown Figure 2-5 (Turkish Electricity Transmission Corporation, 2017).

Figure 2-5. Turkish electricity generation-transmission map (Turkish Electricity Transmission Corporation, 2017)

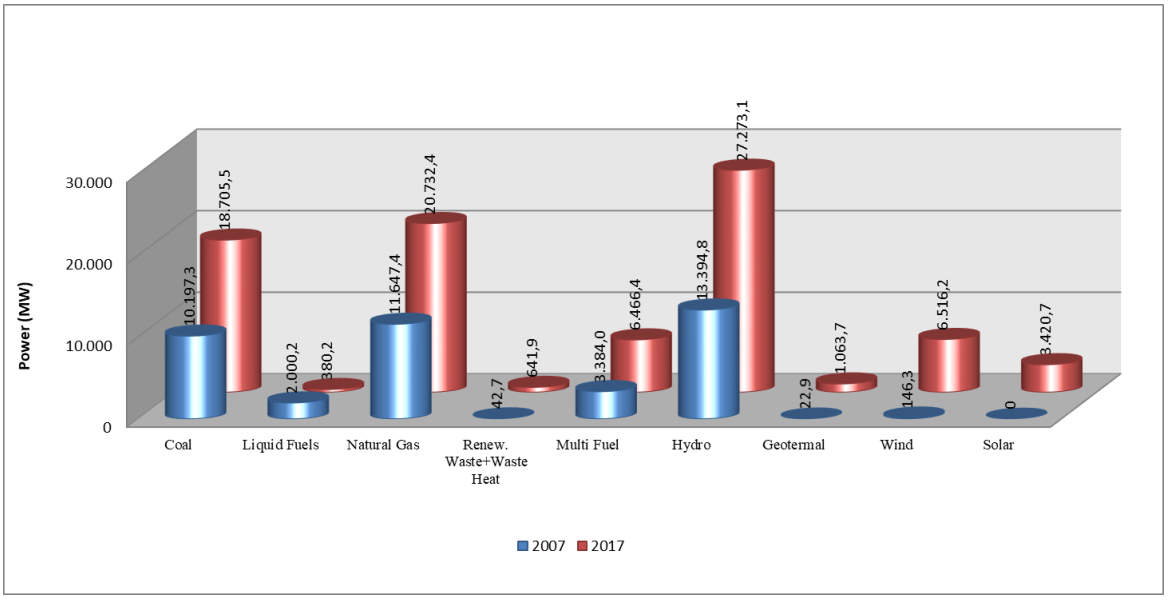

Figure 2-6. Turkey's installed capacity by primary energy resources for the years 2007 and 2017 (“Türkiye Elektrik Üretim-İletim İstatistikleri,” 2017)

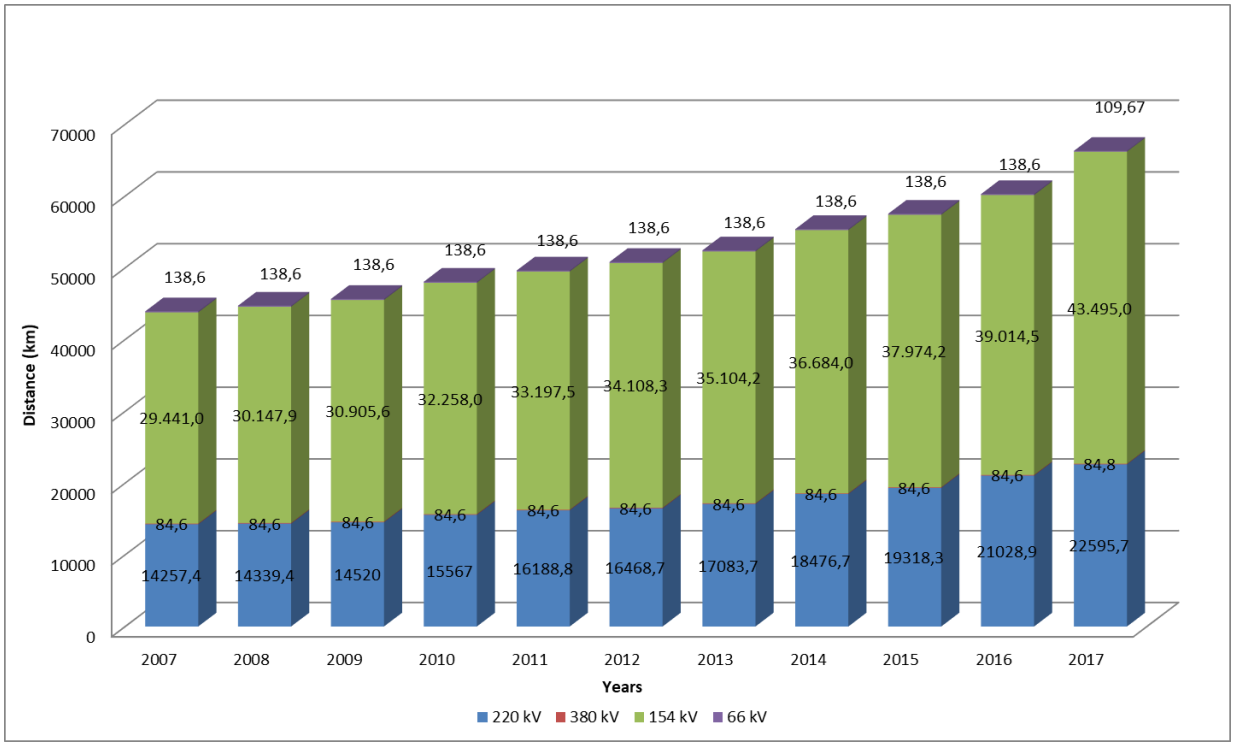

Figure 2-7. The development of transmission lines of Turkey (2007-2017) (Kapasite & Miktar, 2018; "Türkiye Elektrik Üretim-İletim İstatistikleri," 2017)

Currently, Turkey operates about 66.285 km electric transmission lines, 1.750 bigger power transformation and 163.181 MVA transformation power shown in Figure 2-7 (Kapasite & Miktar, 2018; "Türkiye Elektrik Üretim-İletim İstatistikleri," 2017). The total distance of the transmission lines can be detailed between 2007 and 2017 according to their voltages. This can be illustrated in Figure 2-8. When the graphs below are examined, it is seen that transmission lines has four voltage level the distance of the 66 kV is 109,67 km, 154 kV is 43.495 km, 380 kV is 84.8km and lastly 220 kV is 22.595,7 km.

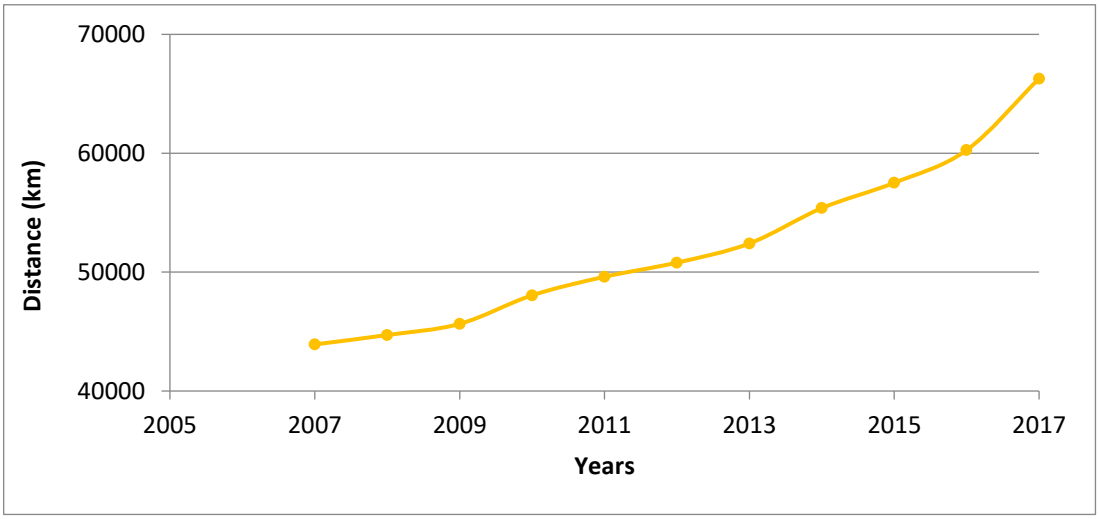

Figure 2-8. Transmission lines long in Turkey (2007-2017)

The interconnection among power plants, transmission power lines, distribution power lines and the customers is handled by a balancing authorities and regional transmission organizations. The aim of the organisation, authorities and institutions which are liable to distribution and transmission in Turkey, ensures be tasked with reliable and sustainable. In 1980s, Turkish electricity distribution system has gone through unbundling period in order to reach a liberal and sustainable economic development. In 1970 Turkish Electricity Authority (TEK), was responsible the production, the transmission and the distribution of electricity, was constituted, until 1984 it was performed by a vertically integrated as a statutory monopoly. A law was implemented and private sector was included with law no 3096 in 1984. A significant majority of these investments consisted of;

- Build-Operate-Transfer (BOT)
- Build-Own-Operate (BOO)
- Transfer of Operating Rights (TOOR)

A power plant is constructed and managed by a private company within the scope of a BOT approval during to 49 years (it was 99 years at the beginning of the

implementation). Thereafter the private company transmit to the state free of charge. Nevertheless, A present publicly owned plant is operated with the TOOR agreement (Cetin & Oguz, 2007). The vertically integrated value chain of TEK has been split into Turkish Electricity Generation Transmission Company (TEAS) and the public owner of the now-privatized distribution asset Turkish Electricity Distribution Company (TEDAS) to separate into generation, transmission, distribution and sales activities in 1994 (Asan & Tasaltin, 2017; Kincay & Ozturk, 2010; Uzlu, Akpinar, & Kömürcü, 2011) as seen from Figure 2-9.

Figure 2-10 presents Turkey started New Economic Stability Program in 2001 with Energy Market Regulatory Authority (EMRA). Hereunder, TEAS has been discretizated namely Public Generation Company (EUAS), TEIAS and Public Wholesale Company (TETAS) as three new different sub-sectors, generation, transmission and wholesale. EUAS was split into six main set as hydropower and thermal power plant which were lignite and natural gas within the scope of that program (Camadan & Erten, 2011).

Since EMRA's main goal was diaphanous, vying and cost effective power sector market for efficient, reliable, low priced and sustainable connection, in contradistinction to former attempts it reconstructed of the electricity energy market (Şirin, 2017; Ulusoy & Oguz, 2007). A territorial tariffing was launched based on price in 2003. Thus, method decreased the cost in less unregulated usage localities. Anyhow, contrary to those regions, some part of Turkey had more illegal usage (Os. Sevaioğlu, 2003). Due to this, proposal expedient has ended up by government (International Energy Agency, 2009). The foundation of Electricity Market Balancing and Settlement Regulation (BSR) implemented the open market regulations in power generation and distribution in the country in 2004 (Administration, 2017). On August 1, 2006 The Balancing and Settlement (B&S) Market considered in MFSC (Market Financial Settlement Centre - PMUM in Turkish).

It has been effectuating the base cost for the Turkey's energy market with the intent of supply-demand balance (Asan & Tasaltin, 2017). This provides receive and sell the electricity with a day-ahead market on an hourly basis (Osman Sevaioğlu, 2013). In 2010, 54 dedicated wholesale permission existed in Turkey ("Energy Market Regulatory Authority (EMRA)," 2010).

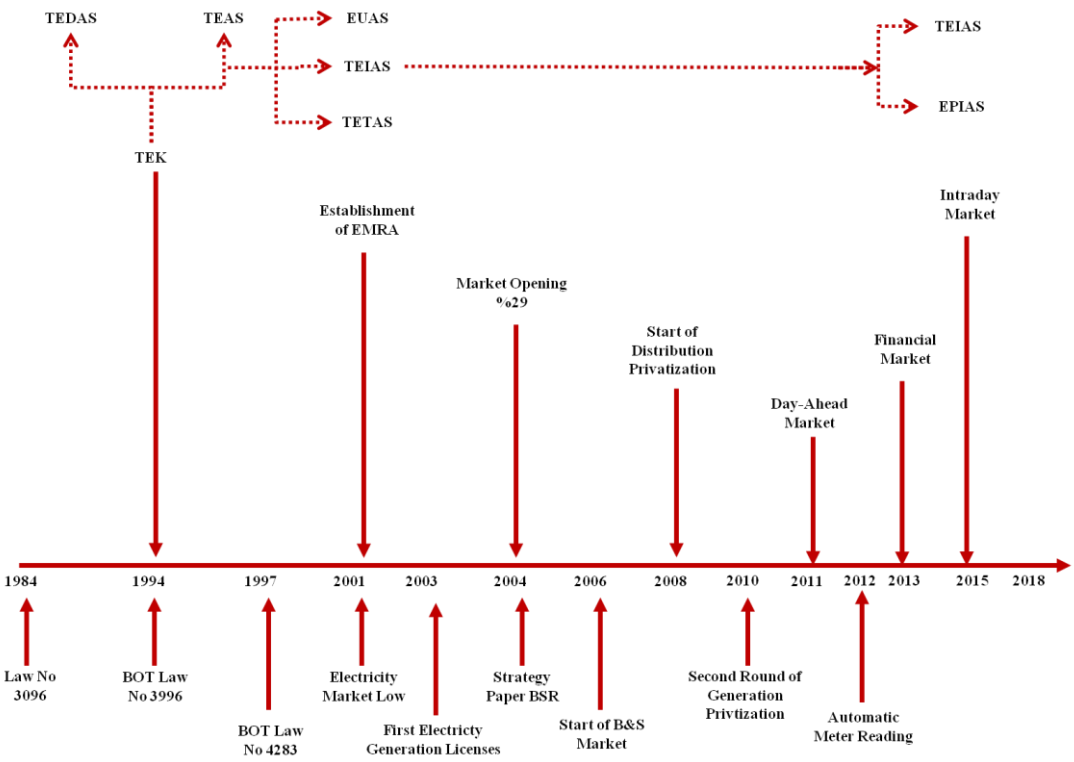

Figure 2-9. Key milestones of electricity restructuring in Turkey (Colak et al., 2014)

It has been effectuating the base cost for the Turkey's energy market with the intent of supply-demand balance (Asan & Tasaltin, 2017). This provides receive and sell the electricity with a day-ahead market on an hourly basis (Osman Sevaioğlu, 2013). In 2010, 54 dedicated wholesale permission existed in Turkey ("Energy Market Regulatory Authority (EMRA)," 2010).

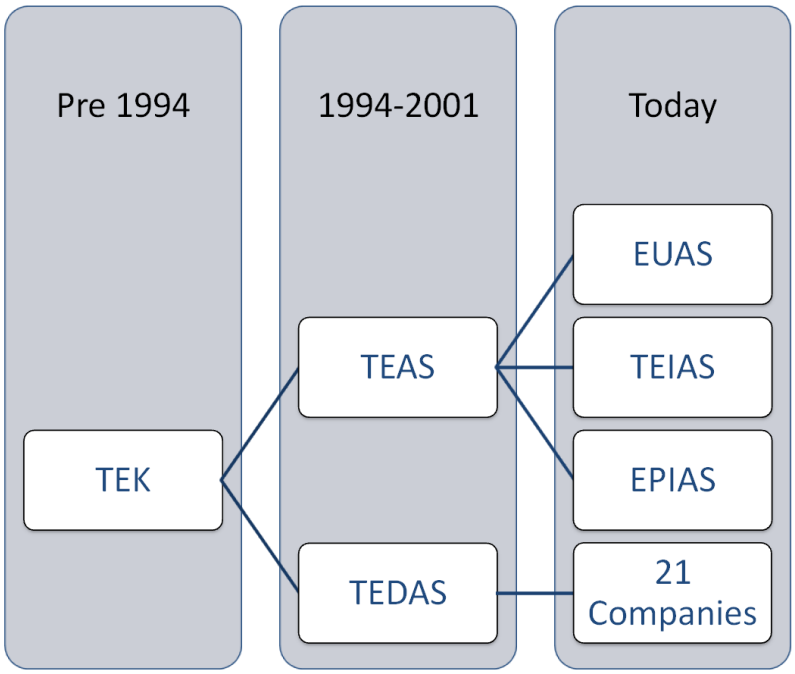

Figure 2-10. Prime ministry, privatization administration in Turkey (Çelıkkol & Köse, 2015)

There are 21 distribution regions in Turkey as illustrated regional in Figure 2-11. Twenty ones of them is TEDAS subsidiaries and one of them is KCETAS is an exclusive establishment, according to Law No. 3096 AKEDAS and AYDEM were privatized. First of all the regions of Başkent, Sakarya and Meram were privatized in 2009 for $2.3 billion. The privatization pursued by Uludag, Yesilirmak, Osmangazi, Coruh, Camlibel and Firat in 2010 for $3 billion. In 2011 Trakya region was sold for $575 million.

The privatization was ended up in 2013 with Bogazici, Gediz, Akdeniz, Vangolu, Dicle, Aras, Toroslar and Ayedas for $7.32 billion. Therefore, the total income of the privatization is 13 billion US dollars tabulated in (Özbuğday, Öğünlü, & Alma, 2016). Although TEDAS is possessions the distribution, according to ToOR-backed share-sale model which is used by Turkey, the company's moral is owned only by financier (Administration, 2017; “Energy Market Regulatory Authority (EMRA),” 2010;

International Energy Agency, 2009; Nyman & Dilli, 2015; Policies & Countries, 2016; Os. Sevaioğlu, 2003; Şirin, 2017)

Figure 2-11. Electricity distribution regions in Turkey ("Elektrik Dağıtım Şirketleri Listesi," n.d.)

Table 2-4. *21 Distribution operators (Özbuğday et al., 2016)*

Distribution Company	**Operator**	**Transfer Date**	**Parent Company**
Boğaziçi	CLK Energy Investment INC.	28.05.2013	Cengiz Holding &
Başkent	Enerjisa Elektrik Dağıtım	28.01.2009	Sabancı Holding &
Gediz	ELSAN-TÜMA Karaçay Joint Partnership	29.05.2013	Bereket Enerji
Toroslar	Enerjisa Elektrik Dağıtım	30.09.2013	Sabancı Holding &
Uludağ	Uludağ Enerji Dağıtım	31.08.2010	Cengiz Holding &
Akdeniz	AkDen Enerji Dağııtm	28.05.2013	Cengiz Holding &

Sakarya	Akcez Enerji	11.02.2009	Akkök Holding &
Yeşilırmak	Çalık Elektrik Dağıtım	29.12.2010	Çalık Holding
Meram	Alcen Enerji Dağıtım	30.10.2009	Alarko Holding &
Vangölü	VanGölü Elektrik Dağıtım	26.07.2013	Türkerler Holding
Dicle	Dicle Enerji Yatırım	28.06.2013	Eksim Yatırım
Osmangazi	Osmangazi EDAŞ	31.05.2010	Zorlu Osmangazi
Çoruh	Coruh Aksa Elektrik	30.09.2010	Aksa Elektrik
Trakya	IC Yapı Elektrik	30.12.2011	IC Holding
Aras	Doğu Aras Enerji	28.06.2013	Kiler Holding &
Çamlıbel	Çamlı Enerji Dağıtım	31.08.2010	Cengiz Holding &
Fırat	Fırat Aksa Elektrik	31.12.2010	Aksa Elektrik
Ayedaş	Enerjisa Elektrik Dağıtım	31.07.2013	Sabancı Holding &
Akedaş	Adıyaman ve Kahramanmaraş Elektrik Dağıtım	01.01.2011	Kipaş Holding
Kcedaş	Kayseri ve Civarı Elektrik Türk A.Ş	01.03.1990	Kayseri Büyükşehir
Aydem	Aydem Elektrik	20.07.2008	Bereket Enerji

2.3. Smart Grid Technique

The electric energy industry has been approaching to a revolutionary conversion since beginning of the this centenary. It attempts to become widespread using Smart Grid Control technologies to correspond the requirements of our last digital community. Since safe information is needed immediately, available and on easy terms, end users' anticipations and Utility Commission penalties are engender some alterations. Superior trustworthiness and major preference are required by customers and are appetence in order to investigate and modify their electric power consumption patterns. The Smart Grid control is a vital importance to obtain ultimate objectives avowed above. As a result of insulated improvement activities will be an electric power system which is disturbed by insular resolution. Afterwards, the future's electric energy system can only be realised in restricted regions or on a little scaling factor (Nadar, 2016).

Increasing intensity of interest of smart grid technologies leads that several improvements were performed in the literature. The authors carried out some surveys about Real Time Frequency Analysis, Wavelet Transform and Filter Banks Applications, Wavelet Executions, Transmission and Distribution System in Smart Grid, Implementation of Communication Network, Electric Vehicles in Smart Cities and Load Forecasting of Smart Grid (Carvalho, Duque, Silveira, Mendes, & Ribeiro, 2012; Carvalho, Duque, Silveira, & Ribeiro, 2013; Güngör et al., 2011; V. Cagri Gungor et al., 2013; V. Hamidi, Smith, & Wilson, 2010; Hauttekeete, Stragier, Haerick, & De Marez, 2010; Khan & Khan, 2013; Lu, Lu, Wang, & Wang, 2010; Richardson, 2013; Silva, Duque, & Ribeiro, 2015; Uddin, Ahmad, Qamar, & Altaf, 2018; Yan, Qian, Sharif, & Tipper, 2013).

A smart grid refers to modernized electrical grid that brings digital information and communications technology. The Smart Grid builds in a two-way communication and flow of energy between a utility and customers, rather than the traditional unidirectional flow from traditional electricity and information systems with a digital

technology (Cardenas, Gemoets, Ablanedo Rosas, & Sarfi, 2014; Fadlullah, Kato, Lu, Shen, & Nozaki, 2012; Ramchurn, Vytelingum, Rogers, & Jennings, 2012).

Smart grid is defined as a intelligent electricity network since the reciprocal connections integrated smart grid provides efficiently deliver economic, sustainable and secure electricity supplies thereby it maximize reliability, availability, efficiency, economic performance and higher security (Keyhani, 2011; Platform, n.d.; Tuballa & Abundo, 2016). This modern electric power grid is a promising technology to permit consumers to take more governance over their energy tenancy (Oğuz, Akkemik, & Göksal, 2014). Since the traditional network render services one way communication where the electricity connects from power production plants to the consumers, the smart power grid shines out when it compared with traditional grid because of smart grid intelligence presented in Table 2-5 (Bari, Jiang, Saad, & Jaekel, 2014; Tuballa & Abundo, 2016). Briefly smart grid control system is described with the actors given in Table 2-5 as (Nadar, 2016);

- An electrical energy system improvisation of several robotised transmission and distribution (T&D) systems, whole managing in a co-ordinated, productive and believable mode,
- An electrical energy system that overcome insecureness terms with 'self-healing' behaviours and is satisfying to energy-market and utility needs,
- An electrical energy system that serves millions of end users and has a discoverable conversations platform enabling the timely, secure, and favorable data flow required to ensure energy to the advancing digital economy.

From the below definitions, the smart grid control can be concluded;

- Estimated to forestall hazards
- Assure from threats and dangers
- Interactive with end users and markets
- Decentralized in disposition with both assets and data
- Self-healing to correct/bypass predicted/detected problems

- Optimizable to make the optimal utilization of resources
- Transformational to turn data into information

Table 2-5. *Actors of smart grid control*

Actor Name	Actor Responsibilities
Distributions System operator (DSO)	Has the accountableness to manage the interconnected network, increasing the maintenance and development of the substructure and the respect of the quality of supply. The DSO is also accountable to monitor and meter.
Prosumer	Prosumers, who are generating their own electricity from alternative energy sources such as solar, wind and geothermal may use storage facilities in order to control their energy requirement. They can sell the electricity to the interconnected grid when the electricity costs are high or use for themselves when costs are low. The utilities will use storage facilities to ensure a secure, continuous electricity supply.
Stationary Battery Management System (SBMS)	The smartness can be into the SB. It is the link between the MS and the SBs. It has to manage the storage and the available power in the SBs to be able to offer up or down frequency regulation (discharging or charging), when it is necessary.
Market Operator	Avoid selling energy at price zero due to production surplus, namely for renewable sources.
DER Information Provider	Provides production and unit cost information of renewable energy resources.

The consumers of the grid can be given as the following (O. Sevaioğlu, 2016c);

- Electricity retailer – The first customer segment for the electricity retailer are other electricity retailers. The other electricity retailers might be interested in buying pooled demand flexibility resources as a service from the original electricity retailer.
- Prosumer – Retailer could offer the prosumers energy contracts with lower fees, where the prosumers offer his/hers available flexibility (consumption / production) in exchange.
- Consumer – Consumer's offer the retailer their consumption forecasts and controllable loads in exchange for electricity contracts with lower fees.
- Industry – Industry, meaning factories etc., may buy a service from the electricity retailer where they both plan the production for the next day so that the electricity costs are as low as possible. Or the industry might offer their electricity generation capacity for the retailer to be used in the flexibility pool.
- SME's – Small and medium sized enterprises may offer their flexible loads for the retailer to be used as flexibility pools. SME's would get compensation for the use of their resources.
- DSO's – Distribution system operators might buy a service from the electricity retailer where the electricity consumption in their electricity distribution grid is optimized in order to avoid power outages.
- TSO's – Transmission system operators could use similar service as the DSO's offered by the electricity retailer.
- Municipalities – Municipalities might buy a service from the electricity retailer which for example, controls the lighting in the municipality or different loads to lower the electricity costs and deliver greener image for the municipality.

A 'Prosumer' is defined as a consumer with generation capacity at the point of consumption acting as a PROductive conSUMER. Prosumer installs and owns the generation capacity (i.e. rooftop solar photovoltaic sets, small-scale wind turbines on

the roofs or available garden areas, or back-up diesel generator sets etc.) and aims to meet a certain portion of its electricity demand with these capacities. The generation capacity, as well as the consumption equipment, are installed in the low-voltage electricity distribution grid. Different meters are installed for measuring the consumptions and generations at the grid connection point, as the consumptions and generations may have different prices within the context of tariff structure determined by the regulatory authority (for example, fixed prices may be implemented on the feed-in tariffs for renewable generation and three-rate tariffs may be implemented for the consumptions charged by the retail companies) (O. Sevaioğlu, 2016a).

Local consumers are those, who do not have any generation capacity, but connected to the low-voltage grid for consumption. They are usually concentrated within the same region that prosumers are located, hence using the same portion of grid which make them prone to the effects arising from grid operations. Prosumers and consumers are informed by grid operator in real time, about the operating condition of the grid and demand response actions (voltage fluctuations, load shedding actions or disconnection of some prosumers and/or consumers for a certain period of time).

Grid operator has to take all the measures for secure and efficient operation of the grid as well as maintaining safe and secure energy transfer service to all participants connected to grid. In addition to those, grid operator is responsible for supplying the necessary information about the operating condition of the grid, giving orders for the required actions and remedies to be taken by prosumers or consumers. Grid operator provides the necessary information concerning the operational state of the grid, present state and combination of the energy generation profile. Information will be provided about the percentage of the generation provided by each prosumer, energy consumed by the local consumers within the area, in addition to the energy generation profile on the regional/national scale. This will not only increase the awareness of the prosumers about their contribution to local energy generation profile, , but also help consumers to be aware of the contribution of the prosumers in the local grid (O. Sevaioğlu, 2016a).

The Smart Grid control technology must ensure enduring, confidential and trustworthy intercommunication right along with IED and operations in order to perform the required system evaluations when required. The industry have to melt into copper and steel (electricity generation and transmission substructure) with silicon and glass (evaluation and communication substructure) to obtain a smart grid. Coming of age of the both above technology fields is an intersection for the smart grid control technologies (Nadar, 2016).

Table 2-6. *The comparison of traditional grid vs smart grid*

Traditional Grid	**Smart Grid**
Electromechanical	Digitized
Unidirectional Power Flow	Multi Directional Power Flow
Fewer User Options	More User Option
Centralized	Distributed
Manuel Control & Monitor	Automatic Control & Monitor
Few Sensors	Sensors Throughout
Radial Topology	Network Topology
Failures & Blackouts	Adaptive & Islanding
Slow or No Response	Extremely Quick Response
No Energy Storage	Energy Storage

Since Smart Grid involves a diversity of technologies, this control system has lots of opportunities given in the Table 2-6. Smart grids bring a range of advantages takes hold of both the short and long-term. The benefits of integration of a number of smart grid technologies can be categorized as technical, environmental, security and economic. It subscribes to be more reliable, secure, economic, efficient and

environmentally friendly and safe (Balijepalli, Pradhan, Khaparde, & Shereef, 2011; M. Grid, 2008; Yan et al., 2013).

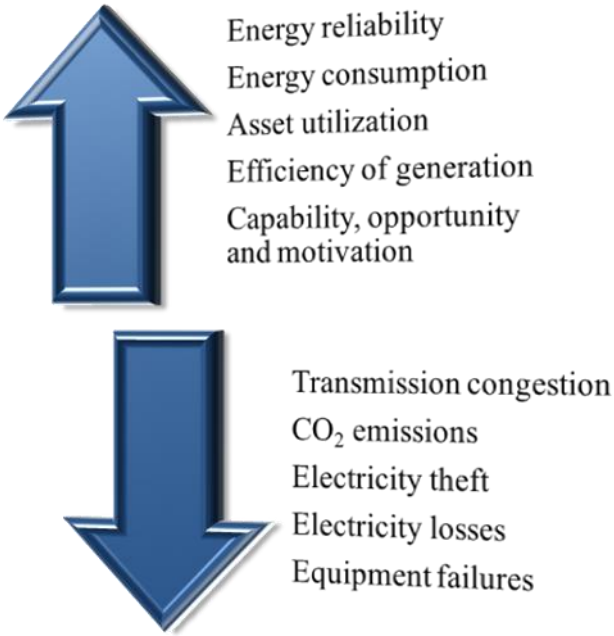

Figure 2-12. Smart grid benefits

Figure 2-12 illustrates a general serviceableness for smart grid control. It is responsible of the electric power grid's benefits and requirements are given below (Hamilton, Miller, & Renz, 2010);

- ✓ Improving energy reliability and quality
- ✓ Enhancing electric energy consumption
- ✓ Optimizing asset utilization
- ✓ Making better efficiency of power generations
- ✓ Ameliorating capability, opportunity and motivation
- ✓ Reducing the transmission congestion
- ✓ Minimising greenhouse gas emissions
- ✓ Impairing the losses and the thefts
- ✓ Moderating equipment failures

Table 2-7. *Categorizing of smart grid technology's pros*

Benefit Category		
Customer	Reduction consumer bill	Optimizing Generation Capacity Investments Decreasing Service Cost Reducing Congestion Cost
	Increasing reliability	Power Interruptions Enhancing Response
	Better customer service	Bidirectional Communications Energy Storage
	Promoting networking display	Improving Monitoring More Sensors
Power Grid	Multi directional network	Extensive Control System
	Minimising losses	Dispersed Network Distributed Power Generation Minimising Energy Theft
Operating	Load Forecasting	Peak Load Reduction Load Prediction & Planning
	Enhancing O&M cost	Optimizing Equipment Maintenance Cost Decreasing Operations Cost Enhancing Meter Reading
Social	Air emissions	Reducing Carbon Emissions Reduction Energy Consumption
	Renewable generation	Using Wind and Solar Energy

The contribution of the improving of the electric system shown Table 2-7 is procurable by key technologies of smart grid control (Fang, Misra, Xue, & Yang, 2012; Menghani, 2016; Sood, Fischer, Eklund, & Brown, 2009; Su, Eichi, Zeng, & Chow, 2012).

Figure 2-13 illustrates the smart grid technology programs enhance the effectiveness, managing demand and reducing lifecycle costs with the improved network security (Staff, 2013).

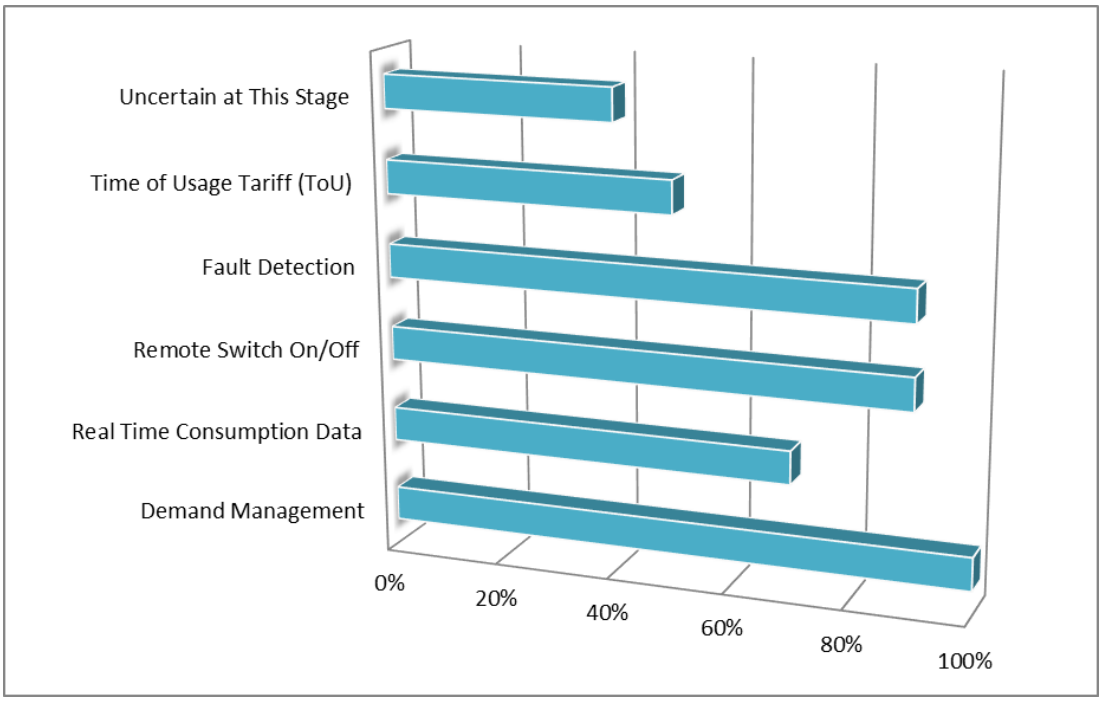

Figure 2-13. Major changes with smart grid for prosumers (Staff, 2013)

People of an organization requires an executional information to be influential and drive progression. At the moment, data is aggregated through cyclical dredging of a restricted set of measurements and periodic variation manual supervision of assets.

The Smart Grid view of the substation has changed this specimen in multiple ways:

- More of the assets in a substation, compilation data, and assembling the collected data into information is monitored by IED. Timely information about a yield permits proper utilization of that asset,
- The IED is able to communicate, on exception, the semantics of the situation. Semantic-based communication makes available to a preset, accurate view of the information and minimizes the paperwork and pattern attempt,
- The automation aspect ensures irreproachable information accumulation, storage, and propagation.

The comprehensive influence of the Smart Grid technologies in this field is to develop utilization of labor force through automation, and optimized asset utilization through monitors operates automatically (Nadar, 2016). There are multiple appeal domains that commitment to drive its development as the Smart Grid is participated presence.

Despite all of the above usefulness the smart grid infrastructure is faced some difficulties which is imperative to fact in demand response models represented in Figure 2-14 (Chunyan An, 2015; Folly, 2013).

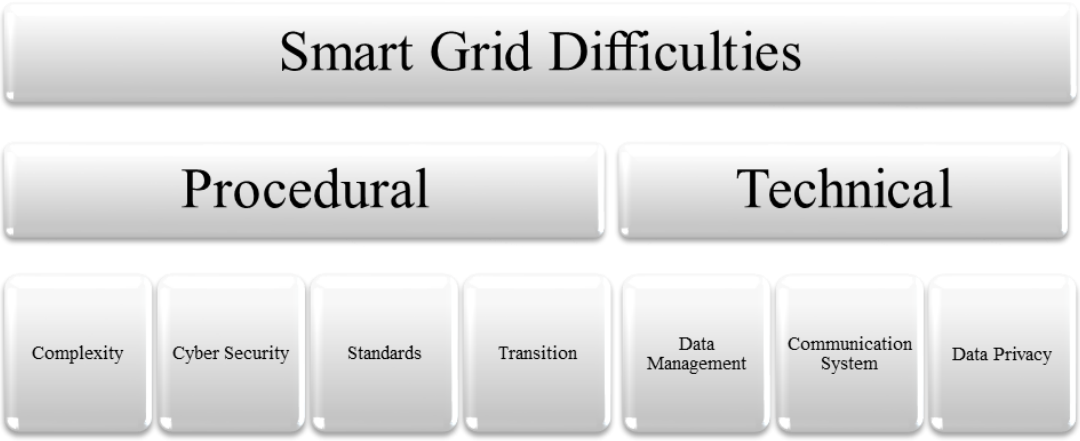

Figure 2-14. Smart grid difficulties diagram (Chunyan An, 2015; Folly, 2013)

The main challenges of managing a power grid with a smart grid control technology is related with renewable resources. Since these alternative energy resources: are less foreseeable than conventional fuel based traditional power plants, cannot handle with the load variability (Joy, Jasmin, Rajan John, & Professor, 2013). The generated energy has an abrupt fluctuation depending upon weather dependence, and required to be tightly coupled to storage. It is important to improve quality and reliability of power supply.

Cyber security is the one of the most critical issue among the smart grid difficulties. Unwanted third parties will hack into the system and may mislead the actors with incorrect or outdated information or take over the control of the grid components and the storage units which will create technical problems (O. Sevaioğlu, 2016e).

The other significant difficulty is designing load side management contains the requirement and response of the demand (Bari et al., 2014). Smart grid technologies require prosumer attendance, developing decision-theoretic tools, optimizing pricing, and accounting for electricity energy grid restrictions.

The last but not the least difficulty in the smart grid implementation is poverty of consumer mindfulness about the communication system and complexity in the system technology. Demand side promote is a necessity to control load management (Amin, 2011; Torres, n.d.; Vineetha & Babu, 2014).

2.3.1. Application Domains

Smart Grid Technology is qualified by a bidirectional electricity power (Sood et al., 2009). Since the smart grid technology is a combination of four system; generation, transmission, distribution, and consumption. Since smart grid technology provides the fundamental link between the consumer and the grid, it help to motivate the consumers with including them in the system. Advanced Metering Infrastructure (AMI),

Advanced Distribution Operations (ADO), Advanced Transmission Operations (ATO) and Advanced Asset Management (AAM). Figure 2-15 represents how users participate the smart grid control and applications with details (Yang, Chen, Li, Zio, & Kang, 2014).

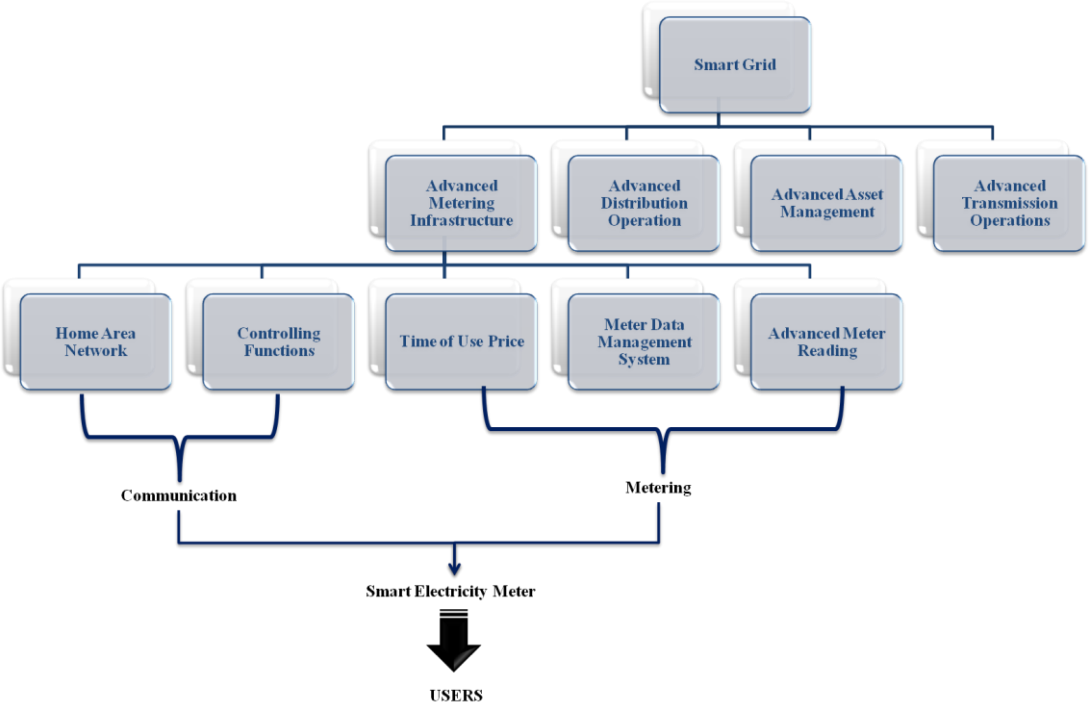

Figure 2-15. Smart grid control domains (Yang, Chen, Li, Zio, & Kang, 2014)

Figure 2-16 gives information about the infrastructure of basic sequence among AMI, ADO, ATO and AAM (US Department of Energy, 2016). The smart grid control technology includes widely-used system communication, asset management, transmission and distribution alternatives while having advanced network topology structure.

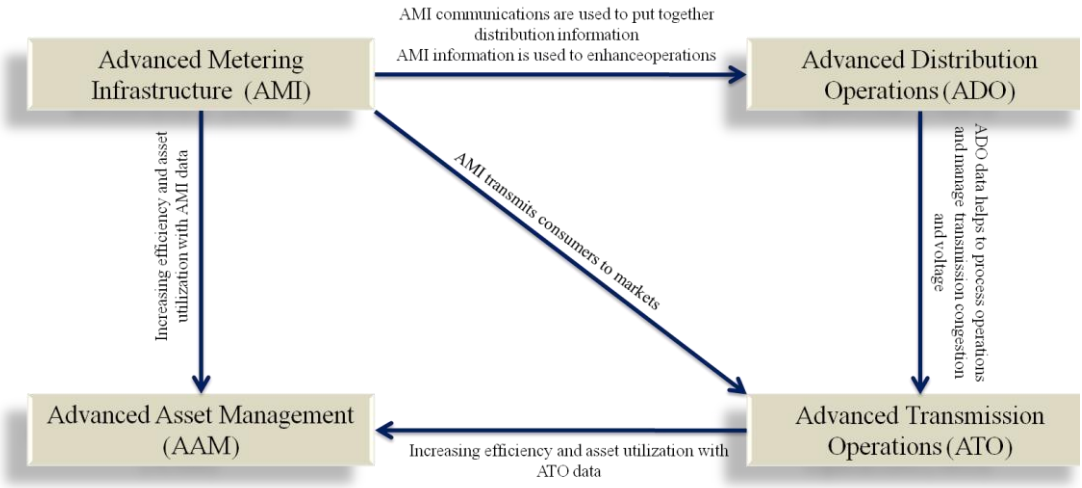

Figure 2-16. The relationship between AMI-AAM-ATO-ADO (US Department of Energy, 2016)

In order to obtain a smarter electricity generation, transmission and distribution network and consumer, advanced technologies and applications AMI, Smart Meter, Wide Area Measurement and Control Systems (WAMACS), Power Line Communication (PLC), Time of Use (ToU), Advanced Distribution Automation (ADA), Phasor measurement units (PMU), Distributed Energy Resources (DER) and Home Energy Management System (HEMS) are in use (Güngör et al., 2011). The following figure shows the smart grid network for the cities.

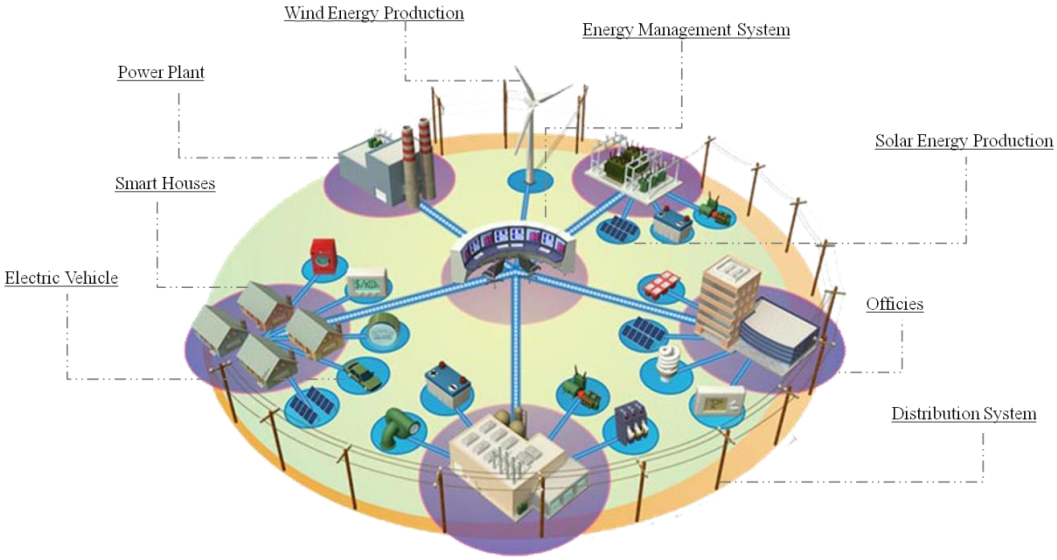

Figure 2-17. Smart grid network (EPRI, 2012)

2.3.1.1. Advanced Metering Infrastructure (AMI)

As a requirement of two way communication with a smart utility meter, prosumers and the utility company communicate each other using AMI. The power consumption is determined by a smart electricity meter which is an advanced meter presents more detail acknowledgement than a traditional meter and correspond the accumulate data between the consumer and the generated side to monitor load transaction and pricing of the using energy (Yan et al., 2013). AMI will serve a purpose for relieve load reducement at the end user's site by communicating instantaneous kWh pricing and voluntary load reducement schedule events to the end users and to several enabling devices related to the AMI, via a Home Area Network (HAN), each of that involves the requisite AMI-specific functionality at the customer’s aspect. Figure 2-19 shows the working relation of AMI and demand side (US Department of Energy, 2016). The communication can be done by wired or wireless. The following figure is summarized the categorization of basic communication technologies of AMI;

Wired

- **Fiber optic cable**
- **Power-line communications (PLC)**
- **Telephone dial-up modem**

Wireless

- **Radio frequency (RF) – mesh network**
- **RF – Point to multipoint**
- **RF- Cellular**

Figure 2-18. AMI communication technologies

Voluntary load reduction events may be scheduled with a large amount of advanced notice (24 hours) or near real-time. Timely pricing, event and usage information must be provided by utility to receive the desired customer response (O. Sevaioğlu, 2016b). AMI consists of smart meters and utility systems and the integration of advanced sensors, smart meters, monitoring systems, computer hardware, software, and data management systems, thus enabling the picking and distribution of data between smart meters and utilities, permitting the attend of prosumer in the power network (V. Cagri Gungor et al., 2013; Vehbi C Gungor et al., 2012; Paudyal, Canizares, & Bhattacharya, 2011; Sauter & Lobashov, 2011; Zaballos, Vallejo, & Selga, 2011).

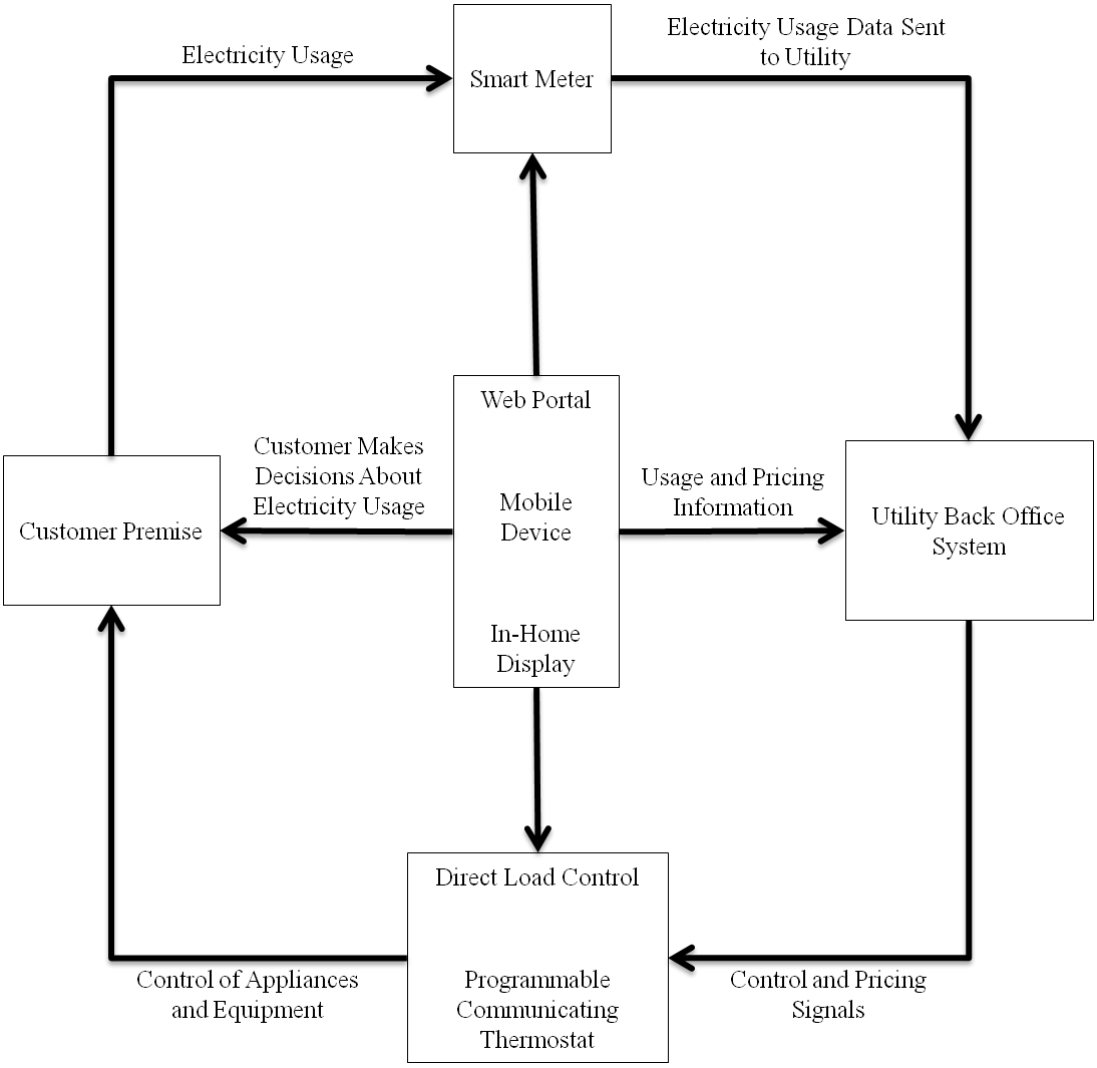

Figure 2-19. Working of AMI and customer systems (US Department of Energy, 2016)

Researches have already discussed the smart meters represented in Figure 2-20 in the literature from the early 1990´s (Efficiency, 1994; Koponen, 1996). Since solid state meters had a limited usage for customer, electromechanical meters were more expensive 10 - 20 times than the solid state meters during the those years (Pekka et al., 2008). After the years the number of remotely readable smart meters have been increased by reason of necessity to develop better systems for meter reading and data management. The required features are considered for the smart meters;

- reciprocal communication
- addition of consumption data for demand side evaluation, tariffing, load forecasting, and planning
- programmable time resolution
- tariff administration
- control of load
- information to prosumers
- monitoring the quality of supply (Pekka et al., 2008).

Figure 2-20. A smart meter ("Sms Metering," 2018)

Critical Peak Pricing (CPP) day is determined specification the following day by the utility. A multifariousness of techniques that may involve the AMI via the meter or HAN-connected prosumers monitor, website, email, etc. are used by the prosumer of the oncoming incident. Additionally, the utility procumers emissaries are enounced of the incident wherefore they can expect anxieties of prosumers.

The AMI will deliver the contingent information to the meters in the influenced region, supplied to the highest degree asseveration, which an incident is planned, the date of incident and start/end time and quotation information. The meter will log the incident information, forward a receipt to the AMI and transfer the message to the prosumer's monitor appliance (O. Sevaioğlu, 2016b).

The AMI can dispatch another episode message to the influenced meters which the episode has started or actuating the meters for the event autonomously if it start time reaches. When another action message is dispatched by AMI, the meter accepts this message, log the event and dispatch a receipt to the AMI. Furthermore, the measuring device sends a message to the display device connected to the HAN of the customer and any pre-configured load controller to reply to the utility event statement displaying that the event is continuing. The prosumers can get into the act to individually decrease their load demand or let load control equipment for relying to the appeal. The load controllers can be pre-programmed to perform a significant action by the industry or by the prosumer according to the cost or specific event. Prosumers may surpass the automated load drop of their appliances for the selecting ones. The control device forward a message to the meter and the meter registers the receipt and sends a message to the AMI when it is activated. The each message from the meter for future audit is logged indissolubly by AMI. The prosumers can be viewed CPP activity information and commenced and concluded times for the action in the display device, meter and mobile phone application before and while the action. The prosumers can observe their load consumption data for the most recent finished utilization interval (e.g. in terms of energy), momentarily requirement and hourly price. When the prosumers are not at their location, they can observe their expenditure, cost and action information a utility website.

When the event finish time is reached, the AMI can transmit another action message to the impressed meters, or the counter can end the action autonomously. Meters indicates that the action is finished and logged. A message is sent to the prosumers'

monitor and structured load control device at the prosumer's place. HAN appliances arrange their operating situation, depending on messages imported, to implement with the executional states either pre-programmed by the producer or softwired by the customer in convenience with pricing, depletion or load rules. The message was obtained is confirmed by the load control equipment, terminated the control of load and logged the operation. Each message is continuously logged by the AMI from the meter for the following observing and become the information disposable to other utility systems (e.g., billing system and utility softwired) (O. Sevaioğlu, 2016b).

2.3.1.2. Wide Area Measurement and Control Systems (WAMACS)

Wide Area Measurement and Control Systems (WAMACS) is one of the essential scope area that is swiftly improve. Such systems help to synchronously denomination and intercommunicate the momentary status of the electrical power system through a indication known as the Synchrophasor. Since the system able to dynamically analyze the condition of the electric grid system, it is likened to a beating heart. Standard and under tension system states can be evaluated in real time and can be activated to influence dynamic control. The operators of grid system at the present time transact in the multiple seconds to minutes time range, in other respects WAMACS can take a decision and carry out the action in the 0.1 second time range.

The substructure of WAMACS has been developing needs the equipments which measure and consolidate of data in substations, data aggregate, screening and believable wide area communication network. Some studies are progressing in all related subjects. The utilities are imperative to awaken of necessity of productivity dictated by real time transmission. Therefore, they constitute their communication substructure. The most of the related workings occupy more than five years to reach sufficient level.

2.3.1.3. Time of Use (TOU)

In smart grid technologies demand response can be determined by Time of Use (TOU). Household electricity demand is used according to electricity unit price tariffs demand on TOU comprehensively scouted in the literature (Vandad Hamidi, Li, & Robinson, 2009; Pallonetto, Oxizidis, Milano, & Finn, 2016). During the varied time of the day, electricity unit price is adjusted as below TOU. Electricity is used throughout the cheapest prices are available (off-peak). On the other hand the usage should not be preferable when electricity is most expensive (Phy, n.d.). Utilities may even improves a TOU schedule for winter and summer demands on periods on- and off-peak times.

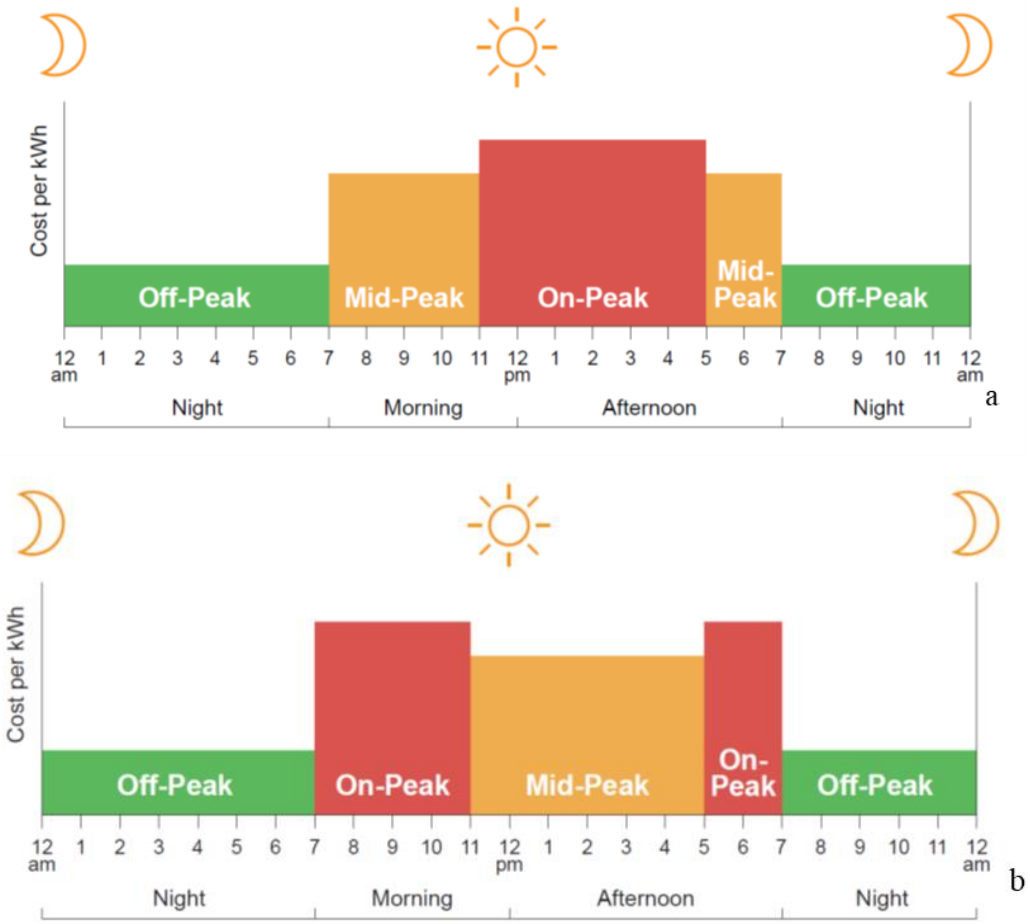

Figure 2-21. TOU schedule for summer (a) and winter (b) ("Hydro Ottowa," 2018)

Figure 2-21 shows schedules for summer and winter. Since daylight is less during the winter, load demand curve has peaks twice: once of them is in the morning to wake up and the other is towards the end of afternoon because of turning on their lights and appliances at home. In other respects when summer, the peak demand occurs in the afternoon due to run the air conditioners on high ("Time of Use," 2018).

2.3.1.4. Advanced Distribution Automation (ADA)

The distribution system has a role in the network as connector. It behaves like a hyperlink between transmission system and the consumers. Distribution grid provides delivering the electricity power in the system. In the smart grid technology, ADA has a best option in the transaction to reach electricity from utilities to consumers as an efficient, confidential and high quality (V. Cagri Gungor et al., 2013). It is a known fact that the power/energy generated by prosumers are usually more expensive than those supplied by the distribution company, particularly during the night and day periods. Generation capacity of the prosumers are mostly solar and small size-wind type renewables, standby diesel sets, and bio/waste-energy resources. These kind of energies exhibit a rather high fixed cost term in tariffs, as their daily generation profiles are irregular and their capacity factors are low, hence a reasonable payback period such as seven or eight years for the investments cannot be achieved, as in the fossil or hydro power plants. This fixed cost unless subsidized by feed-in incentives, causes the overall tariff to be excessively high, thus discouraging their commitment during the night and daily periods.

These power plants however may be committed during the evening period, when the prices rise excessively, hence their commitment becomes feasible. It should be borne in mind that that above claim is valid only for power plants with storable fuels, such as dam type hydroelectric plants and diesel generator sets. Other types of power plants with unstorable fuel resources, such as geothermal, solar, wind and regulator type hydroelectric power plants exhibit an uncontrollable generation profile, hence they are

committed with a schedule determined by the nature, i.e. daily sunlight schedule, etc. not by the electricity tariffs.

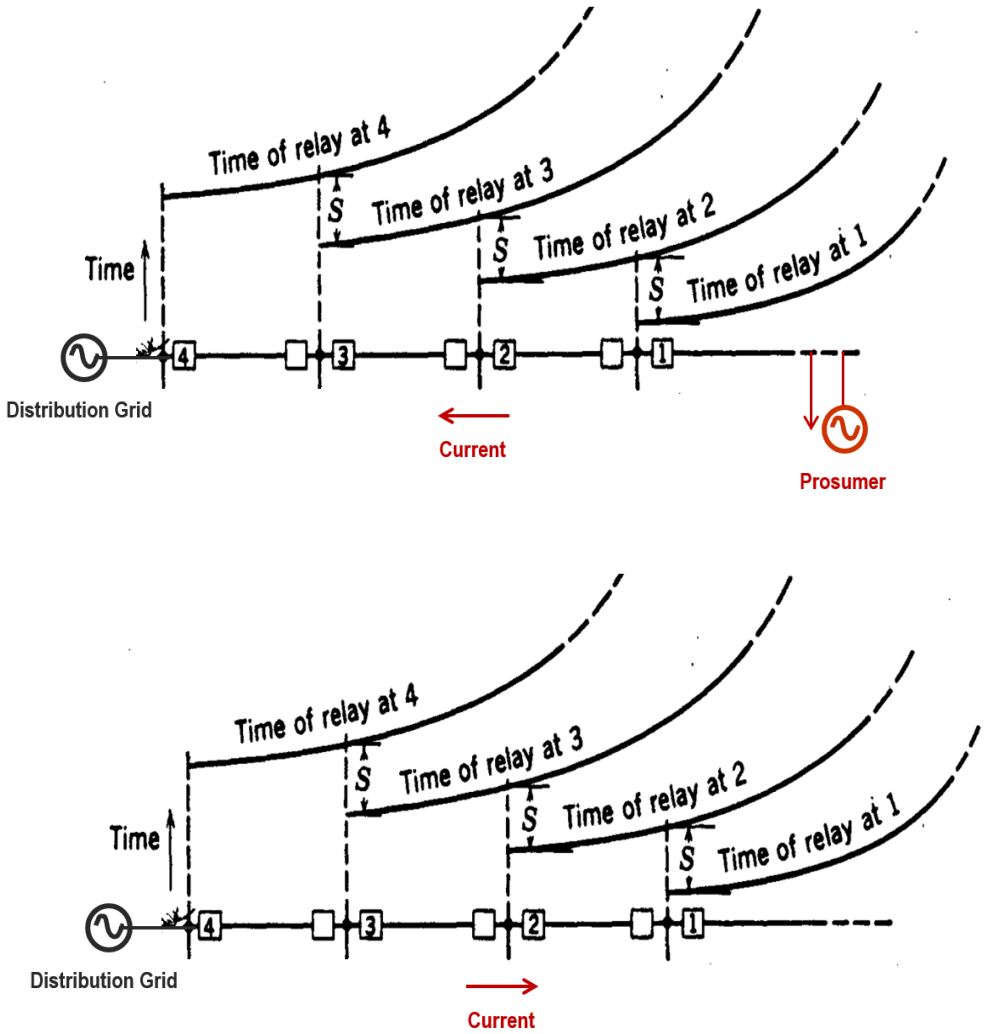

Figure 2-22. Selectivity of the overcurrent relays

Form the above description, it may be understood than the daily generation profiles of prosumers exhibit irregular patterns, hence these plants generate electricity only within certain periods of time and during the remaining periods consumers find alternative ways of meeting their energy demands, such as the energy obtained from the distribution company or from the third party suppliers in the distribution grid (Sevioğlu, 2016). Figure 2-22 irregular patterns of generation profile in a micro-grid

create frequent changes in the magnitude or direction of the load current, creating difficulties in the selectivity of the overcurrent relays.

The first figure shows the case, where the prosumer plant is in service, generating electricity in the direction show, while in the other, prosumer plant is out of service, generating no electricity, hence current flow from the distribution grid to the consumers on the feeder. Obviously, depending upon the generation profile of the prosumer plant, current reverses its direction, thus, creating a need for relays with adjustable The Time Current Characteristics (TCC) characteristics and as discussed in the above sections, TCC characteristics of these relay must be controlled by the commands issued from the SCADA in the distribution grid.

2.3.1.5. Phasor Measurement Unit (PMU)

PMU ensures to measure synchronized phasor computation. According to global time base, voltage and current's phasor values are measured by PMU. The block diagram of the PMU is given in the Figure 2-23 (Gopakumar, Chandra, Reddy, & Mohanta, 2013; Nuqui & Phadke, 2005; Phadke, 1983).

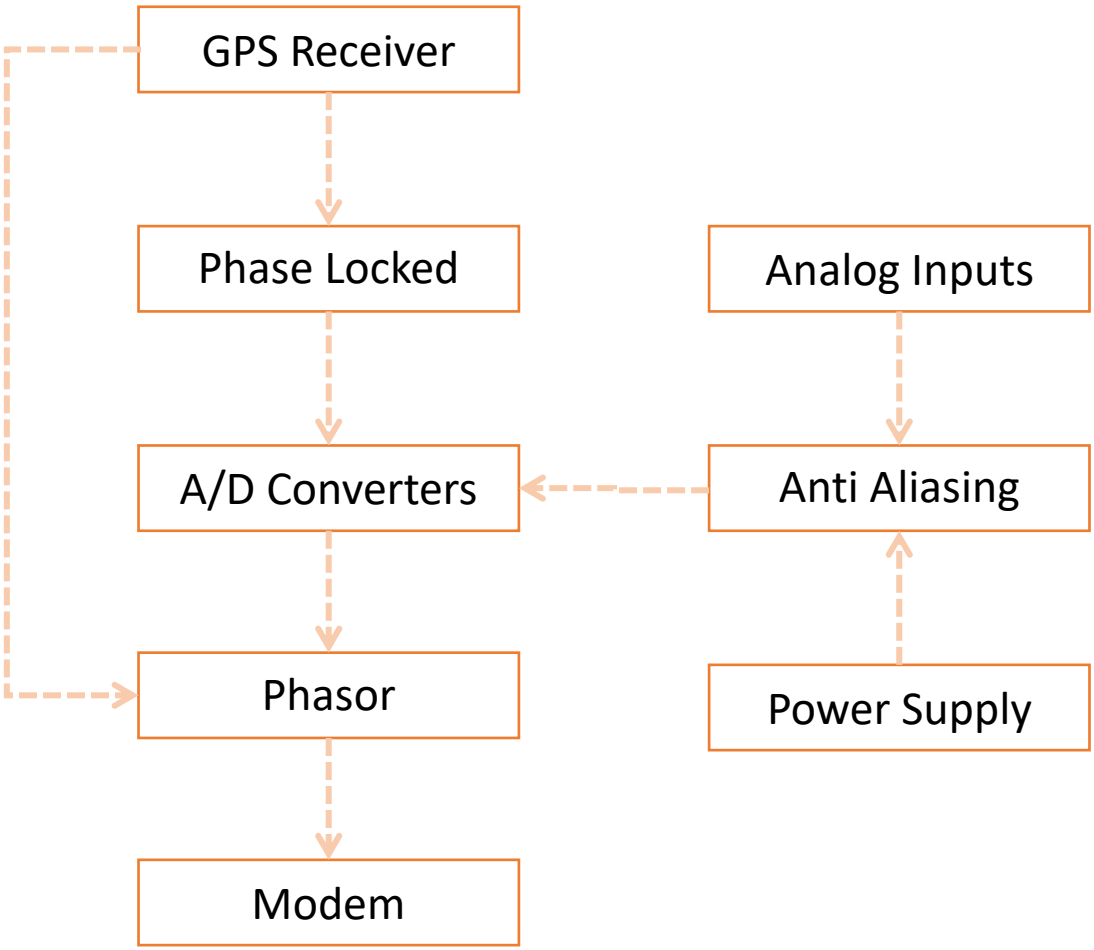

Figure 2-23. The block diagram of PMU (Gopakumar et al., 2013)

PMU provides to monitor and control the Real time data, a protection of the network and State estimation (Hurtgen & Maun, 2008; Rihan, Ahmad, & Beg, 2011).

Smart Grid Technologies provide more reliable, sustain and quality power with DER which are small scaled power plant and energy storage like wind turbines, photovoltaic panels and biofuels. In this way the energy production can be done distributed. Thus DER system implements a non-radial power flow, this technology induces carbon emissions, reduced fuel costs and lost on network lines (Brown, 2008; V. Cagri Gungor et al., 2013).

PLC is an advanced technology to sustain the information system on a power line network, power transmission and distribution. It handles the power feeder line as communication media (Yan et al., 2013). During the past ten years removed metering and control sub-systems have been used all around the world (Fang et al., 2012; Hendrik C. Ferreira, Lutz Lampe, John Newbury, 2011). To communicate in smart grid technology, PLC has a vital role in the electricity network to contact with the smart meter and advanced application of AMI to correspond the requirements of utilities (Güngör et al., 2011; Lewis, Igic, & Zhou, 2009).

HEMS market field is one of the substantial stair of evolvement as it is first needed to have a smart meter and the operation network in place in order to produce and interchange the prosumer data (Oleg Gulich, 2010).

Advanced Asset Management (AAM) enhances asset management. It compounds the electricity energy grid guidance to obtain the other milestones with new and existing asset management applications. This integration improves utilities the following factors (S. Grid, n.d.);

- Decreasing the capital cost of Operations and Maintenance
- Better utilize assets during day-to-day operations
- Developing the performance of volume envisioning, maintenance, engineering and facility design
- Power supply management

2.3.2. Advanced Distribution and Transmission Operation/Microgrids

Distributed Generation/Microgrids is One of the key scope driving the Smart Grid's control technologies. Day by day Distributed Energy Resources (DER) have been become more dissipated, widespread along the communication and electronic enterprise to the different supplies since therefore aggregate power system or

Microgrids can manage the wieldier grid. The drivers are clear - the desire for great - usability and high-quality electric grid for the digital community (Nadar, 2016).

Micro-grid is a part of the main grid, i.e. the larger network, connected through a tie-line including prosumers, consumers and grid management system. Contrary to general belief, MV side of a distribution system is not a single intact system, but consists of a number of subsystems electrically disconnected from each other, each being supplied by a different HV/MV transformer.

Since the configuration each of these subsystems are radial, MV sides of each of these HV/MV transformers may be assumed to be independent micro-grid networks operated at MV voltage level. Thus, each of the regions encircled in the Figure 2-24 may be assumed to be an independent micro-grid network.

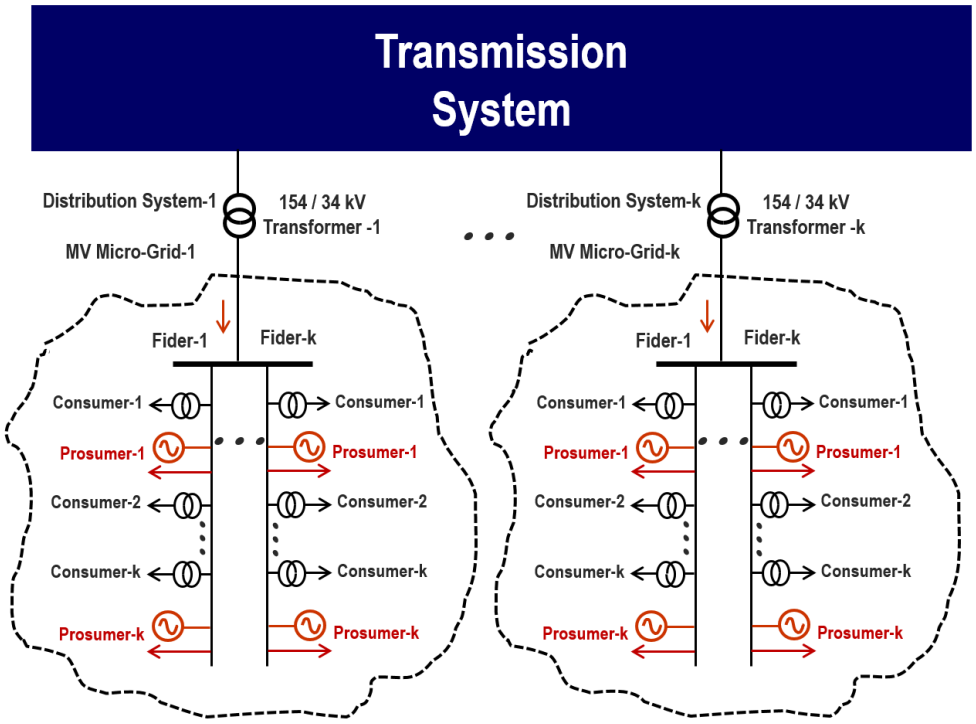

Figure 2-24. An independent micro-grid network

Similarly, depending upon particular application and objective, the micro grid may be designed as the LV part of an MV/LV transformer operated at LV voltage level. In this case, the configuration of the micro-grid will consists of the radial network at the LV side of the MV/LV transformer as shown in the following diagram.

Please note that region of authority of the micro-grid management starts from the MV terminals of the transformer, which acts as a tie-line, not from the LV terminals, in order to include the MV/LV transformer to the region of the micro-grid and hence to be able to charge the transformer losses to the account of the micro-grid management.

In principle, the main difference between the MV and LV micro-grid systems are the size and the measurement locations, while the structures and operating principles are quite similar. In MV micro-grid systems measurements are made at the primary side of the MV/LV transformers, while in LV micro-grid systems measurements are made by meters installed right at the supply point of the customers (Sevioğlu, 2016).

The assumption of micro-grid system being a commercial identity, immediately leads to the obvious consequence that, the power exchange between the micro-grid and the main grid must be precisely measured, as power and energy are expensive commercial commodities. In other words, power exchange of the micro-grid system with the main grid must be precisely measured by meters installed through tie-line point of the grid and these measurements must be recorded, charged, billed and the corresponding amounts must be collected from the grid/main grid participants concerned as shown in the following diagram.

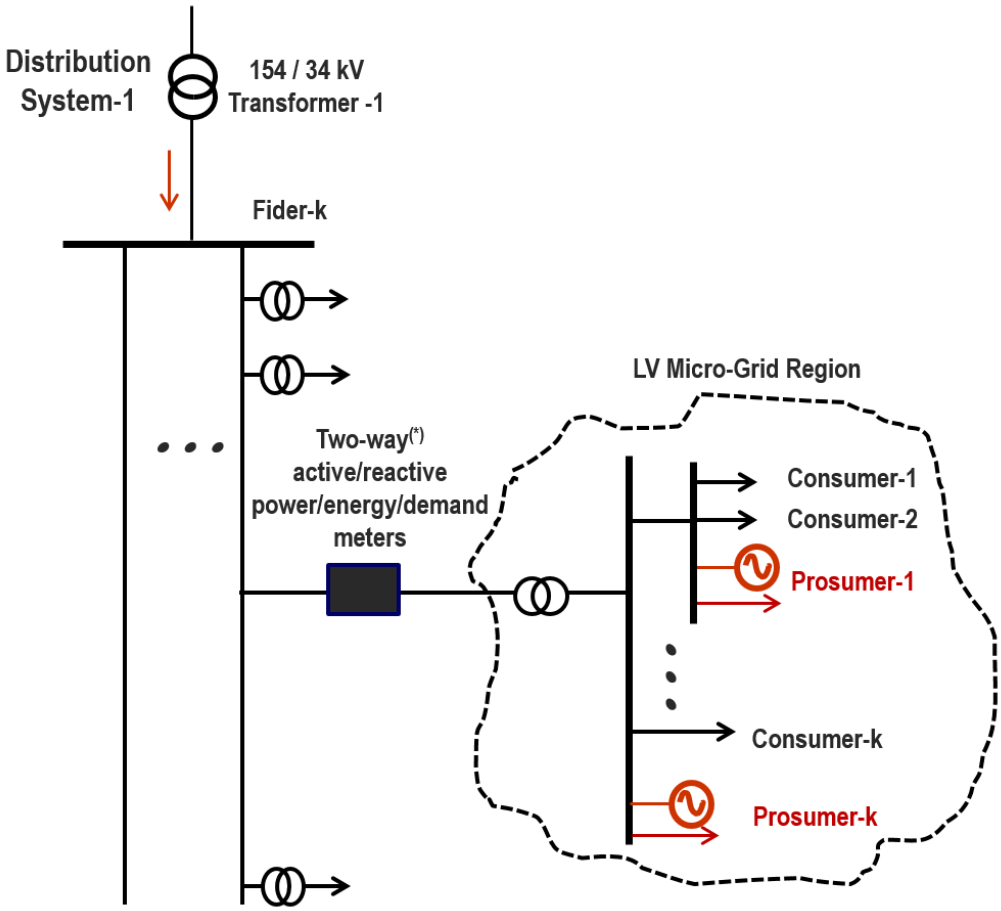

Figure 2-25. Two way power flow

As seen in the diagram given Figure 2-25, six meters, for two-way[1] active/reactive/capacitive power/energy measurements and one for demand measurements are installed through tie-line point, seven in total. Power flows being measured through tie-line point, the micro-grid may be assumed to be an eligible customer registered to PMUM/DAM[2] (Sevioğlu, 2016).

---

[1] *Two way: Both the incoming and outgoing powers/ energies*
[2]*PMUM/DAM: Turkish Electricity Market Center, responsible for carrying out the Balancing Settlement Task and Day Ahead Markets. PMUM is being recently re-structured in the name of EPIAS, a new company with a larger scope of commercial and trading activities.*

The usual kind of commercial activity of the micro-grid operator with PMUM is to exchange power/energy with DAM, one day earlier than market clearing. Micro-grid operator must therefore be commercially eligible to make energy trading with DAM, i.e. it must satisfy the conditions on the commercial structure and financial requirements for being a member of PMUM.

Reflection of the bills and payments made between DAM and micro-grid operator to grid participants is another part of the task. It can simply be said that micro-grid will act in an exactly same way as the retail/wholesale trading branch of a distribution system operator, but in a smaller scale. In other words, micro-grid operator will operate the micro-grid system, safely and securely, while satisfying the power demands of the grid participants, i.e. supply power to customers from third parties and sell powers generated by the consumers to third parties, while maintaining a balancing procedure through tie-lines with the main grid operator. The term “third party” here stands for commercial entities, acting either in or outside of the micro-grid system (Sevioğlu, 2016).

2.3.3. Structure of the Micro-Grid Management

In principle, the management of micro-grid system is assumed to be owned, operated managed by the distribution company. The distribution company owns all the SCADA-related computer hardware, software, power distribution infrastructure, power equipment, measuring devices and related electronic equipment in the micro-grid. In this type of commercial structuring, all kinds of technical and commercial activities, system planning, maintenance, repair, recording, measuring tasks are carried out solely by the distribution company.

However, this type of structuring is not unique. An independent private company may be established for managing the commercial activities in the micro-grid, such as arranging power/energy trading activities among the micro-grid participants, PMUM/DAM and the distribution company.

The establishment and existence such a private owned micro-grid management however, does not remove the authority and responsibility of the distribution company on carrying out all kinds of necessary technical tasks, such as system operation, maintenance, repair, planning, recording, measuring activities on the computer hardware, software, power distribution infrastructure, power equipment, electronic devices in the micro-grid. In fact, this authority and responsibility are the main features of the distribution company, which can never be shared with anyone else, since the distribution company holds the Concession Agreement for the Transfer of Operation Right (TOOR) of the overall distribution region for 25 years of operation period.

In the view of the above description, it may be stated that, the establishment and existence of such a private-owned grid-management does not result in transfer of authority from distribution company to this private owned grid management company for carrying out the technical activities, such as system operation, maintenance, repair, planning, recording, measuring activities on the computer hardware, software, power distribution infrastructure, power equipment and electronic devices (Sevioğlu, 2016).

Within the direction of the above description, it may be said that, a "virtual" micro-grid management, operated only on the basis of commercial management and accounting, may be established, while all the authority and responsibility on operation, maintenance, repair, planning, recording, measuring activities on the computer hardware, software, power distribution infrastructure, power equipment, electronic devices lie solely on the distribution company. In such a structuring, the tasks carried out by the micro-grid management case is narrowed only to the context of commercial management and accounting of the trading activities. The distribution company in this case will continue collecting the "Distribution System Connection" and "Distribution System Usage" fee from the micro-grid participants, thus recovering the expenditures made for the repair and maintenance services carried out in the micro-grid region.

The type of structuring is exactly the same as that seen in the relation between TEIAŞ and PMUM/DAM. TEIAŞ holds all the responsibility on operation, maintenance,

repair, planning, recording, measuring activities on the computer hardware, software, power distribution infrastructure, power equipment, electronic devices, while PMUM carries out the activities within the context of commercial management and accounting of the trading.

Similar to the structure of PMUM, the grid management will be equipped with a highly sophisticated computer based communication and data/information storage/exchange system for managing the commercial activities among the grid participants, distribution company and PMUM/DAM. This computer based communication and data/information storage/exchange system however will solely be devoted to the managing the commercial activities among the grid participants, distribution company and PMUM/DAM, but not to the physical operation of the distribution system.

Within the direction of the above description, it may be said that the management of micro-grid may be structured in two alternative forms, depending upon whether it may or may not belong to the distribution company, depending upon commercial preferences and agreements (Sevioğlu, 2016).

Before building the microgrid, there are some important aspects by means of infrastructure which should be provided by microgrid (S Chowdhury, Peter Crossley, n.d.);

- Grid connected mode and standalone mode fault detection equipments should work in collaboration,
- Standalone microgrid should have an proper grounding,
- After islanding, the fault detection in islanding mode should be taken in to account no matter how big is the ratio between fault current and maximum load current,
- Microgrid area should be coordinated with the utility in case of load shedding made by utility.
- In order to maintain stability and prevent undesirable loss of DER, existing anti-islanding structures should be examined and modified if require,

There are some problems belonging to protection of microgrids, which are;

- It may affect close-loop and meshed distribution grid topologies included with DERs,
- Short circuit currents' values and their directions differ according to which DER is connected to the grid,
- Spurious tripping of utility breakers for fault in adjacent lines due to DER's fault contribution,
- DSO line breaker policies which are auto-reclosing and fuse-saving may fail for the microgrid,
- Existing switchgears incapacity due to increase in fault levels, can cause an investment for new switchgear deployment,
- Inverter based DER may decrease the fault contribution especially in islanding mode,
- Speed and Sensitivity of the fault detections are reduced when DER connections are tapped,
- It may create a conflict between feeder protection and DSO requirements for FRT (Fault Ride Through) which is a part of power system code of many countries where DERs connected to DSO widely.

2.3.3.1. Distribution System Connection and Distribution System Usage Agreements

At first glance, it might seem that, there is no need for the micro-grid management to make "Distribution System Connection" and "Distribution System Usage" agreements with the distribution company, since each grid participants have already made them. Consumers sign the "Distribution System Connection" agreement, while prosumers sign and "Distribution System Usage" agreement in addition this.

Conditions in these agreements bind/force the prosumers/consumers to obey to the rules on the limits of maximum and minimum power/energy transfer through tie-lines

between the companies and the main grid. Any violation of these rules brings penalties to the consumer/prosumer concerned.

Agreements signed by prosumers/consumers however, do not impose any binding force on the micro-grid management for obeying to the same rules, since the management is not a side of these agreements. Hence, making the micro-grid management to be a side of the “Distribution System Connection” and “Distribution System Usage” agreements is highly essential for increasing the efficiency of operation and reducing the cost and prices for the micro-grid participants.

Active/reactive/capacitive power and energy consumptions of the consumers/prosumers are continuously measured and recorded in two way, while the overall power and energy consumptions are measured at through tie-line of the micro-grid given in the Figure 2-26.

In general, the indicators of the power quality are Voltage Variations, Voltage Unbalance, Voltage Dips/Swells, Flicker, Voltage Harmonics, Current Harmonics and Frequency. These parameters are generally being monitored by distribution company in Medium Voltage level continuously. With developing smart grid applications and expanding distributed generation, the quality issues gains more and more importance. Regarding these challenges for the grid, monitoring the power quality at low voltage level is mandatory. This use case proposes a quality management system for distributed generation points at low voltage level.

In many countries, distribution companies are legally responsible for the quality of power and they report to Transmission Company or any other responsible authority. Likewise, distribution companies have a right to hold consumers and/or producers (prosumers) responsible for their consumption or generation characteristics in regards to power quality (O. Sevaioğlu, 2016d).

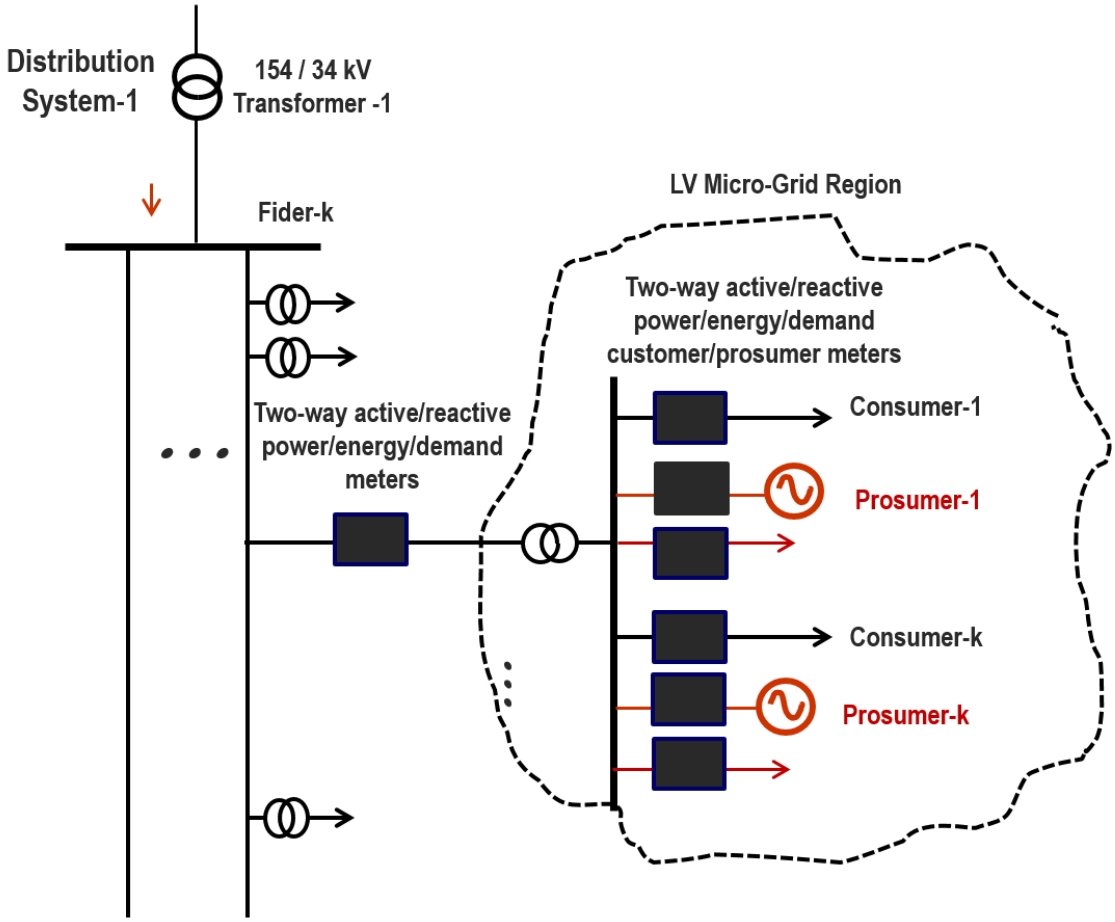

Figure 2-26. The structure of the measurement of power and energy consumptions

In order to be able to obey the maximum/minimum power demand and energy conditions through tie-line, written in the "Distribution System Connection" and "Distribution System Usage" agreements, the micro-grid management must be very keen in watching and controlling the maximum/minimum power and energy demands of each of these consumers/prosumers. Violation of the conditions on the limitations, given in the "Distribution System Connection" and "Distribution System Usage" agreements, will result in penalties to be implemented to the micro-grid management, creating losses in the revenues that should be reflected to the consumers/prosumers. Thus, in order to be able to force the micro-grid management to obey these limitations "Distribution System Connection" and "Distribution System Usage" agreements must

be made between the distribution company and the micro-grid management, in addition to those made with the consumers/prosumers.

Any penalty implemented to the micro-grid-management due to a violation in these limitations will be recorded by the meters through tie-line point, and then reflected immediately to the concerned consumer/prosumer, who created this violation micro-grid-management.

The micro-grid management is merely a commercial re-structuring with the aim of achieving higher efficiency and operational advantages in system operation. The physical structures of the distribution system with or without the micro-grid management are exactly the same, the only difference being in the concept and understanding of the system operation.

The structure of the two supply systems are exactly identical, except that the range of the regions enclosed by the dashed lines are different. Concerning the commercial benefits and operational advantages to be expected from the micro-grid structure and operation.

Another commercial benefit and operational advantage that may be expected from the micro-grid structure and operation is the replacement of the expensive power/energy supply obtained from the distribution company by the relatively cheaper power/energy supply obtained to be prosumers in the micro-grid during the evening hours. It is a widely known fact that the rise in electricity prices due to commitment of relatively expensive generation plants, during the evening hours are reflected to the end user customers through three-rate tariff. This rise in the tariff may be avoided and the customers may be protected against high rates, by implementing a special commitment schedule during the evening period, by committing the domestic resources offered by prosumers within the micro-grid. As shown in the following diagram, power flow through the tie-line in this type of commitment schedule, may be reduced or even be reversed during the evening periods (Sevioğlu, 2016).

2.4. Load Forecasting in Smart Grid

Smart Grid Technology ensures a proximate electricity energy network utilising data processing technologies. The electricity is supplied from power plants to consumers with a two-way communications lead the way increasing energy efficiency, reliability and sustainability in Smart grid control due to measuring power and controlling appliances using bidirectional way power grid. Therefore, customers can attend the grid control and play a very important role in electricity generation, transmission and distribution. Thus, smart grid leads to consumers use appliances according to cost of electricity by virtue of load forecasting in smart grid technology (Byun, Hong, Kang, & Park, 2011; Zhang, LI, & Bhatt, 2010).

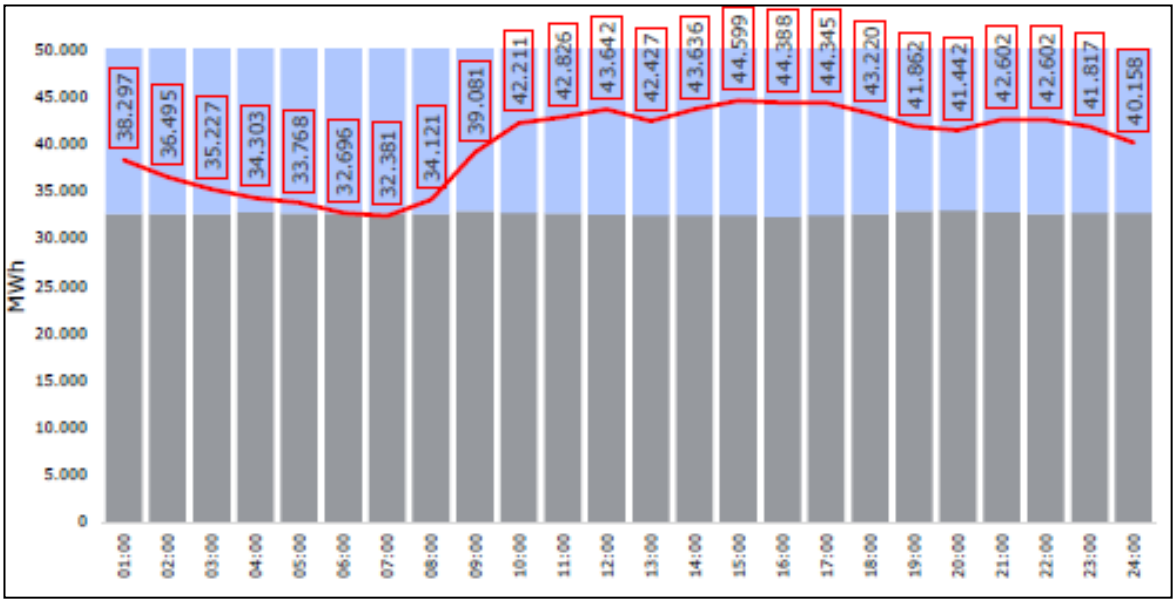

Figure 2-27. Daily load demand curve on 19.07.2018 in Turkey (Kapasite & Miktar, 2018)

It provides larger savings for the electricity generation and energy bill. The load demand presented in Figure 2-27 indicates average load, fluctuation of load during different time of the day and maximum load data. It is indicated that the difference between day and night time is seen obviously. It can be scheduled according to peak time periods of the load demand curve proffered in Figure 2-28. As can be seen from

the following table instantaneous and hourly peak loads of Turkey has been increasing year by year between 2007-2017 ("Türkiye Elektrik Üretim-İletim İstatistikleri," 2017).

Load features mainly four factors, these areas can be briefly categorized as follows:

- Demand factor

$$Demand\ Factor = \frac{Maximum\ Demand}{Connected\ Load}$$

- Load factor

$$Load\ Factor = \frac{Average\ Demand}{Maximum\ Demand}$$

- Diversity factor

$$Diversity\ Factor = \frac{Sum\ of\ individual\ maximum\ demands}{Maximum\ demand\ of\ power\ station}$$

- Utilization factor

$$Utilisation\ Factor = -\frac{Maximum\ demand\ on\ power\ station}{Rated\ capacity\ of\ power\ station}$$

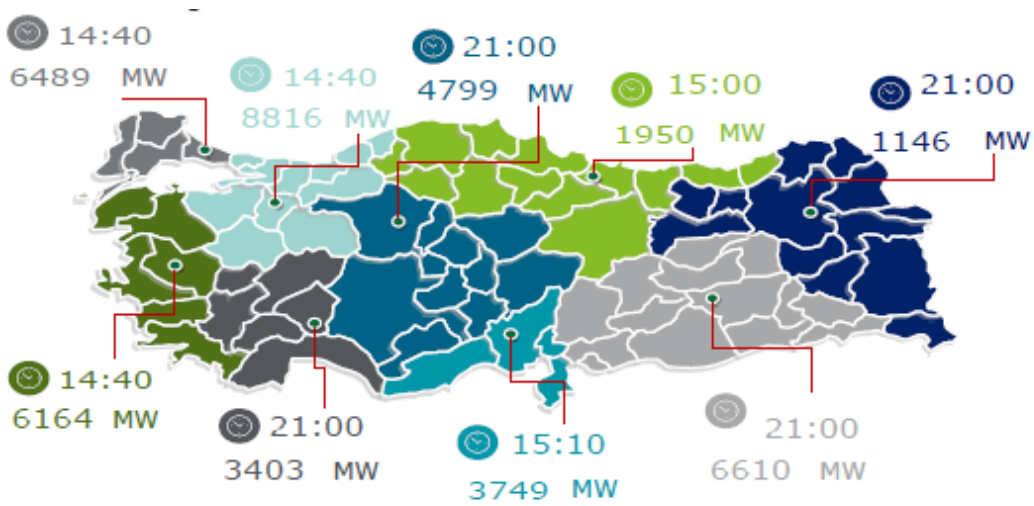

Figure 2-28. Regional and hourly peak demand on 19.07.2018 in Turkey

Table 2-8. *Annual development of the instantaneous and hourly peak loads of Turkey interconnected systems by months (*The highest peak load in the year, I: Instantaneous H:Hourly Unit:MW) ("Türkiye Elektrik Üretim-İletim İstatistikleri," 2017)*

MONTHS	Peak Load Type	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017
JANUARY	I	26642,6	29865,2	28012,6	30011,6	32499,5	35751,5	36135,0	36239,4	39061,1	41138,0	42335,9
	H	26388,0	29703,0	27830,0	29719,0	32147,0	35357,0	35951,2	36009,0	38624,2	40871,8	41956,4
FEBRUARY	I	26911,5	29256,8	27486,9	29175,0	32675,3	35543,2	34939,7	36005,4	38359,7	38551,7	42452,9
	H	26476,0	28994,0	27343,0	29158,0	32190,0	35168,0	34310,8	35651,0	37964,8	38035,2	42174,1
MARCH	I	25800,2	26401,5	26598,9	27624,6	32915,3	34567,0	33286,1	35042,6	36796,8	36858,7	40271,0
	H	25544,0	26306,0	26434,0	27218,0	32518,0	34253,1	32996,9	34691,0	36261,9	36497,8	39661,9
APRIL	I	24764,1	26098,6	25000,6	27775,7	30238,8	31377,9	32654,9	33881,8	35196,9	36205,9	37495,8
	H	24567,0	25939,0	24900,0	27395,0	29840,0	31182,0	32314,0	33549,6	34924,2	35837,9	37230,5
MAY	I	24358,0	26614,2	25175,7	28045,5	29109,2	30776,0	33070,9	33863,7	35420,7	35848,8	37603,9
	H	24208,0	26392,0	24808,0	27885,0	28691,0	30483,0	32916,0	33835,1	35206,9	35677,1	37053,3
JUNE	I	28144,8	29679,5	27936,5	30672,1	31219,8	36216,9	36914,8	38656,7	36463,7	42333,0	43427,5
	H	27946,0	29468,0	27693,0	30654,0	30925,0	35847,8	36563,0	38072,9	36135,5	42055,6	43015,8
JULY	I	28732,5	30516,8*	29457,2	32570,6	36122,4*	39044,9*	37277,0	39191,6	43289,3*	42848,9	47659,7*
	H	28708,0	30482,0*	29239,0	32165,0	35634,0*	38431,0*	36955,1	38970,0	42345,0	42510,5	47062,4*
AUGUST	I	28793,7	30359,0	29870,0*	33391,9*	34929,1	37582,3	38274,0*	41002,9*	42582,7	44733,9*	47131,9
	H	28573,0	30130,0	29604,0*	33191,0*	34731,0	37293,0	38116,0*	40734,3*	42482,2*	44341,3*	46840,1
SEPTEMBER	I	28203,6	28046,5	27550,6	29637,1	33693,8	35052,3	36020,0	39207,9	40958,0	40828,9	42872,7
	H	27992,0	27884,0	27398,0	29395,0	32877,0	34773,5	35723,0	39125,7	40829,8	40505,1	42566,5
OCTOBER	I	25851,1	25209,3	25732,0	27582,9	32181,9	31568,9	32880,6	33625,3	33797,5	35284,6	37827,3
	H	25461,0	24607,0	25475,0	27291,0	31840,0	31465,0	32590,6	33507,3	33710,0	35301,5	37540,8
NOVEMBER	I	28892,4	27461,2	28521,1	30107,9	34869,6	33604,0	35164,0	37620,1	37589,9	39916,3	41185,2
	H	28796,0	27002,0	28131,0	29596,0	34423,0	33261,7	34751,0	36954,5	37249,7	39989,6	40802,7
DECEMBER	I	29248,5*	28286,3	29335,4	32961,7	35066,2	35848,7	37553,1	37756,1	40562,3	42361,0	42175,6
	H	29150,0*	27951,0	28961,0	32145,0	34637,0	37798,0	36979,0	37210,7	39885,6	42228,5	42034,0

*The highest peak load in the year. I: Instantaneous H:Hourly Unit:MW

When the electric power consumption isn't at the extreme points, the load can be consumed without any limitation and electrical energy storage devices are put into use. On the other hand, during the rest of the time - peak time, attention should be paid to electricity consumption and electricity power may be used from the stored energy. Such like this methods demand management can be done and peak requirements is degradable (Mo et al., 2012). The reduction of peak demand for electricity power can be made.

Load Management can be done by direct and indirect methods can be seen in Figure 2-29 with integrated smart grid technology solutions (Kostková, Omelina, Kyčina, & Jamrich, 2013; Yumak, Tosun, Varlik, & Bağriyanik, 2016).

One of the most preferred methods is Load Forecasting among the all energy management methods to meet the load demand with regards to plan and operate of

electric utilities (More, 2014). The method of Load forecasting is the load estimation for the future that takes a vital role in the electricity load management system to provide a better anticipating for the electricity energy system (Raza & Khosravi, 2015). The load forecasting can be categorized by Short Term Load Forecasting (STLF), Medium Term Load Forecasting (MTLF), Long Term Load Forecasting (LTLF) based on time interval.

- STLF ==> 1 - 24 hours
- MTLF ==> 1-12 months
- LTLF ==> 1 to 10 years

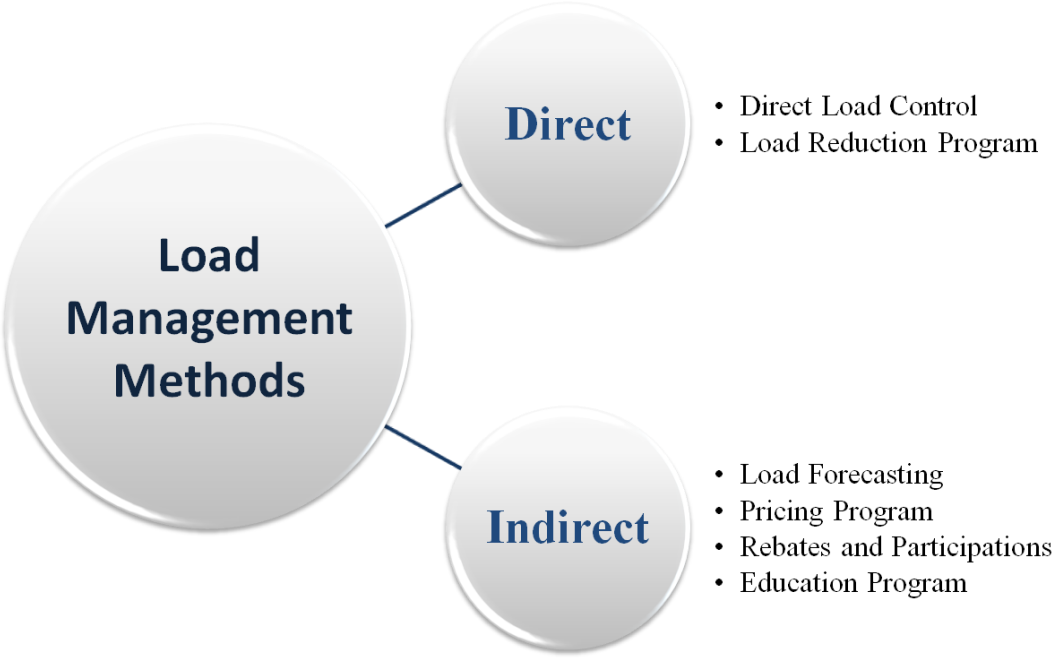

Figure 2-29. Load management methods (Yumak et al., 2016)

The load demand of the consumers varies according to usage of the appliances like air conditioner, refrigerator, television, iron and so on. Therefore, the electrify of some appliances contingent upon weather conditions, population, time of day and day of the week (For example, during the high temperatures, week days at noon air conditioners

works more time). The ones listed below are the factors that influence the load forecasting in Smart Grid Technology (Fahad & Arbab, 2014);

- Wind Direction
- Wind Speed
- Visibility
- Atmospheric Pressure
- Class of Customer
- Temperature
- Day of the Week
- Population

There are various load forecasting methods applied to load forecasting like Regression models, Times series models, Autoregressive Integrated Moving Average (ARIMA) models, Artificial Neural Network (ANN) models, Fuzzy models, Support vector machine models, Particle swarm optimization models, Genetic algorithm models, wavelet transform and ANFIS (Feinberg, E.A., Genethliou, 2005; Hahn, Meyer-Nieberg, & Pickl, 2009; Hippert, Pedreira, & Souza, 2001; Kyriakides & Polycarpou, 2007; Tzafestas & Tzafestas, 2001) given in the Table 2-9. Among the Load forecasting methods ANN method is one of the most largely used method due to its easy execution. During the last ten years, ANN has a large quantity of interest among existing models (Hippert et al., 2001; J. W. Taylor & Buizza, 2002). Several input factors (population, temperature, etc.) and historical load information are trained by ANN for learning algorithm (Amjady, 2001).

Table 2-9. *Forecasting models and their mathematical model (Arunesh Kumar Singh, Ibraheem, Khatoon, Muazzam, & Chaturvedi, 2012; Yazhini & Devipriya, 2016)*

Forecasting Models	**Mathematical Model**
Regression Models	$L(t) = Ln(t) + \sum a_i x_i(t) + e(t)$
Autoregressive Integrated Moving Average (ARIMA) Models	$\emptyset(B)\nabla^d X(t) = \theta(B) * a(t)$
Artificial Neural Network (ANN) Models	$y_i = a(\sum_{k-1}^{n} w_{ik} x_k - \theta_i)$
Fuzzy Models	$V_k = \frac{L_k - L_{k-1}}{T},\ A_k = \frac{V_k - V_{k-1}}{T}$
Particle Swarm Optimization Models	$v_{i,j}(t+1) = v_{i,j}(t) + \alpha\left(y_{i,j}(t) - x_{i,j}(t)\right) + \beta\left(\hat{y}_{i,j}(t) - x_{i,j}(t)\right)$ $Current\ Position(t+1) = Current\ Position\ (t) + v(t+1)$
Genetic Algorithm Models	$A(q) * y(t) = B(q) * u(t) + C(q) * e(t)$

2.4.1. Regression Models

A specified function models data in simple regression model methods. The basic concept of this function is a linear combination of the model parameters and based on one or more independent variables. The model has a rectilinear trend. During the statistical analysis, the data fitting results represent a straight line (Amral, Ö, & King, 2007).

A specified function models data in simple regression model methods. The basic concept of this function is a linear combination of the model parameters and based on one or more independent variables. The model has a rectilinear trend. During the statistical analysis, the data fitting results represent a straight line (Amral, Ö, & King, 2007).

$$y_i = \beta_0 + \beta_1 x_i + \varepsilon_i \tag{1}$$

where y_i is a linear combination of the parameters, x_i is an independent variable, ε_i is a random error, β_0 and β_1 are the parameters. For n independent observing (x_i, y_i), ... , (x_n, y_n) of the predictor, it represents an nxp system of function shown below equation ("Short Term Electricity Load Forecasting With Multiple Linear Regression And Artificial Neural Network," 2012).

$$\begin{pmatrix} y_i \\ \vdots \\ y_n \end{pmatrix} = \begin{pmatrix} f_1(x_1) & \dots & f_p(x_1) \\ \vdots & \ddots & \vdots \\ f_1(x_n) & \cdots & f_p(x_n) \end{pmatrix} \begin{pmatrix} \beta_1 \\ \vdots \\ \beta_p \end{pmatrix} + \begin{pmatrix} \varepsilon_1 \\ \vdots \\ \varepsilon_n \end{pmatrix} \tag{2}$$

Here:

$y = \begin{pmatrix} y_1 \\ \vdots \\ y_n \end{pmatrix}$ model function column vector with n independent observations

$X = \begin{pmatrix} f_1(x_1) & \dots & f_p(x_1) \\ \vdots & \ddots & \vdots \\ f_1(x_n) & \cdots & f_p(x_n) \end{pmatrix}$ design matrix of the system

$$\beta = \begin{pmatrix} \beta_1 \\ \vdots \\ \beta_p \end{pmatrix}$$ p coefficient values

$$\varepsilon = \begin{pmatrix} \varepsilon_1 \\ \vdots \\ \varepsilon_n \end{pmatrix}$$ error

2.4.2. Autoregressive Integrated Moving Average (ARIMA) Models

One of the time series model called is applied to predict ensuring situations with respect to previous parameters. The prediction method analyzes known past measuring data and forecasts future performance pattern using linear filters. ARIMA models consists of integration of AR (Autoregressive Process) and MA (Moving Average) or as an ARMA. The orders "p" and "q" combine with a "d" time difference namely (p, d, q). In this type of model, the following value in the series determines as a linearly assembled of "p" and "q". The general expression can be given as (Deng & Jirutitijaroen, 2010; Gorwar, 2012);

$$X_t = \emptyset_1 X_{t-1} + \emptyset_2 X_{t-2} + \cdots + \emptyset_p X_{t-p} + a_t - \theta_1 a_{t-1} - \cdots - \theta_q a_{t-q} \qquad (3)$$

Generally;

$$\emptyset(B)\nabla^d X(t) = \theta(B) * a(t) \qquad (4)$$

where, p and q are the autoregressive and moving average polynomials respectively, B is the backward shift operator, a(t) denotes random shock component of a time series, θ(B) is a moving average component parameter, X_t is an observation at time t of a time series and $\emptyset(B)$ is the autoregression function (Wang, Zhu, Zhang, & Lu, 2010).

2.4.3. Fuzzy Models

Fuzzy model is a generalized classical set method. The concept of this model is mapping the high degree of non-linear relationship. This method is used when there is a mathematical dependence between the historical data and the prediction parameters. Fuzzy forecasting method is used short term electric power forecasting by a majority with a configuration given in Figure 2-30 (D. Ali, Yohanna, Puwu, & Garkida, 2016; Ganguly & Zayegh, 2017). This methodology requires splitting up weensier slices (Ammar, Sulaiman, Fateh, & Nor, 2017).

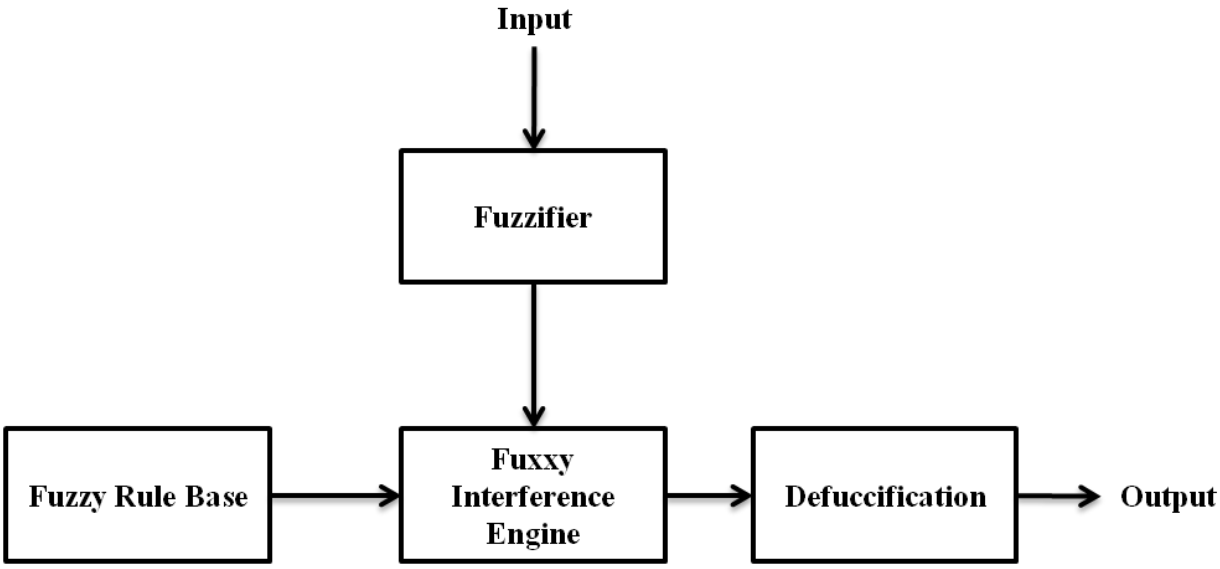

Figure 2-30. Framework of fuzzy method

2.4.4. Particle Swarm Optimization (PSO) Models

One of the swarm intelligence optimization algorithm method is particle swarm optimization model which is depends on repetitive estimation (Cemal, Olaniyi, & Oyedotun, 2018). This method is influenced basically from herd of animals like birds and fish. The idea stems from the fact this model is intellect of birds during fly. The birds which are the closest to food, send a signal for the posterior ones to reach the food. In a similar manner, particles in the related optimization models are supposed as

birds (Niu & Dai, 2017). The solution, direction and velocity are obtained iteratively as if the treatment of particles are specified. In each iteration, the particles update their social behaviour by Equations (Wang et al., 2010):

$$v_{i,j}(t+1) = v_{i,j}(t) + \alpha\left(y_{i,j}(t) - x_{i,j}(t)\right) + \beta\left(\hat{y}_{i,j}(t) - x_{i,j}(t)\right) \quad (5)$$

where,

$v_{i,j}(t)$	previous rate of change
$\alpha\left(y_{i,j}(t) - x_{i,j}(t)\right)$	comparison current position against the personal best
$\beta\left(\hat{y}_{i,j}(t) - x_{i,j}(t)\right)$	the social cognitive term

Here, $\hat{y}$ refers the best position of particles in the swarm, x is the particle's current position, v is existing velocity (Azzam-Ul-Asar, Ul Hassnain, & Khan, 2007).

2.4.5. Genetic Algorithm Models

Genetic Algorithm method originates from natural evolution that based on population probabilistic algorithm given in Figure 2-31 (Gangwar, Arun Kumar, 2014; Heng, 1998; Islam, Baharudin, Raza, & Nallagownden, 2014). This model is very influential at function forecasting and it carries out some approximation during the optimization of function (Gupta & Sarangi, 2012). Since the model is intensely susceptible to the preliminary assets that have effect on the sequent repetitive optimization, a uniform pattern can be achieved by using property of model (Yu & Xu, 2014).

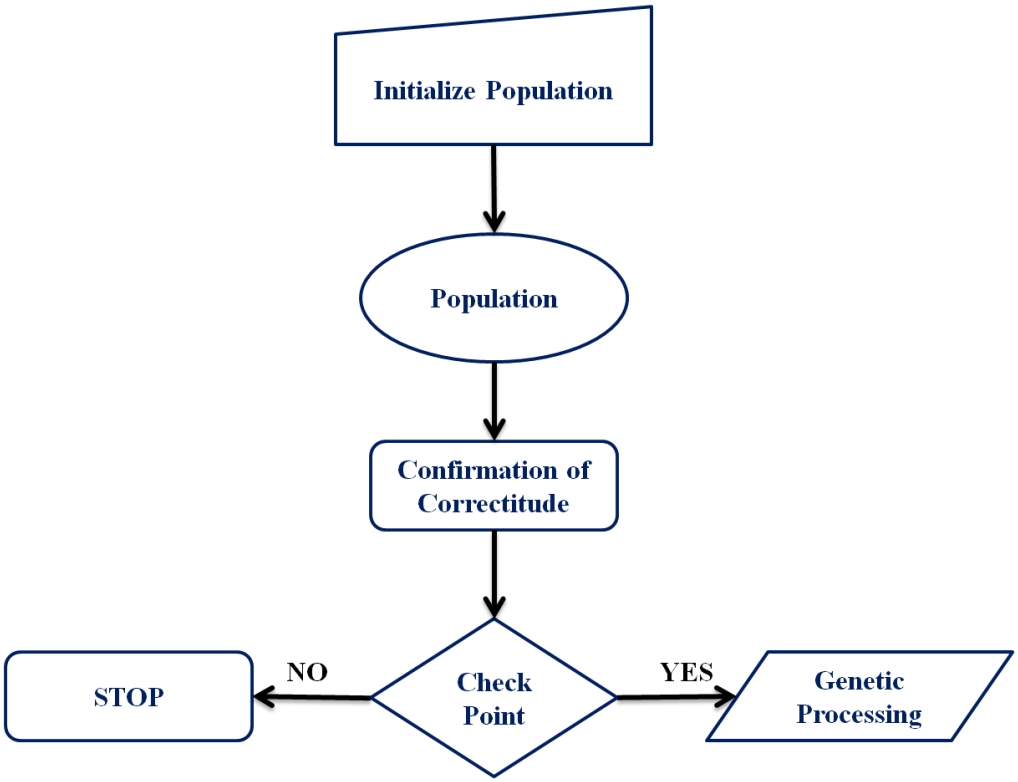

Figure 2-31. Genetic algorithm structure (Gangwar, Arun Kumar, 2014)

2.4.6. Artificial Neural Network (ANN) Techniques

The basic principle of the ANN is a neuron. This technique is taken as a basis by human neural system with neurons given in Figure 2-32. Whole neurons have the same five basic components called as their biological names - cell body, dendrites, nucleus, axon, and synapses. Biological neuron having memory capability between the interconnection of neurons and these connection are named as synaptic weight. The fundamental process is starts with biological neuron's movement which is from the dendrites through the cell body and come out from the axon. It gets inputs from other sources. The signal information is transferred and outputs are reached as a final results by a nonlinear operations.

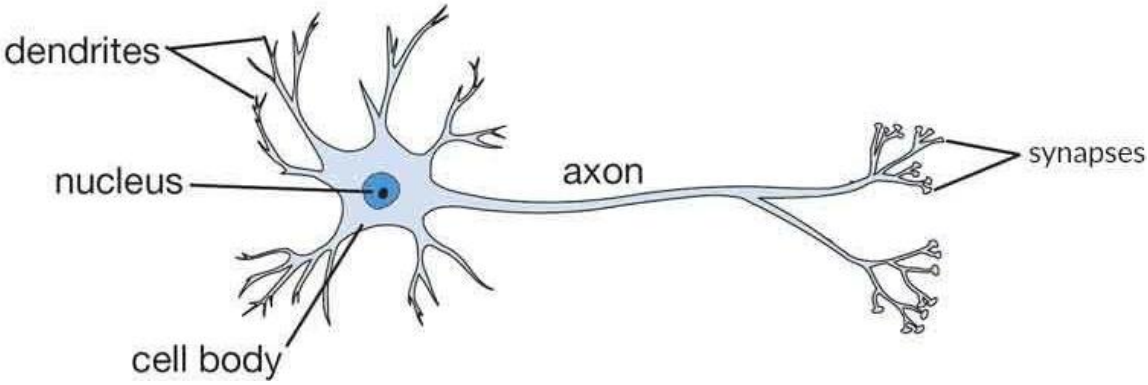

Figure 2-32. A neuron structure (Gill, 2017)

ANN model is one of the strong techniques among the load forecasting methods (Akhbari, 2018; Farug & Hak, 2018). The littlest component of ANN system is neuron which are interconnected to obtain layers of ANN.

The dependence between inputs and outputs are related to weights which connects to reach the outputs with some calculations of activation function of inputs upon neurons. Therefore, inputs and outputs depends on the weights (Christos S, n.d.; Hou, Chen, Lin, & Huang, 2006; Kumar, Chandna, & Pal, 2018).

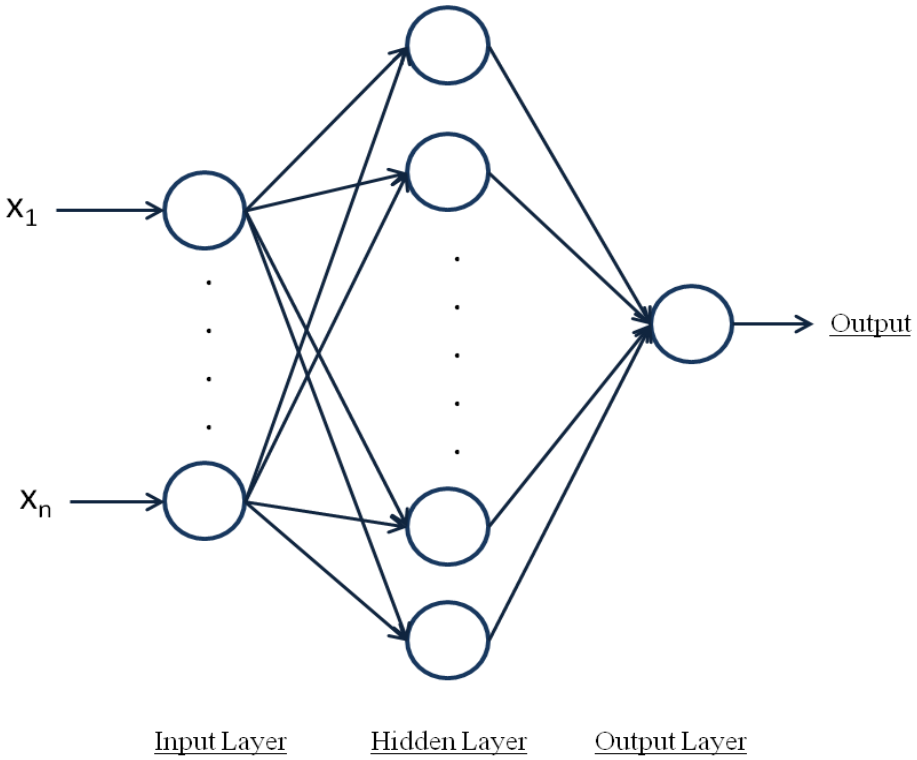

Figure 2-33. ANN structure (Kourou K, Exarchos TP, Exarchos KP, Karamouzis MV, 2014)

The interest of modelling of ANN in power system comprise electricity demand forecasting, defect diagnosis/ defect location, economic dispatch, reliance assessment and transient stability. The usefulness of ANN are as emphasized the following items:

- Promoting a non-linear clipping of input and output variables.
- Speciality like resistant modelling in faulty environments and environments with incomplete data which facilitate it to generalize.
- Making decisions with a measure of reliability.
- Providing high parallel analyzes.

The terminology of the ANN is based upon the neuron whose fundamental mathematical definition given in Eqn (6).

$$A_{i=}g_i(\sum_{i=0}^{n} W_{ji}a_j) \tag{6}$$

A_i - the output of network

g_i - differentiable monotonic function

W_{ij} - the connection weight of jth neuron to i^{th} layer neuron

α_j - the input of the neuron

To calculate the output of network it is necessary to equate the differentiable monotonic function with respect to the input of the neuron and the connection weight.

$$W_{ji} = \eta\delta_i\alpha_j \tag{7}$$

where for output units;

$$\delta_i = (t_i - \alpha_i)g'(\sum_k w_{ik}\alpha_k) \tag{8}$$

and for hidden units;

$$\delta_i = g'(\sum_k w_{ik}\alpha_k)\sum_l \delta_l W_{il} \tag{9}$$

where δ_i is fault in these are only relevant during the training phase, t_i is the target value which are not included in the constant values and g' is the derivative of differentiable monotonic function. It is designated as a separate fault since its function is generally different to that of g_i (B. J. Taylor, 2006).

The methodology is based feature, input, output, target or training value, error and error function (Sarle, 1994).

- Feature: parameter
- Input: uncommitted parameter
- Output: forecasted value
- Target or Training Value: Non independent value
- Error: Remainder value
- Error Function: Forecasting Canon

Neural network can be categorized into two categories as Feed Forward Neural Network and Feedback Neural Network.

Feed Forward Neural Network consists of one hidden layer or multilayer between input and output layer of network. The knowledge transfers from input to output via hidden layer with only forward direction.

Feedback Neural Network has a close loop network structure. The information can move in both direction contrarily Feed Forward Neural Network. The output and the input influence Each other to reach objective function. Dynamic and complex processes, transient and time lagged pattern problems applicable for Feedback Neural Network.

Other important parameter is transfer function which allows to transfer weighted inputs to produce the network output. This function can be classified as;

- Linear function
- Step function
- Log-Sigmoid function
- Tangent hyperbolic function
- Sigmoid function
- Tan-Sigmoid function

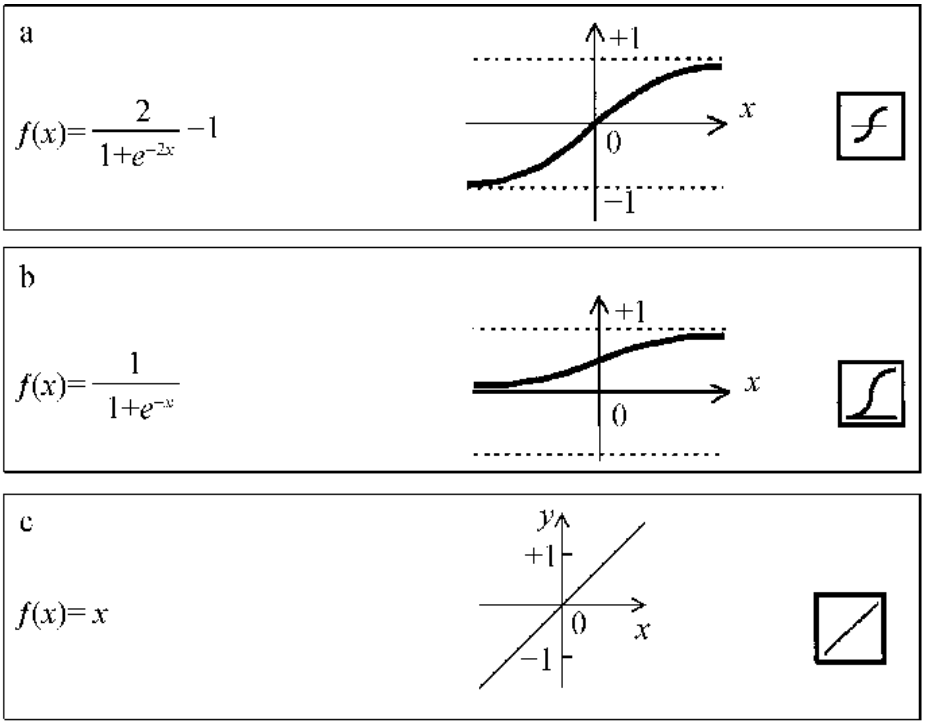

Figure 2-34. Activation functions applied in back propagation

(a) Tan-sigmoid (b) Log-sigmoid (c) Linear function (Miller, 2015)

Table 2-10 gives the transfer functions of ANN and their derivatives (Raza & Khosravi, 2015) . However, basically there are three activation functions applied into back propagation algorithm, namely, Log - Sigmoid, Tan - Sigmoid and Linear Transfer Function. The output range in each function is illustrated in Figure 2-34.

Table 2-10. *Transfer functions of ANN* (Raza & Khosravi, 2015)

Class	**Function**	**Derivative**
Step Function	$f(x) = H(x) = \begin{cases} 1\ if\ , x > 0 \\ 0\ if\ , x < 0 \end{cases}$	$\delta(x) = \begin{cases} 1\ if, x \neq 0 \\ \infty\ if, x = 0 \end{cases}$
Bipolar Step Function	$f(x) = \sin(x) = 2H(x) - 1$	$\delta(x) = \begin{cases} 1 & if \quad x \neq 0 \\ \infty & if\ , x = 0 \end{cases}$
Linear Function	$f(x) = H(x) \begin{cases} 0 & if\ x < -1 \\ 1/2(x+1) & if\ \lvert x \rvert < 1 \\ 1 & if\ \ x > 1 \end{cases}$	$\delta(x) = 1/2[H(x+1) - H(x-1)]$
Bipolar Linear Function	f(x)=H(x)=$\begin{cases} 1\ if\ x < -1 \\ y\ \ if\ \lvert x \rvert < 1 \\ 1\ if\ x > 1 \end{cases}$	$\delta(x) = [H(x+1) - H(x-1)]$
Sigmoid Function	f(x) $= (1/1 + e^{-x})$	$\delta(x) = f(x)(1 + f(x))$
Tangent Hyperbolic Function	f(x)=tanh(x)	$\delta(x) = (1 + \lvert f(x)^2 \rvert)$
Gaussian Radial Basis	f(x) $= \exp(-\lVert x - m \rVert^2/\sigma^2)$	-2(x $-$ m)f(x)$/\sigma^2$

The output of network is related to change in activation function which is two stage operation. Linear combination weighted input and transfer functions can be chosen according to problem.

Synaptic weights link to input layer, hidden layers and output layers in the back propagation neural network. The gradient descent method is used the back propagation learning algorithm in order to update weights and biases. The major limitation of back propagation training algorithm is back propagated error. The back propagation block diagram given in the Figure 2-35.

The target and network output error's difference refers to error which is called as mean square error. The error function can be calculated from the following equation;

$$E(t) = \frac{1}{N}\sum_{i=1}^{N}(O_i^T(t) - O_i(t))^2 \tag{10}$$

where, O^T_i (t) is target value function of ith neuron, O_i(t) is network output value of ith neuron. N is the number of training samples used during learning process of the network.

The minimization process is carried out by modifying the weight vector of the neural networks. Some training algorithms have been presented in order to adapt the weight values in the dynamic recurrent network.

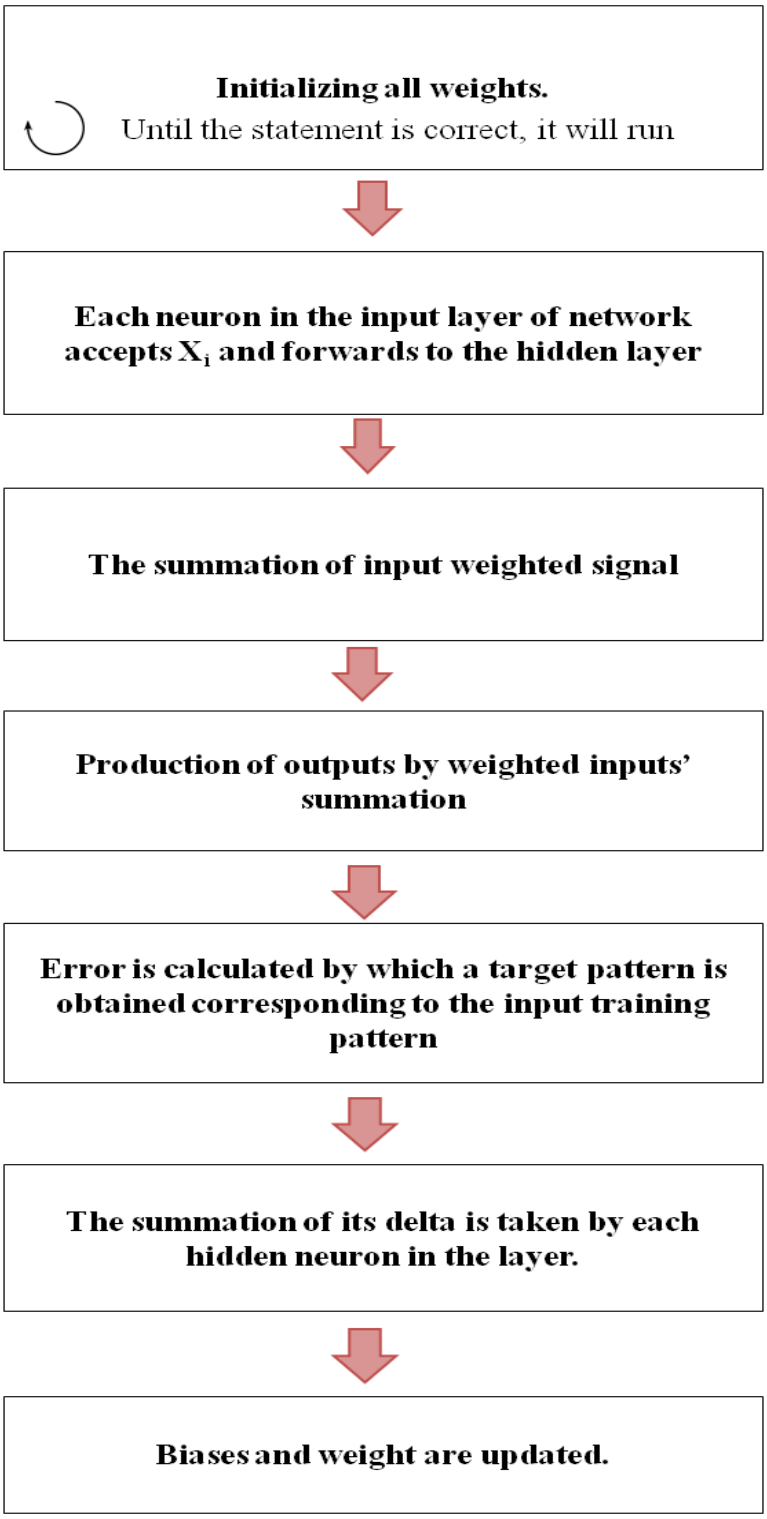

Figure 2-35. The block diagram (A. R. Moghadassi, F. Parvizian, S. M. Hosseini, 2009)

CHAPTER 3

FACTORS AFFECTING THE FORECAST

Our work is presented with details in this section. The factors which affects the load consumption and how the load analysis is done is given in this part of the study. The power demand, given our power grid can be foreseeable for discrete intervals of time.

During the last decades, most researchers have worked on and developed various forecasting methodology to enhance the planning of operation of electric power grids. This work accentuates ANN model is the best one of the option for LTLF. This forecasted method has the best function among the whole methods especially momentous when the functions complex. It can be correctly estimate non linear functions by using non linear elements from the data. These load profiles of Turkey was collected and effects of temperature, population and days of week on load consumption were studied. The results are processed and analyzed with this model.

3.1. Forecasting Factors

The initial stage of the LTLF properly is build the model construction. There lots of factors to affect the load forecasting for a specified region such as temperature, humidity, precipitation, season, time of the day, wind speed, wind chill index, cloud cover, light intensity development level of country and economic parameters. However, load consumption in the previous years, temperature, population growth rate and day of years are the most affecting factors given in literature. In our study the forecasting model predicts Turkey's annually total electric power load by using;

- Measured temperature data
- Weekend-weekday
- Population information

- Historical load consumption

The information on weather conditions, population in 2007 to 2017 daily and weekday and weekend logic in Turkey are defined as training input; the load demand changes in 2007 to 2017 daily in Turkey are defined as training target.

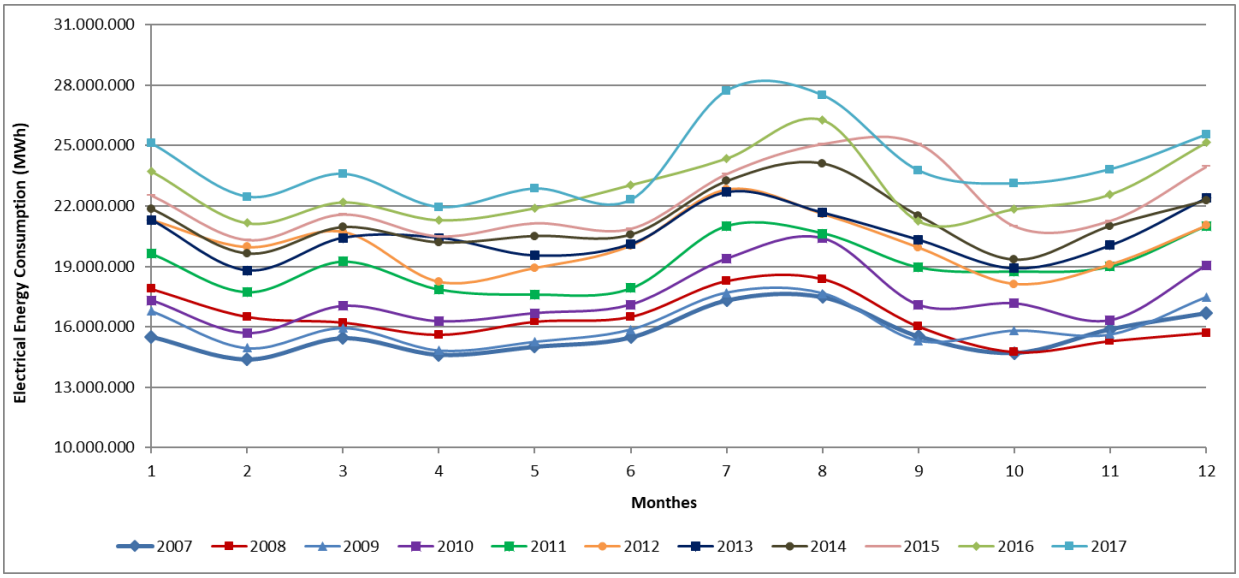

Figure 3-1. Load profile between 2007-2017 ("Gerçek Zamanlı Tüketim," 2018)

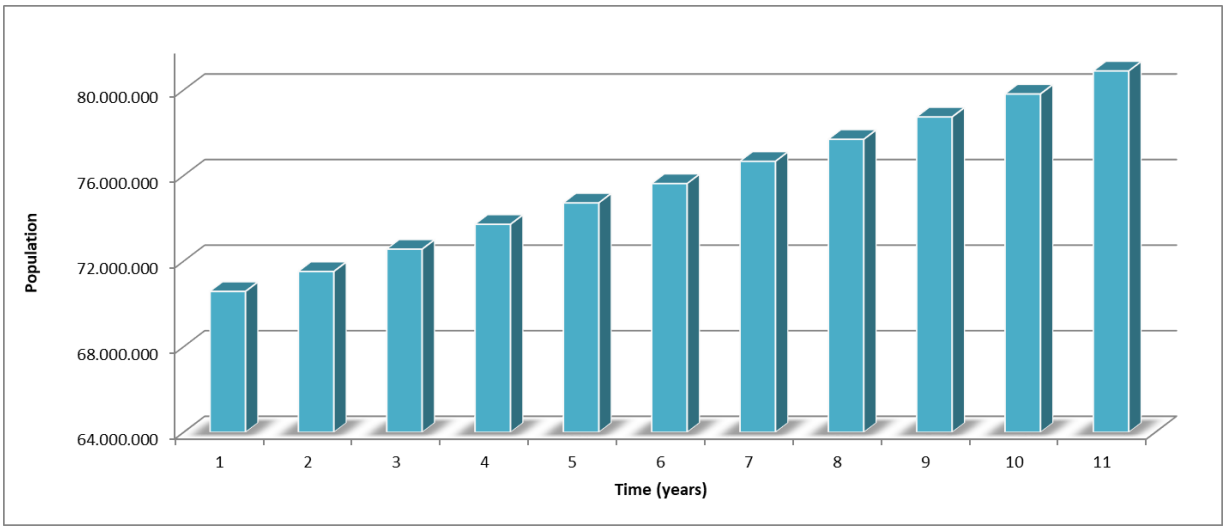

Figure 3-2. Average annually population between 2007-2017 ("Türkiye nüfusu," 2018)

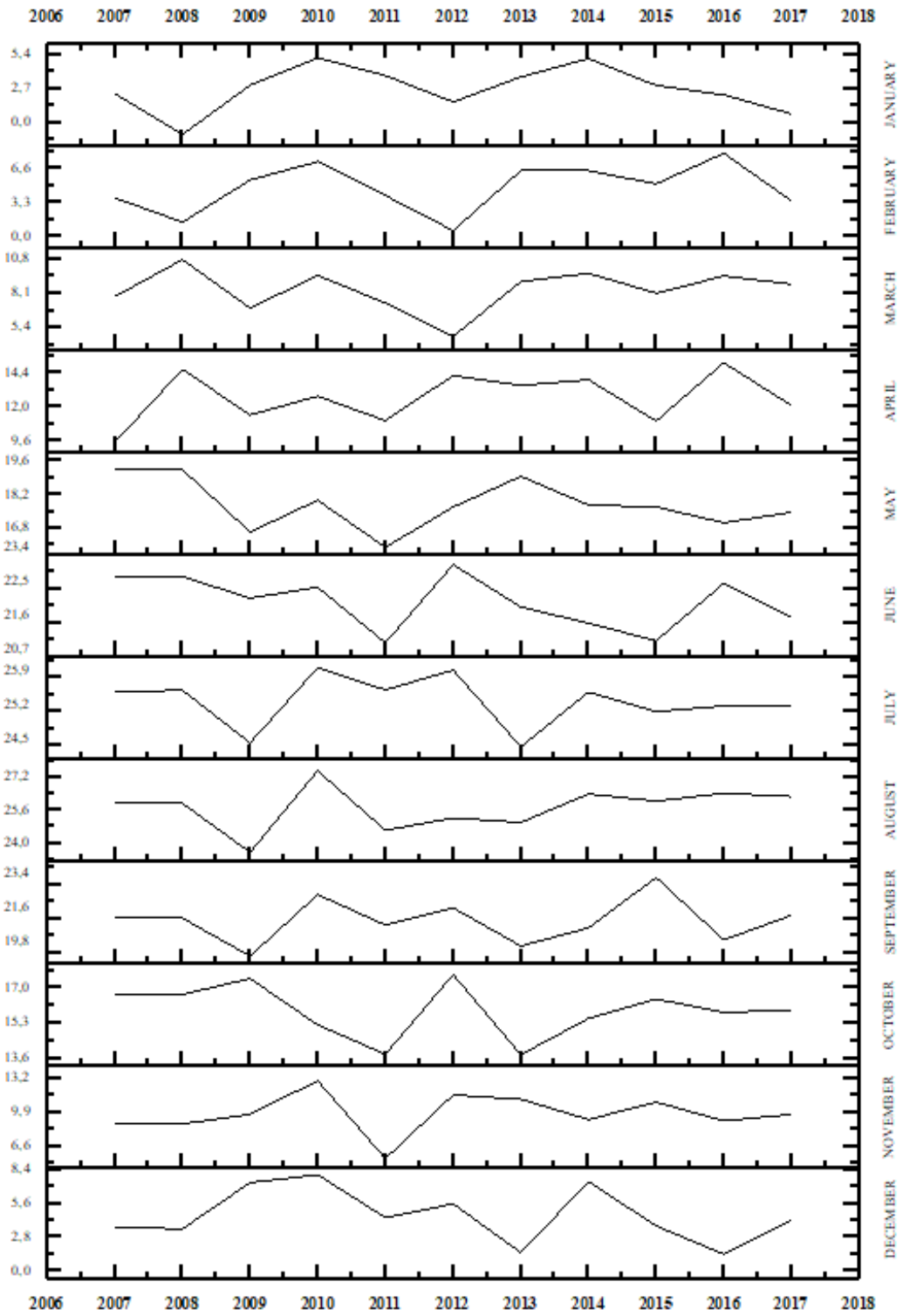

Figure 3-3. Monthly average temperature between 2007-2017

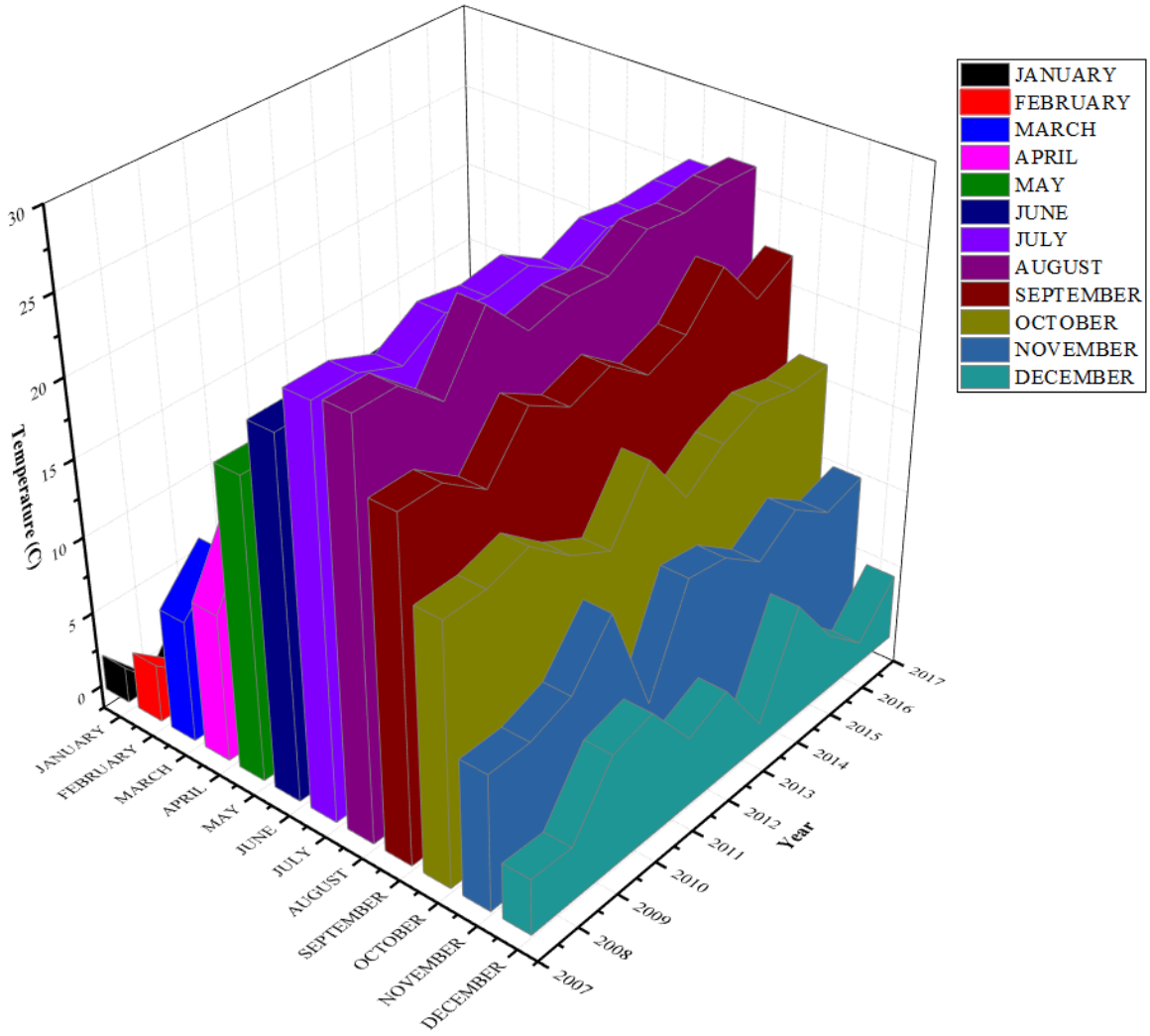

Figure 3-4. Average temperature between 2007-2017

Since Turkey has the 6th largest in Europe and 17th largest economy in the world, Its energy demand has been an increase. In addition to this among the OECD countries in the world, our country has grown into one of the fastest gathering energy markets (Bulvari, 2015). Figure 3-1 shows the monthly electricity consumption from 2007 to 2017. According this data, the consumption of the electricity has increasingly continued year in year out. The consumptive electrical energy has been a visibly peak in summer because of air conditioner usage depending the rising temperature. The

graph of monthly average temperature between 2007-2017 shown in Figure 3-3 is parallel to monthly electricity consumption for the same year. As beginning of 2007 the energy consumption has been 15,5 Million MWh. However, it has reached about 26 Million MWh at the end of 2017.

On the other hand other factor affects the electricity consumption is population. Figure 3-2 indicates average annually population between the years 2007 to 2017. According to various resources Turkey the population has become 82 Million. The population growth has increased day by day. Hereat the electrical energy consumption has also increased.

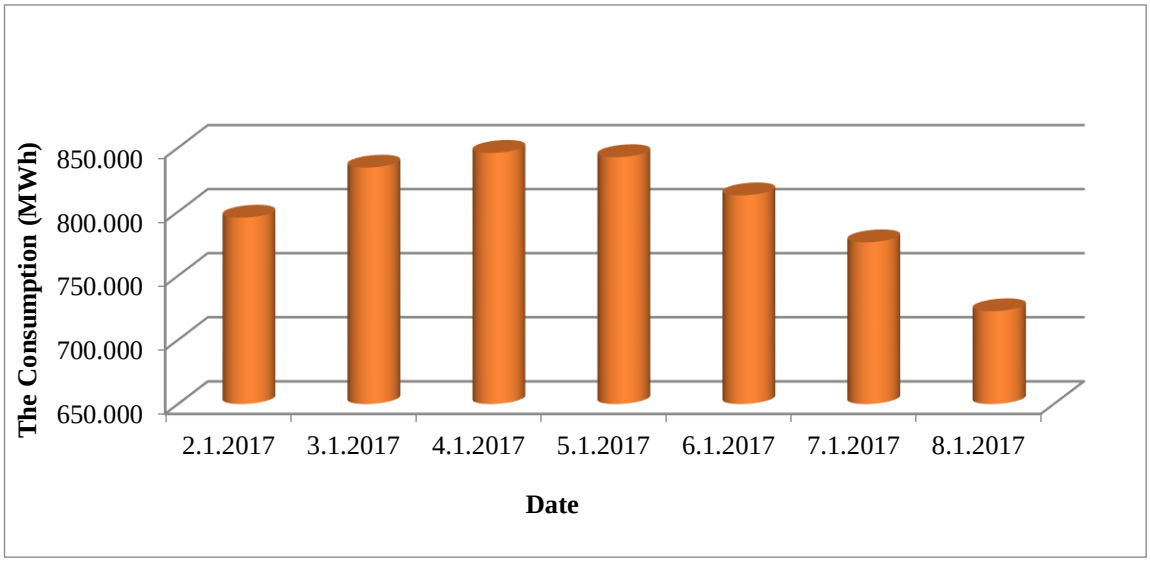

Figure 3-5. Electrical energy consumption between 02.01.2017-08.01.2017

The last but not the least affecting factor in my study is days of week. All days between the years were examined. 1 and 0 is given for the weekdays (Monday, Tuesday, Wednesday, Thursday and Friday) and weekend (Saturday and Sunday) respectively. In consequence of the energy consumption and the related days given in Figure 3-5 and Table 3-1, weekend has the lowest energy consumption in the week.

Table 3-1. *Date and the day*

Date	**Day of the week**
02.01.2017	Monday
03.01.2017	Tuesday
04.01.2017	Wednesday
05.01.2017	Thursday
06.01.2017	Friday
07.01.2017	Saturday
08.01.2017	Sunday

3.2. Load Analysis

The layout of the neural network consists of number of neurons and layers, connectivity of layers, activation functions, and error goal and so on. It is based on the practical situation to set the framework and parameters of the network. The architecture of the ANN could be selected to obtain the optimized consequence. Matlab is one of the best simulation tools to provide apparent solution. A special tool called nntool is used to train the network and forecast the load shown in Figure 3-6. It is adequate to approximate arbitrary function, if the nodes of the hidden layer are sufficient (Nguyen & Widrow, 1990).

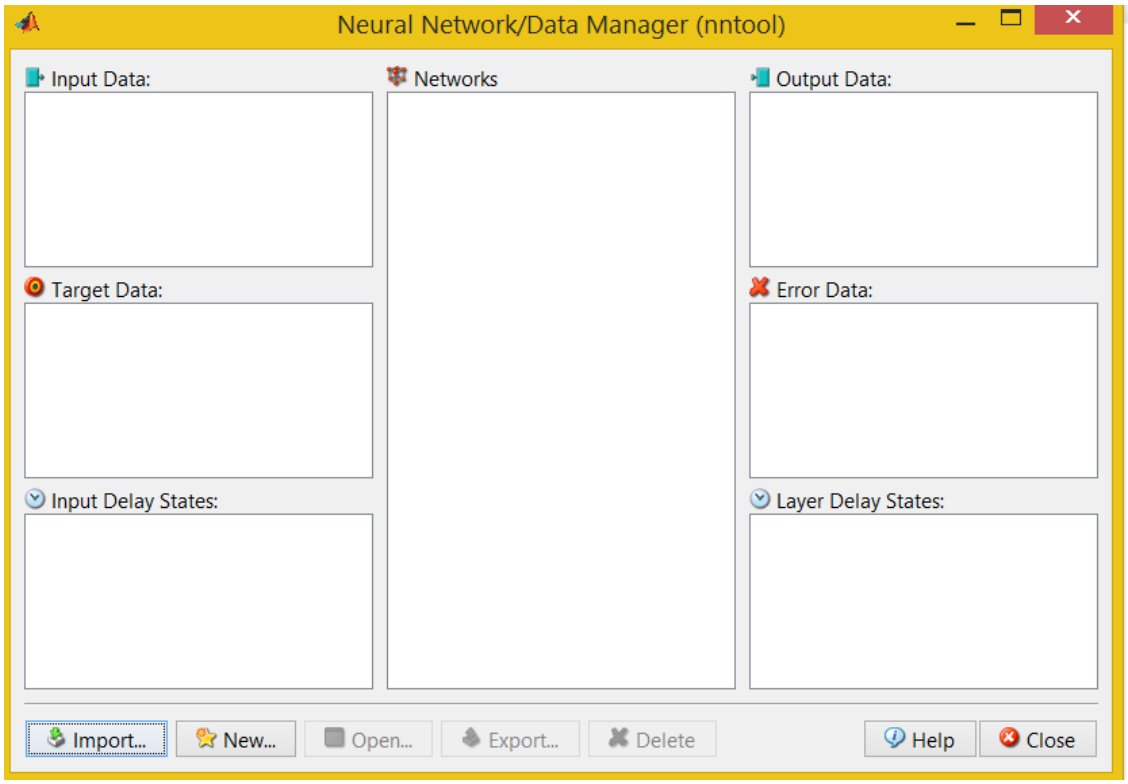

Figure 3-6. The image of nntool

A model network is created with a window indicated in Figure 3-7. Some data have to be entered to perform the network. The ones below are networks type in the tool.

- Cascade-forward backprop
- Competitive
- Elman backprop
- Feed-forward backprop
- Feed-forward distributed time delay
- Generalized regression
- Hopfield
- Layer Recurrent
- Linear layer (design)

- Linear layer (train)
- LVQ
- NARX
- NARX SEries-Parallel
- Perceptron
- Probabilistic
- Radial basis (exact fit)
- Radial basis (fewer neurons)
- Self-organizing map

After input and target data are chosen from the folders, training function which are listed below with its algorithm and adaption learning function (LEARNGD and LEARNGDM) are integrated in the Matlab Neuron network toolbox are selected.

- trainb ==> Batch training with weight & bias learning rules
- trainbfg ==> BFGS quasi-Newton back propagation
- trainbr ==> Bayesian regularization
- trainc ==> Cyclical order incremental training w/learning functions
- traincgb ==> Power-Beale conjugate gradient back propagation
- traincgf ==> Fletcher-Powell conjugate gradient back propagation
- traincgp ==> Polak-Ribiere conjugate gradient back propagation
- traingd ==> Gradient descent back propagation
- traingdm ==> Gradient descent with momentum back propagation
- traingda ==> Gradient descent with adaptive lr back propagation
- traingdx ==> Gradient descent w/momentum & adaptive lr back propagation
- trainlm ==> Levenberg-Marquardt back propagation
- trainoss ==> One step secant back propagation
- trainr ==> Random order incremental training w/learning functions
- trainrp ==> Resilient back propagation (Rprop)
- trains ==> Sequential order incremental training w/learning functions

- trainscg ==> Scaled conjugate gradient back propagation

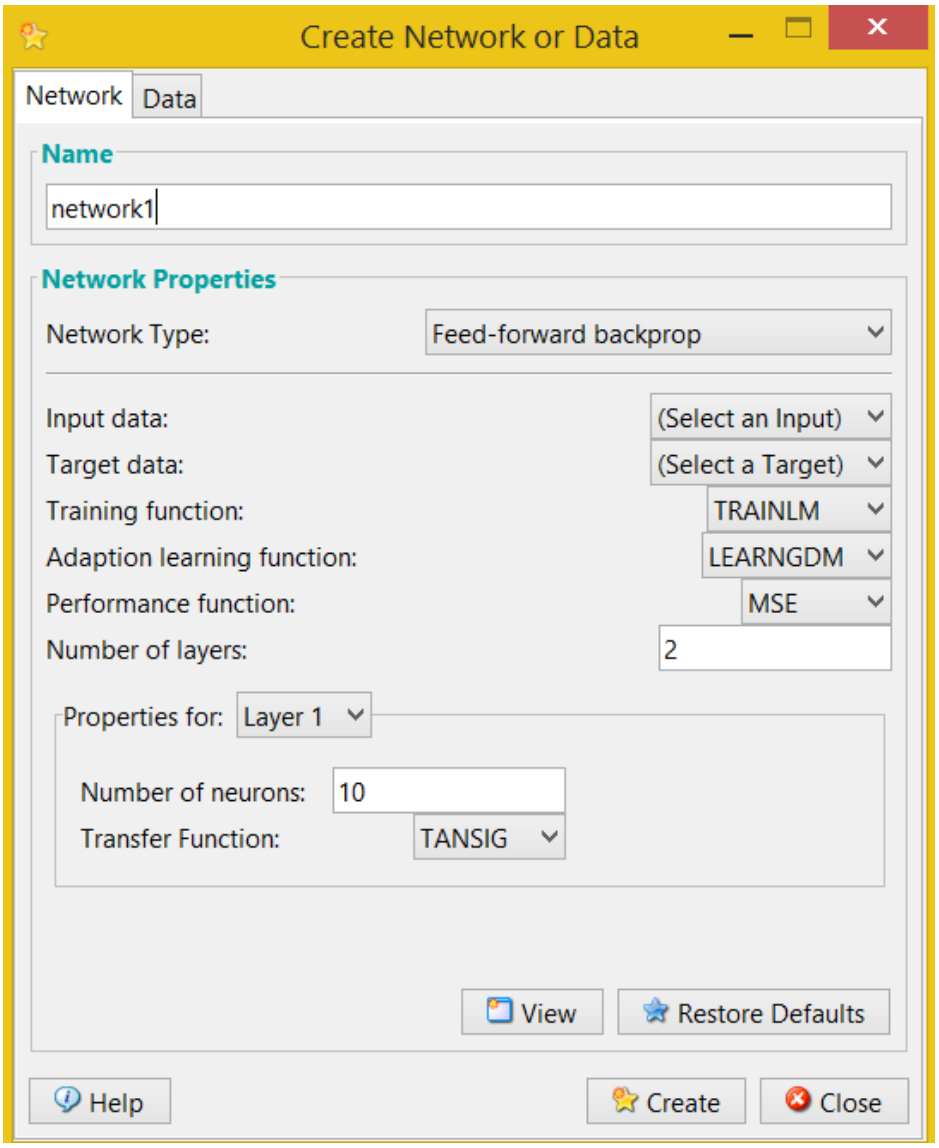

Figure 3-7. Creating network in nntool

In order to reduce a cost function mean squared error (MSE) is used as a performance function. MSE could be calculated as;

$$MSE = \frac{Mean\ (se)}{max(test\ target)} \tag{11}$$

Where:

Mean(se) is the mean value of the difference between the simulation output and the test target

Max(test target) is the maximum value of the test target.

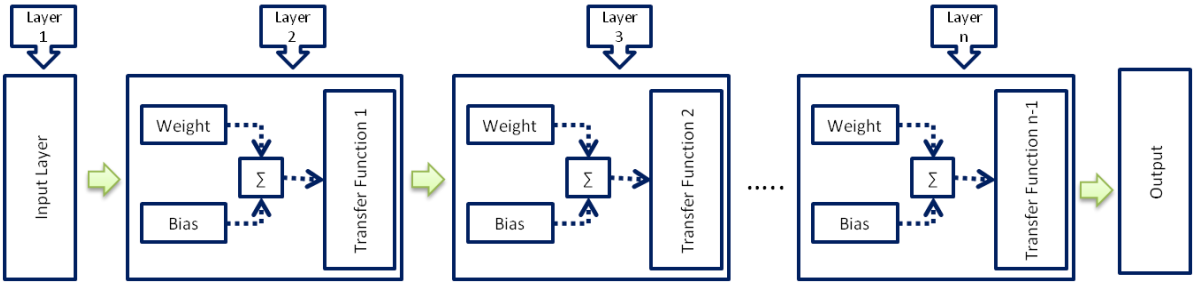

Figure 3-8. Architecture of network

The general structure of the network is given in Figure 3-8. Other important parameter is transfer functions that are LOGSIG, TANSIG and PURELIN to constitute the network.

To achieve a neuronal dynamic modelling LTLF, the neuron structure illustrated in Figure 3-9 was chosen, which represents a typical processing element which forms a weighted sum of its inputs and puts the result via a nonlinear transfer function to the output.

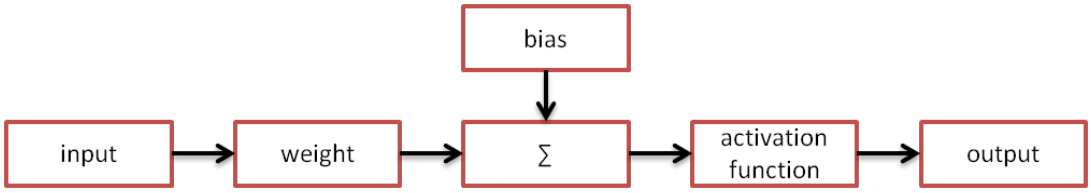

Figure 3-9. Neuron model of back propagation algorithm

CHAPTER 4

LOAD FORECASTING IN MATLAB

4.1. Artificial Neural Network Analysis of Study

In this part of the study, ANN load forecasting methodology is performed. In the present work three factors are used as an inputs data. We investigate the effect of three critical forecasting parameters - weather conditions, weekend-weekday and population - on load changing and demand forecasting. One of the main factors affecting the load predict is the electrical demand data which is determined as a target data. The input and target data are considered for 11 years. These collected eleven years donnee sets are processed and saved in an Excel spreadsheet.

Table 4-1. *Testing of different parameters*

Network Number	Training Function	Number of Layer	Transfer Function	Number of Neurons	Accuracy
Network 1	trainbr	3	all layers tansig	12 - 30	0,925
Network 2	trainbr	3	all layers tansig	20 - 30	0,928
Network 3	trainbr	3	all layers tansig	30 - 30	0,921
Network 4	trainlm	3	all layers tansig	20 - 30	0,910
Network 5	trainlm	3	all layers tansig	8 - 20	0,908
Network 6	trainbr	3	logsig - tansig	20 - 30	0,922
Network 7	trainbr	4	all layers tansig	20 - 30 - 40	0,978
Network 8	trainbr	4	all layers tansig	30 - 40 - 40	0,940
Network 9	trainbr	4	all layers tansig	8 - 12 - 30	0,933
Network 10	trainbr	4	tansig - logsig - tansig - tansig	10 - 20 - 30	0,931
Network 11	trainbr	4	tansig - logsig - logsig - tansig	10 - 20 - 30	0,931
Network 12	trainbr	4	puresig - logsig - logsig - tansig	10 - 20 - 30	0,930
Network 13	trainbr	5	all layers tansig	10 - 20 - 30 - 40	0,924
Network 14	trainbr	5	all layers tansig	8 - 10 - 12 - 20	0,919
Network 15	trainbr	5	all layers tansig	20 - 30 - 40 - 50	0,620
Network 16	trainlm	5	all layers tansig	20 - 30 - 40 - 50	0,710

Different training functions, transfer functions, number of layers and neurons were tried to find the network obtained the best performance during the study. The accuracies of fitting lines were compared for alternate networks. Table 4-1 indicates different testing parameters given better results among the whole trying.

Results off all trials with various training and transfer functions, layer and neuron numbers, Network 7 has been the best accuracy among the whole. The proposal model consists of four layers shown in the Figure 4-1, the input layer, hidden layers and the output layer. The tangent sigmoid function (TANSIG) is used for the activation function of the first three layers, while the linear activation function is used for the output layer. 20 neurons, 30 neurons and 40 neurons are used respectively each hidden layers presented Figure 4-2. There is no theoretical limit on the number of hidden layers but it was decided for the optimum value with the help of iterations in this work. Four layers are required to solve problems of any complexity. Each layer is fully attached to the succeeding layer.

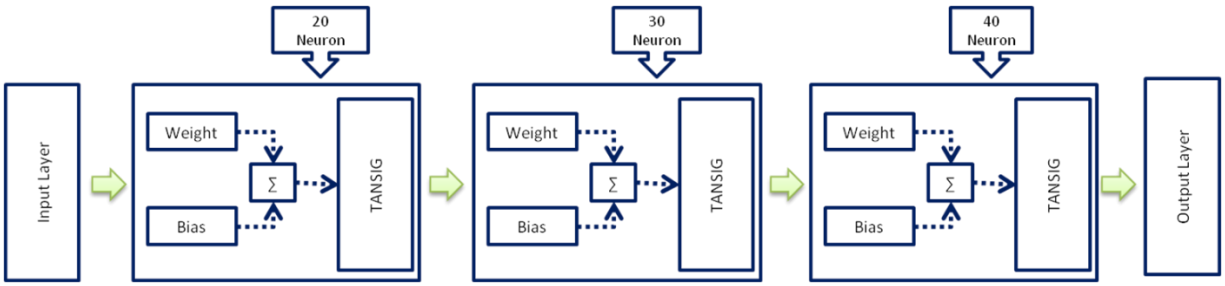

Figure 4-1. Architecture of network of the study

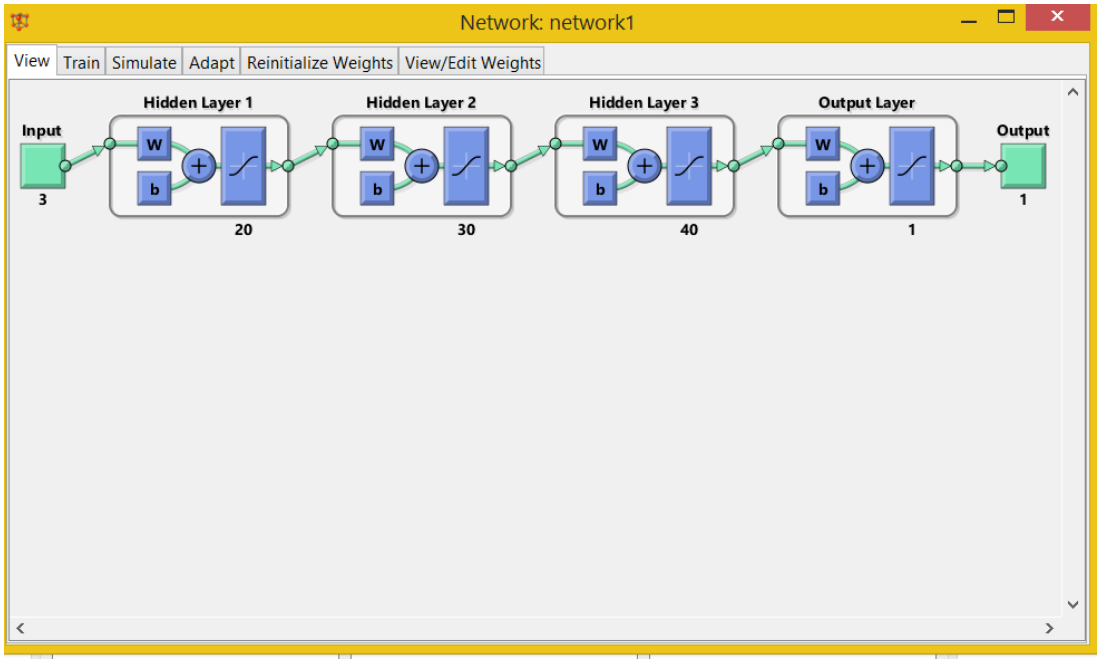

Figure 4-2. The network diagram

On the other hand a typical feed–forward neural network perceptron with Back-propagation (BP) algorithm has been applied in this study. The BP algorithm which has a large classification capacity is widely used in the area of identification and control (Akash K Singh, 2012).

The Levenberg-Marquardt (LM) method which is performed improves, the gradient decent method of back propagation in order to speed up the convergence of the learning process of ANN,

After comparing several architectures, the ANN learned considerably fast to reach the error goal, linear regression was calculated. Figure 4-3 indicates the block diagram of the study. First of all, the collected input data were normalized between the interval 0 - 1. It was requirement for the better convergence of the neural model with the Eqn (12).

$$X_{norm} = \frac{X - X_{min}}{X_{max} - X_{min}} \tag{12}$$

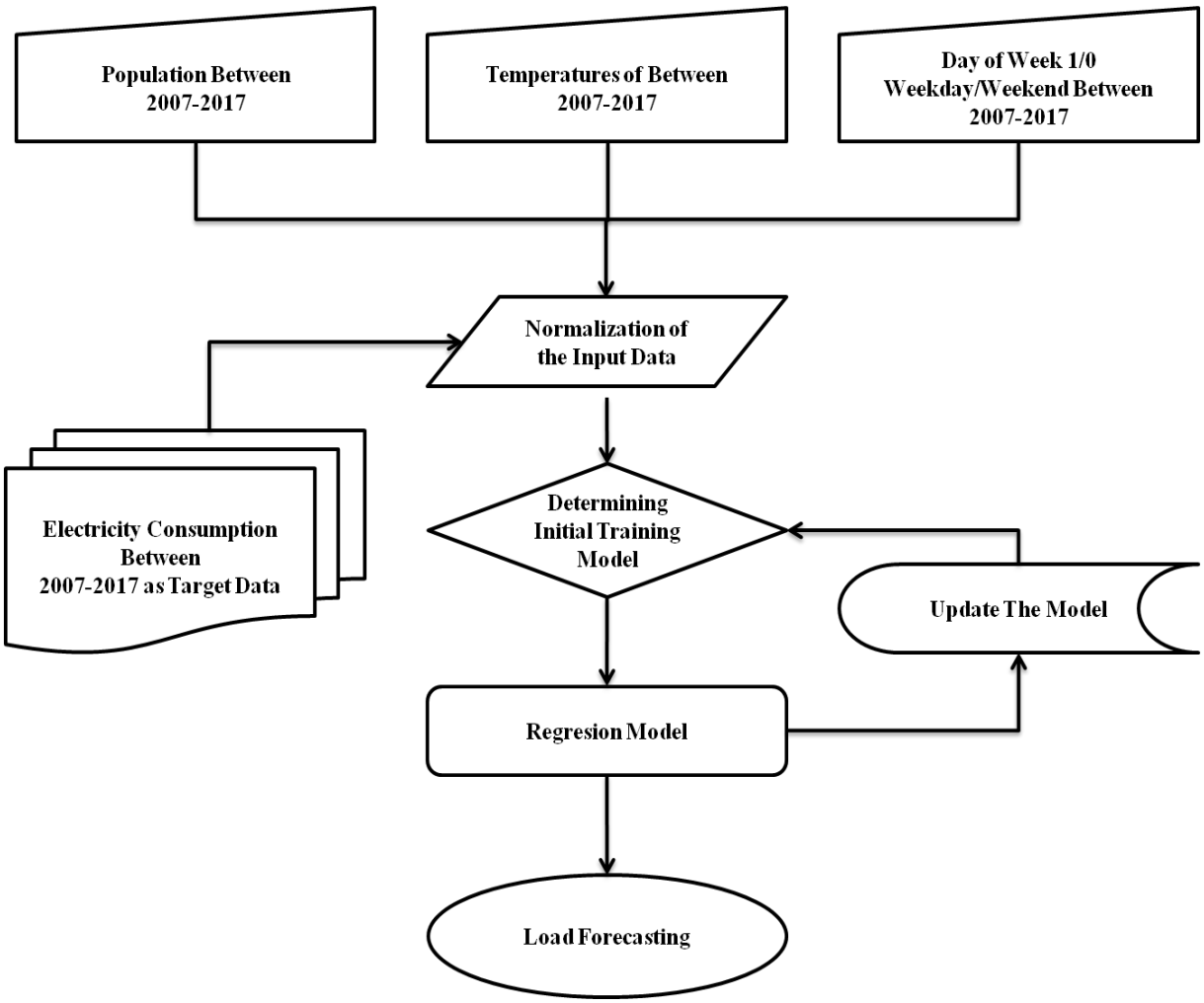

Figure 4-3. Our proposed forecasting scheme

4.2. Performance Evaluation

The MATLAB ANN tool mode has two stages. The first stage contains the training and validation of the related model. This neural network method considers and behaves like a human brain to on the crest of a wave to obtain electrical load forecasting. Afterwards the collected historical data is a requirement to train it.

Table 4-2. *Training parameters*

Maximum number of epochs	8164
Performance goal	$4.3e^{-9}$
Learning rate	0.001
Sum squared parameter	645

After analyzing the aim and probabilities of the neural network technology, the following modelling implications can be noticeable. Table 4-2 summarizes the training parameters which are maximum number of epochs, performance goal, and other training parameters for the neural operating load forecasting.

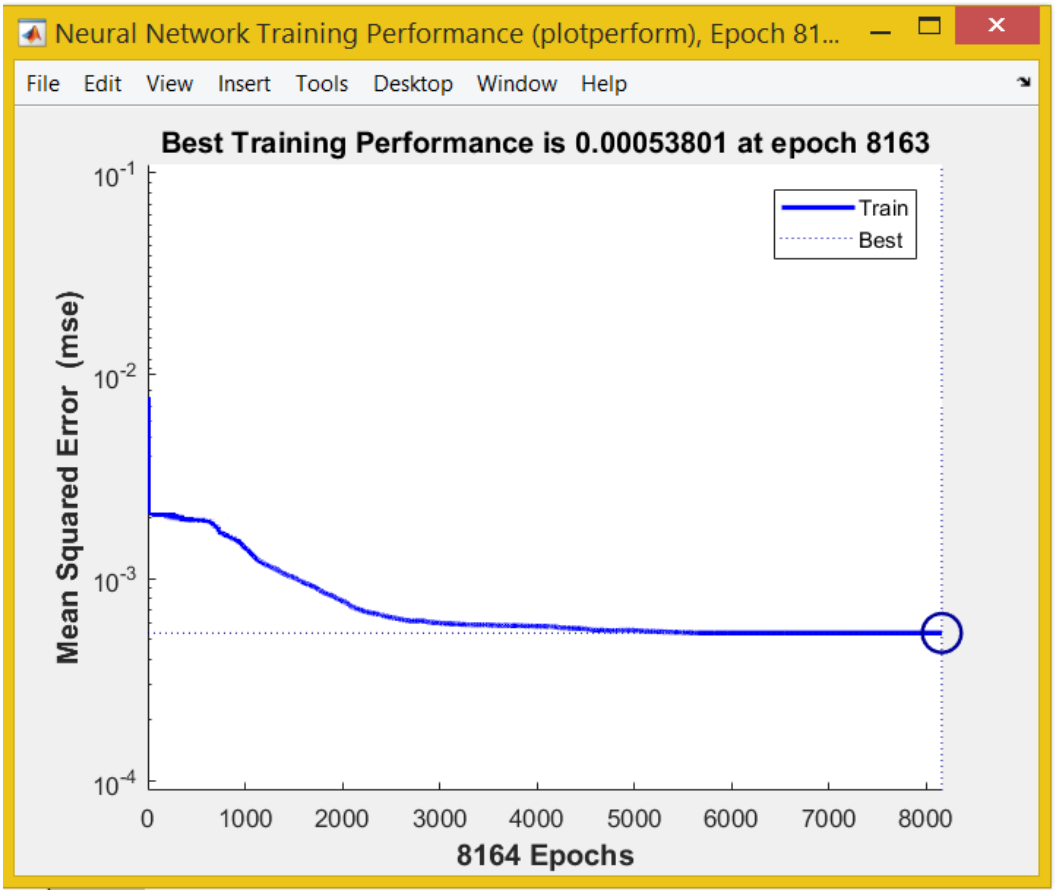

Figure 4-4. Training error of the learning progress

After training, best training performance is obtained using MSE. Figure 4-4 represents a training error of load prediction during the learning process. This diagram gives the best performance is reached at 8164 epochs.

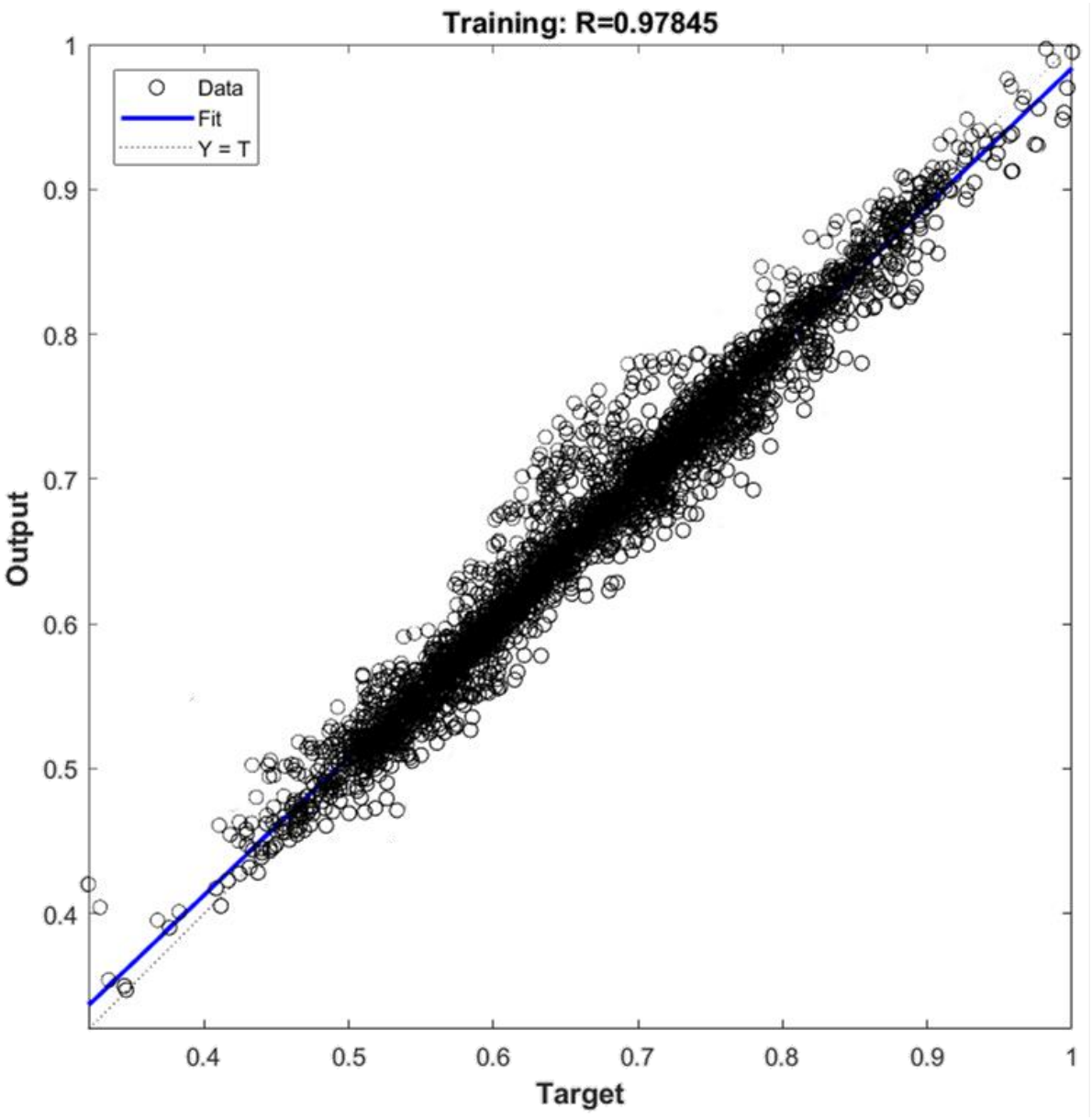

Figure 4-5. Fitting target data to output data

The ANN aims to learn substantially quick to reach the error goal, linear regression among comparing several architectures it was calculated in order to observe interrelation between the output and the target data from the ANN model. Figure 4-5 indicates the success of training, in order to verify that the adequate training. We compare the accuracy performance of our proposed method given in Figure 4-7.

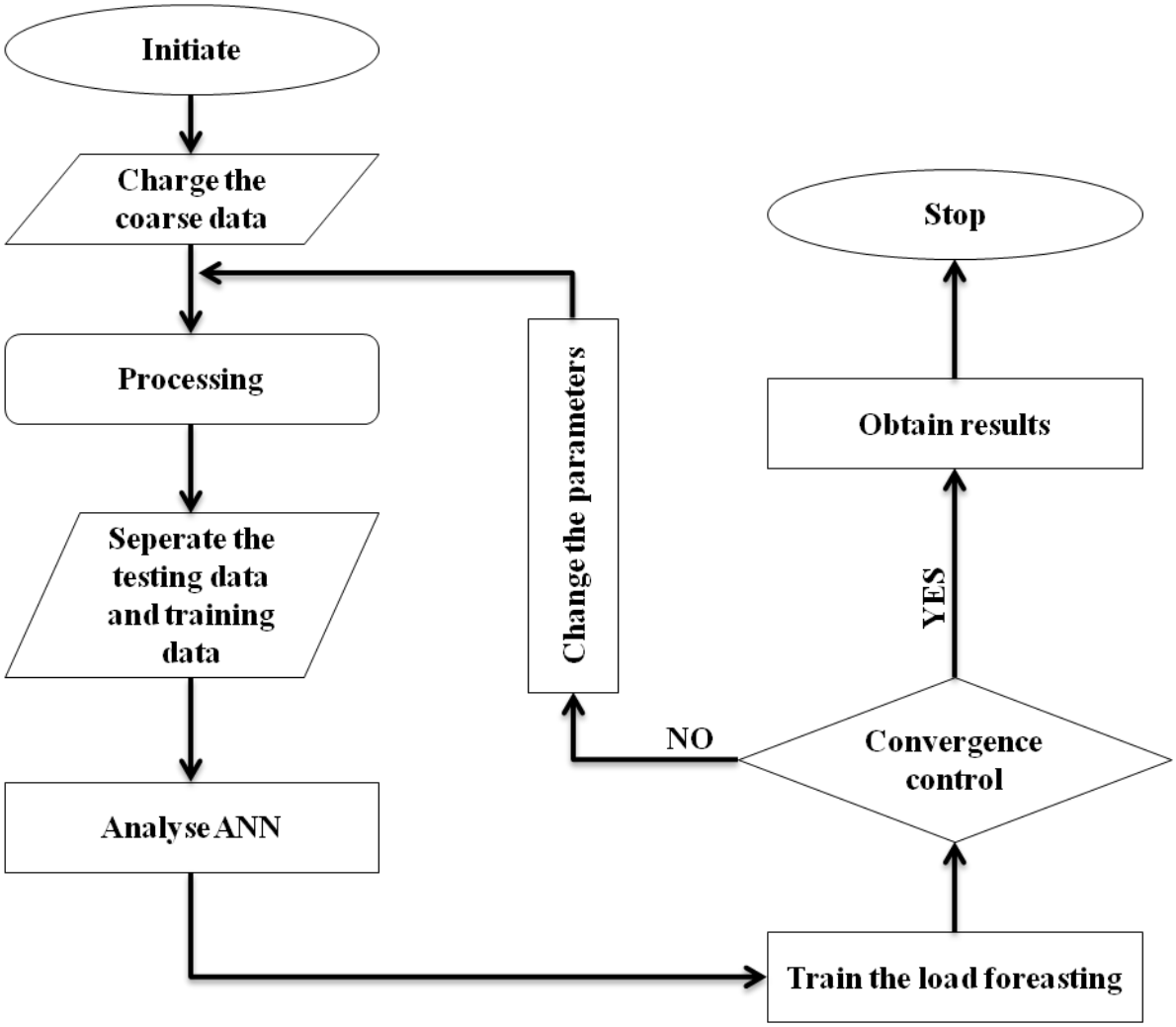

Figure 4-6. The structure of the ANN analyzing model

The pattern of the whole procedure used in the related study is presented with a flowchart in Figure 4-6. This chart clarifies that, the first step of the analysis is training the load model in order to begin the prediction process, Begin with the training parameters which specified during first step thereafter, load forecasting is performed in order to determine the electrical energy load for a specific time zone.

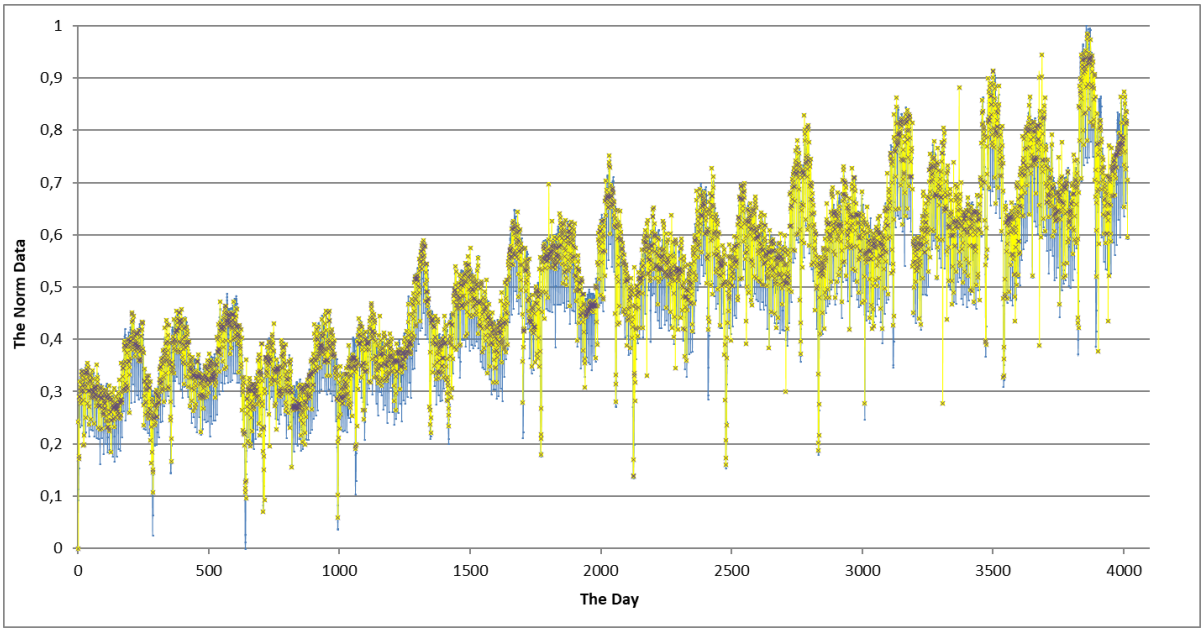

Figure 4-7. The norm data for electricity consumption

4.3. Summative Assessment of Load Forecasting

The given forecasted model is realized for the year 2018. Turkey's annual actual total electric power consumption is 299.633 GWh in 2018 ("Ex-post Consumption," 2019). Also, the consumption is forecasted by the given model for the same year. The amount of annual consumed power in 2018 for Turkey is forecasted as 304.257 GWh. Figure 4-8 gives the realization of the load forecasting model monthly. It indicates that the load trend almost the same with the realization. However, there are about 1,52% differences for overall electric power consumption.

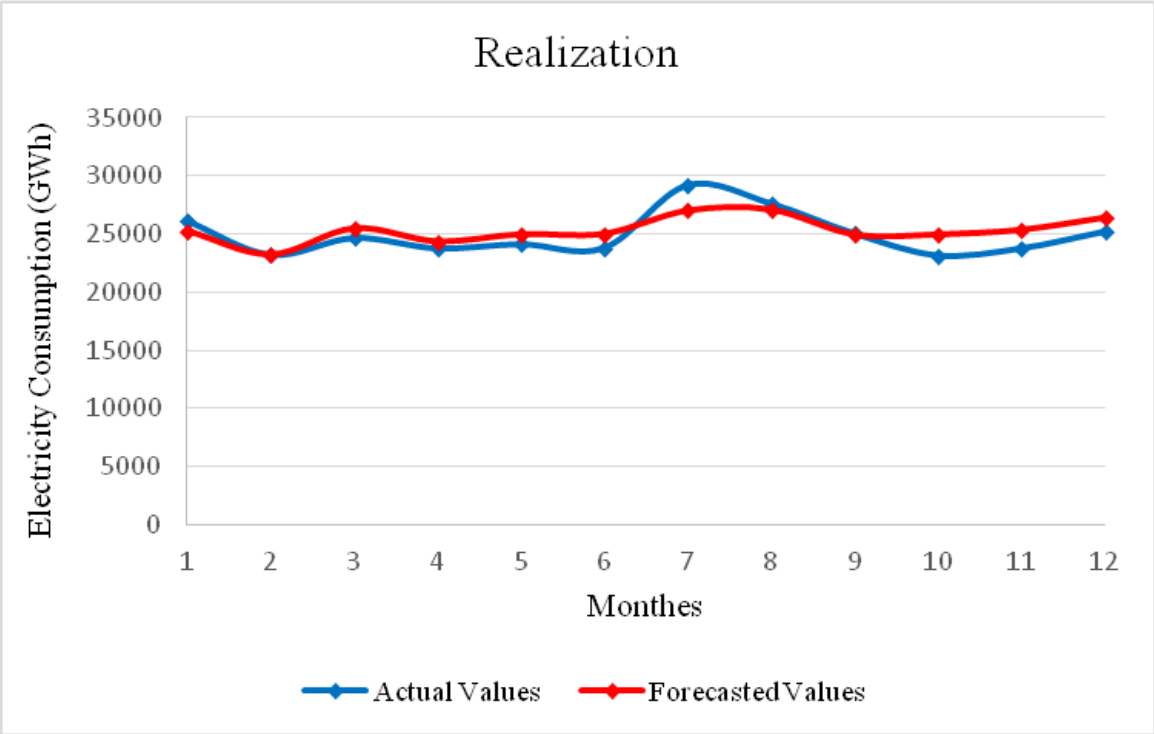

Figure 4-8. The realization of forecasting model for 2018

Monthly electric power realization has been compared just as total electric energy consumption in 2018. Figure 4-9 shows the comparison between the real consumption and the forecasted one monthly. This figure presents us there is a noticeable difference in August, October and November.

Mean absolute error (MAE) method has been used to measure accuracy for variables. The mean values of the errors between the actual value and the predicted value have been calculated by this method given in the Eqn (13).

$$MAE = \frac{1}{n}\sum_{j=1}^{n}\left|y_j - \hat{y}_j\right| \tag{13}$$

Where, n is the number of observations, y_j is the observed value and $\hat{y}_j$ is the predicted value. It is the mean over the test sample of the absolute differences between forecasted and real observation.

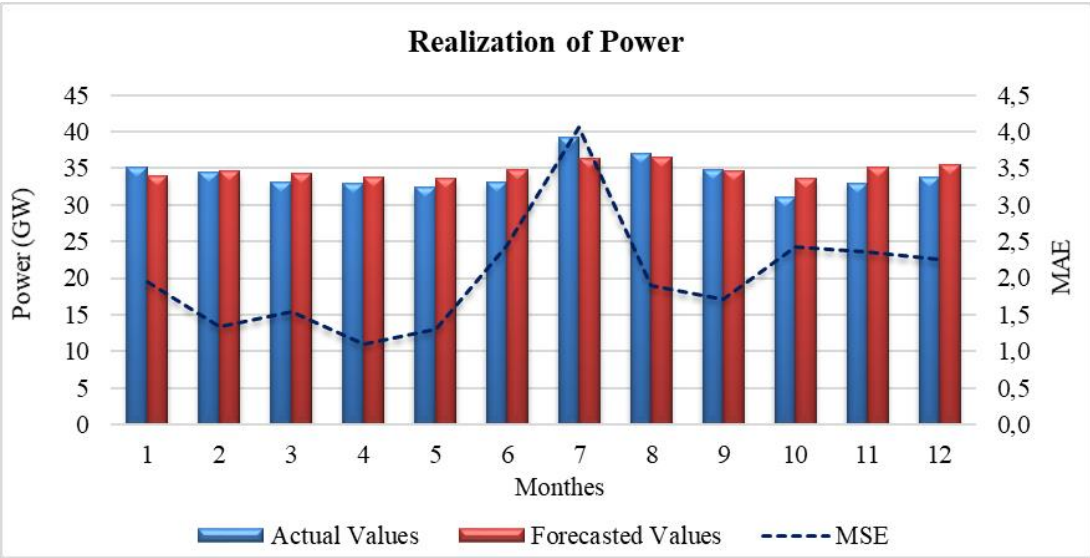

Figure 4-9. Comparison of power for 2018

The results of calculation MSE for each month is given also in Figure 4-9. The reason of this error can be related with the some factors. It is thought that the error may come from the lack of input factors and choice of network parameters. Moreover, variance has been calculated. Variance is the measure of distribution. It shows the change of values in the data set according to the environment. It is calculated with the below equation.

$$s^2 = \frac{\sum(x_i - \mu_i)^2}{n} \tag{14}$$

Here, n is the number of terms in the distribution, μ_i defines the mean and x_i indicates the related term. The variance of the predicted values in 2018 is 1,76. This gives us a measure of the distance of each value from the mean of the forecasted values.

According to EPDK Demand Estimations Report in 2017, Table 4-3 indicates that electricity demand is expected to reach 420 billion kWh in 2027 with an average increase of 4.0% for the low scenario and electricity demand, an average demand increase of 4.7% for the baseline scenario and an electricity demand exceeding 450

billion kWh; it is expected that electricity demand will exceed 500 billion kWh with an average increase of 5.7% for the high scenario.

Table 4-3. *Turkey gross electricity consumption forecast between 2019-2027 ("Türkiye Elektrik Enerjisi Talep Projeksiyonu Raporu," 2017)*

Year	Low	Increment (%)	Base	Increment (%)	High	Increment (%)
2019	315807	4,7	319457	4,9	323788	5,4
2020	328409	4,0	334985	4,9	343242	6,0
2021	341037	3,8	350696	4,7	363443	5,9
2022	354156	3,8	367263	4,7	384848	5,9
2023	367876	3,9	384638	4,7	407889	6,0
2024	381814	3,8	402308	4,6	431664	5,0
2025	396139	3,8	420509	4,5	456471	5,7
2026	410530	3,6	439171	4,4	482263	5,7
2027	429973	3,5	457876	4,3	508611	5,5

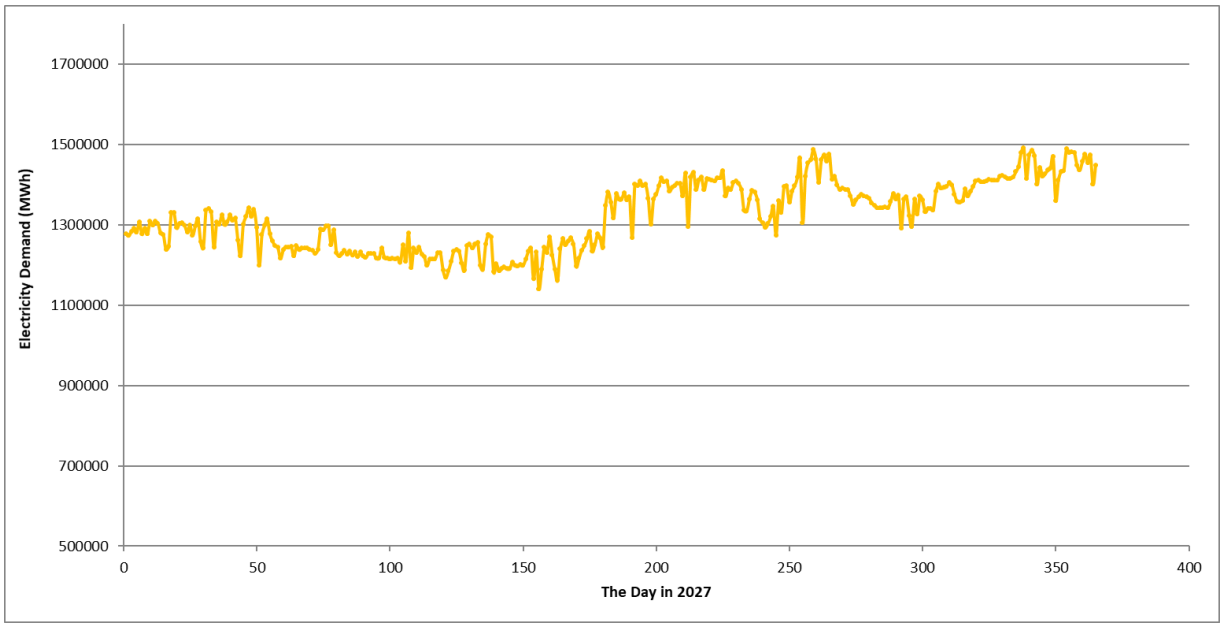

Figure 4-10. Load forecasting in 2027

Gross Electricity Consumption Forecast is given as 457.876 GWh EPDK Demand Estimations Report. As a result of this thesis Turkey electricity demand in 2027 is predicted as 482.380 GWh by intelligent methods. Figure 4-10 indicates the load forecasting results in 2027 for whole year.

ANNs have emerged as a technology with a great expectance to identify and model data patterns that are not handily discernible by smart grid. In order to counterbalance the rising electricity energy requirement, construct more power plants and addition of transmission and distribution potentials have been used for several years.

CHAPTER 5

CONCLUSION OF STUDY

Most of retailers' electricity through the day-ahead electricity market are procured by electricity retailers. This means that the retailers have to forecast their electricity energy consumption for the following day as accurately as feasible so as to attain just the right amount of electricity. When the electricity energy retailers fail to predict their electricity consumption as accurately as possible, they risk to exposing themselves to the imbalance electric power risk.

To achieve more straight consumption predicts the retailers could utilize the most recent historical consumption data accumulated by the AMR/HEMS-systems. The related data helps as the basis of the consumption forecast. Furthermore the consumption forecast could also be weather corrected by using the most current weather data.

Now, having the most accurate electricity energy consumption forecast the retailers can make their procurement bids with less tentativeness and with limited derangement risk exposure. This should lead to lower electricity energy procurement costs which could translate to lower electricity prices for the end-users. These customers, who are no longer only consumers but also producers have allowed to a new theme of ‘prosumers’; that play a key role in distributed generation.

Throughout this study, the significance of the smart grid control and load forecasting was highlighted, as well as the components that must be simulated throughout the power grid. Development and learning functionality has increased in last decades. Last technologies for simulating the smart grid were indicate. An overview for modeling and simulation of load forecasting in smart grid control was introduced.

Smart grid technology is one of the substantial technological advancement for the demand forecasting of electrical energy. In this study, we have offered an accurate long term load forecasting method which can potentially provide greater intelligence (smartness) to the upcoming smart grids. By using this prediction, the data about customers' electrical energy usage praxis can be provided so that prosumers can make more efficient and economic use of electricity together with power market pricing signals from smart grid. Then the prosumers can save a lot of money by making better energy management and informed usage of electrical equipment with smart grid control. Moreover it will lead to consuming less energy and reducing the control system complexity.

This thesis adopts the Artificial Neural Network forecasting technique incorporated with online learning. The neural model approximates with a good accuracy to predict the electric power. Moreover long-term load forecast result strongly depends on factors taken into account.

The data set that was collected was segmented information as four layers of neuron. This number of neuron is generally accepted value as adequate to typify any non-linear function approximation.

Output layer neuron and each hidden layer was connected to the neurons. 20 neurons, 30 neurons and 40 neurons were used respectively for the last 3 hidden layers. There was a link between neurons called as weights.

In this work electricity consumption, population, weather conditions and day of week were taken into. To show the correctness of forecasted model, electric power consumption in 2018 has been realized for Turkey. While the actual consumption has been 299.633 GWh in 2018, predicted one is about 304.257GWh. This show us, this forecasting model can be used for any other specific year. Moreover, Turkey electricity requirement in 2027 is forecasted as 482.380 GWh with a successful predictions of the neural network models. We surveyed thesis to compare with EPDK

Demand Estimations Report. As a result of this thesis Gross Electricity Consumption Forecast is given as 457.876 GWh.

Smart grid technology has an intelligent transmission and distribution network with multidirectional power flow. It provides more reliable and secure information continuously. Therefore, the required data for load forecasting can be achieved by using smart grid control domains. In addition to that, predicting electricity power demand handles to use distributed energy sources efficiently in smart grid technology. Since predicted values are similar to each other, this method shows that load forecasting in smart grid control with ANN provides intelligent, reliable and efficient way to predict in real time. The model results have revealed that this load forecasting is important for the transmission and distribution company to schedule long-term estimation.

REFERENCES

A. R. Moghadassi, F. Parvizian, S. M. Hosseini, A. R. F. (2009). A new approach for estimation of PVT properties of pure gases based on artificial neural network model. *Braz. J. Chem. Eng.*, *26*.

Abdoos, A., Hemmati, M., & Abdoos, A. A. (2015). Short term load forecasting using a hybrid intelligent method. *Knowledge-Based Systems*, *76*, 139–147. https://doi.org/10.1016/j.knosys.2014.12.008

Administration, U. S. E. I. (2017). Country Analysis Brief : Turkey, (July 2016), 1–17.

Akhbari, M. (2018). Project Time and Cost Forecasting Using Monte Carlo Simulation, *29*(2), 231–239. https://doi.org/10.22068/ijiepr.29.2.223

Alfares, H. K., & Nazeeruddin, M. (2002). Electric load forecasting: Literature survey and classification of methods. *International Journal of Systems Science*, *33*(1), 23–34. https://doi.org/10.1080/00207720110067421

Ali, A. B. M. S. (2013). Smart grids: Opportunities, developments, and trends. *Green Energy and Technology*, *132*. https://doi.org/10.1007/978-1-4471-5210-1

Ali, D., Yohanna, M., Puwu, M. I., & Garkida, B. M. (2016). Paci fi c Science Review A : Natural Science and Engineering Long-term load forecast modelling using a fuzzy logic approach. *Pacific Science Review A: Natural Science and Engineering*, *18*(2), 123–127. https://doi.org/10.1016/j.psra.2016.09.011

Almeshaiei, E., & Soltan, H. (2011). A methodology for Electric Power Load Forecasting. *Alexandria Engineering Journal*, *50*(2), 137–144. https://doi.org/10.1016/j.aej.2011.01.015

Amin, S. M. (2011). Smart Grid : Overview , Issues and Opportunities . Advances and Challenges in Sensing , Modeling , Simulation , Optimization and Controlg, (August), 547–567. https://doi.org/10.3166/EJC.17.547

Amjady, N. (2001). Short-term hourly load forecasting using time-series modeling with peak load estimation capability. *IEEE Transactions on Power Systems*, *16*(4), 798–805. https://doi.org/10.1109/59.962429

Ammar, N., Sulaiman, M., Fateh, A., & Nor, M. (2017). Analysis Load Forecasting of Power System Using Fuzzy Logic and Artificial Neural Network,

(September).

Amral, N., Ö, C. S., & King, D. (2007). Short term load forecasting using Multiple Linear Regression Short Term Load Forecasting using Multiple Linear Regression, (July 2015). https://doi.org/10.1109/UPEC.2007.4469121

Ananda Kumar, V., Pandey, K. K., & Punia, D. K. (2014). Cyber security threats in the power sector: Need for a domain specific regulatory framework in India. *Energy Policy*, *65*, 126–133. https://doi.org/10.1016/j.enpol.2013.10.025

Asan, G., & Tasaltin, K. (2017). Market efficiency assessment under dual pricing rule for the Turkish wholesale electricity market. *Energy Policy*, *107*(March), 109–118. https://doi.org/10.1016/j.enpol.2017.04.024

Atilgan, B., & Azapagic, A. (2016). Renewable electricity in Turkey: Life cycle environmental impacts. *Renewable Energy*, *89*, 649–657. https://doi.org/10.1016/j.renene.2015.11.082

Azzam-Ul-Asar, Ul Hassnain, S. R., & Khan, A. (2007). Short term load forecasting using particle swarm optimization based ANN approach. *IEEE International Conference on Neural Networks - Conference Proceedings*, 1476–1481. https://doi.org/10.1109/IJCNN.2007.4371176

Balijepalli, V. S. K. M., Pradhan, V., Khaparde, S. A., & Shereef, R. M. (2011). Review of demand response under smart grid paradigm. *2011 IEEE PES International Conference on Innovative Smart Grid Technologies-India, ISGT India 2011*, 236–243. https://doi.org/10.1109/ISET-India.2011.6145388

Bari, A., Jiang, J., Saad, W., & Jaekel, A. (2014). Challenges in the smart grid applications: An overview. *International Journal of Distributed Sensor Networks*, *2014*. https://doi.org/10.1155/2014/974682

Brown, R. E. (2008). Impact of Smart Grid on Distribution System design. *IEEE Power and Energy Society 2008 General Meeting: Conversion and Delivery of Electrical Energy in the 21st Century, PES*. https://doi.org/10.1109/PES.2008.4596843

Bulvari, T. G. (2015). Renewable Energy Turkey. *Resource-Efficient Technologies*, (5), 1–24.

Byun, J., Hong, I., Kang, B., & Park, S. (2011). A smart energy distribution and management system for renewable energy distribution and context-aware services based on user patterns and load forecasting. *Consumer Electronics, IEEE Transactions On*, *57*(2), 436–444.

https://doi.org/10.1109/TCE.2011.5955177

Camadan, E., & Erten, I. E. (2011). An evaluation of the transitional Turkish electricity balancing and settlement market: Lessons for the future. *Renewable and Sustainable Energy Reviews*, *15*(2), 1325–1334. https://doi.org/10.1016/j.rser.2010.10.010

Camarinha-Matos, L. M. (2016). Collaborative smart grids – A survey on trends. *Renewable and Sustainable Energy Reviews*, *65*, 283–294. https://doi.org/10.1016/j.rser.2016.06.093

Campo, R., & Ruiz, P. (1987). Adaptive Weather-Sensitive Short Term Load Forecast. *IEEE Transactions on Power Systems*, *2*(3), 592–598. https://doi.org/10.1109/TPWRS.1987.4335174

Canaria, G., Cabrera, P., & Lund, H. (2018). Smart renewable energy penetration strategies on islands : The case of, *162*. https://doi.org/10.1016/j.energy.2018.08.020

Cardenas, J. A., Gemoets, L., Ablanedo Rosas, J. H., & Sarfi, R. (2014). A literature survey on Smart Grid distribution: An analytical approach. *Journal of Cleaner Production*, *65*, 202–216. https://doi.org/10.1016/j.jclepro.2013.09.019

Carvalho, T. C. O., Duque, C. A., Silveira, P. M., Mendes, M. A. S., & Ribeiro, P. F. (2012). Review of signal processing techniques for time-varying harmonic decomposition. *IEEE Power and Energy Society General Meeting*, (1), 1–6. https://doi.org/10.1109/PESGM.2012.6345341

Carvalho, T. C. O., Duque, C. a., Silveira, P. M., & Ribeiro, P. F. (2013). Considerations on signal processing for power systems in the context of Smart Grids. *2013 IEEE Power & Energy Society General Meeting*, 1–5. https://doi.org/10.1109/PESMG.2013.6672732

Castelli, M., Vanneschi, L., & De Felice, M. (2015). Forecasting short-term electricity consumption using a semantics-based genetic programming framework: The South Italy case. *Energy Economics*, *47*, 37–41. https://doi.org/10.1016/j.eneco.2014.10.009

Çelıkkol, H., & Köse, F. (2015). SWOT analysis of Turkish Energy Market in the context of Electricity Market in the context of electricity market. *Copernican Journal of Finance & Accounting*, *4*(2), 27. https://doi.org/10.12775/CJFA.2015.014

Cemal, O., Olaniyi, E. O., & Oyedotun, O. K. (2018). ScienceDirect ScienceDirect

Short term load forecasting using particle swarm optimization neural network. *Procedia Computer Science*, *120*, 382–393. https://doi.org/10.1016/j.procs.2017.11.254

Cetin, T., & Oguz, F. (2007). The politics of regulation in the Turkish electricity market. *Energy Policy*, *35*(3), 1761–1770. https://doi.org/10.1016/j.enpol.2006.05.014

Çevik, H. H., & Çunkas, M. (2014). A Comparative Study of Artificial Neural Network and ANFIS for Short Term Load Forecasting. *ECAI 2014 - International Conference – 6th Edition Electronics, Computers and Artificial Intelligence*, 0–5. https://doi.org/10.1109/ECAI.2014.7090206

Çevik, H. H., & Çunkaş, M. (2015). Short-term load forecasting using fuzzy logic and ANFIS. *Neural Computing and Applications*, *26*(6), 1355–1367. https://doi.org/10.1007/s00521-014-1809-4

Christiaanse, W. R. (1971). Short-Term Load Forecasting Using General Exponential Smoothing. *IEEE Transactions on Power Apparatus and Systems*, *PAS-90*(2), 900–911. https://doi.org/10.1109/TPAS.1971.293123

Christos S, D. S. (n.d.). *Neural networks*.

Chunyan An, P. S. (2015). *Power Electronics for Renewable Energy, Smart Grids*.

Colak, I., Bayindir, R., Fulli, G., Tekin, I., Demirtas, K., & Covrig, C. F. (2014). Smart grid opportunities and applications in Turkey. *Renewable and Sustainable Energy Reviews*, *33*(January 2018), 344–352. https://doi.org/10.1016/j.rser.2014.02.009

Deng, J., & Jirutitijaroen, P. (2010). Short-Term Load Forecasting Using Time Series Analysis : A Case Study for Singapore, 231–236.

Dudek, G. (2016). Pattern-based local linear regression models for short-term load forecasting. *Electric Power Systems Research*, *130*, 139–147. https://doi.org/10.1016/j.epsr.2015.09.001

Efficiency, E. (1994). <ADVANCED MONITORING TECHNOLOGIES FOR THE EVALUATION OF DEMANDSIDE MANAGEMENT PROGRAMS.pdf>, *19*(6), 661–678.

Electricity Production in 2016 in Turkey. (2016). Retrieved from https://www.teias.gov.tr/en/node/2119

Elektrik Dağıtım Şirketleri Listesi. (n.d.). Retrieved from https://encazip.com/elektrik-dagitim

Elhawary, M., & Mbamalu, G. (1990). Short-term power system load forecasting using the iteratively reweighted least squares algorithm. *Electric Power Systems Research*, *19*(1), 11–22. https://doi.org/10.1016/0378-7796(90)90003-L

Energy Market Regulatory Authority (EMRA). (2010). Retrieved from www.epdk.org.tr/lisanssorgu/elektriklisanssorgu.htm

Engineering, I., & Is, I. E. (2017). SHORT TERM LOAD FORECASTING IN ELECTRICTY MARKETS IN TURKEY.

EPRI. (2012). EPRI.

Ex-post Consumption. (2019). Retrieved from https://seffaflik.epias.com.tr/transparency/tuketim/gerceklesen-tuketim/gercek-zamanli-tuketim.xhtml

Fadlullah, Z. M., Kato, N., Lu, R., Shen, X., & Nozaki, Y. (2012). Toward secure targeted broadcast in smart grid. *IEEE Communications Magazine*, *50*(5), 150–156. https://doi.org/10.1109/MCOM.2012.6194396

Fahad, M. U., & Arbab, N. (2014). Factor Affecting Short Term Load Forecasting, *2*(4). https://doi.org/10.7763/JOCET.2014.V2.145

Fang, X., Misra, S., Xue, G., & Yang, D. (2012). Smart Grid — The New and Improved Power Grid: A Survey. *IEEE Communications Surveys & Tutorials*, *14*(4), 944–980. https://doi.org/10.1109/SURV.2011.101911.00087

Farhangi, H. (2010). The path of the smart grid. *IEEE Power and Energy Magazine*, *8*(1), 18–28. https://doi.org/10.1109/MPE.2009.934876

Farug, H., & Hak, A. (2018). Availab bility Pr rediction n of the Repaira able Equ uipment using Artificial Neural Networ k , EWM MA , AR , MA and d ARMA A Models s Hiwa Fa Hakimi an d Reza Kamranra, *201*(1).

Feinberg, E.A., Genethliou, D. (2005). Load forecasting, 269–285.

Feng, Y., & Ryan, S. M. (2016). Day-ahead hourly electricity load modeling by functional regression. *Applied Energy*, *170*, 455–465. https://doi.org/10.1016/j.apenergy.2016.02.118

Folly, K. (2013). Challenges in Implementing Smart Grid Technologies in Africa.

13th Annual African Utility Week, 1–25. Retrieved from http://www.esi-africa.com/wp-content/uploads/i/p/Komla-Folly_SmartGrid.pdf

Friedrich, L., & Afshari, A. (2015). Short-term Forecasting of the Abu Dhabi Electricity Load Using Multiple Weather Variables. *Energy Procedia*, *75*, 3014–3026. https://doi.org/10.1016/j.egypro.2015.07.616

Ganguly, P., & Zayegh, A. (2017). SHORT TERM LOAD FORECASTING, (May).

Gangwar, Arun Kumar, F. C. (2014). Electric Load Forecasting Using Genetic Algorithm – A Review. *IJMER*, *4*(6), 15–20.

Gerçek Zamanlı Tüketim. (2018). Retrieved from https://seffaflik.epias.com.tr/transparency/tuketim/gerceklesen-tuketim/gercek-zamanli-tuketim.xhtml

Ghansah, I. (2012). Smart Grid Cyber Security Potential Threats, Vulnerabilities And Risks. *Pier*, (May), 93. Retrieved from http://www.energy.ca.gov/2012publications/CEC-500-2012-047/CEC-500-2012-047.pdf

Gill, N. S. (2017). *Artificial Neural Networks, Neural Networks Applications and Algorithms*.

Gopakumar, P., Chandra, G. S., Reddy, M. J. B., & Mohanta, D. K. (2013). Optimal placement of PMUs for the smart grid implementation in Indian power grid-A case study. *Frontiers in Energy*, *7*(3), 358–372. https://doi.org/10.1007/s11708-013-0257-7

Gorwar, M. (2012). Short Term Load Forecasting Using Time Series Analysis : A Case Study for Karnataka , India, (January).

Gözde, H. (2018). Integration of Renewable Energy Sources into Turkey Electric Energy Network General problems and solution proposals, 289–292.

Grid, M. (2008). The Smart Grid – Benefits and Challenges. *Energy*, 1–18.

Grid, S. (n.d.). What is the Smart Grid ? A Vision for the Smart Grid.

Gungor, V. C., Sahin, D., Kocak, T., Ergut, S., Buccella, C., Cecati, C., & Hancke, G. P. (2012). Smart grid and smart homes: key players and pilot projects. *IEEE Industrial Electronics Magazine*, *6*(4), 18–34.

Gungor, V. C., Sahin, D., Kocak, T., Ergut, S., Buccella, C., Cecati, C., & Hancke, G.

P. (2013). A Survey on smart grid potential applications and communication requirements. *IEEE Transactions on Industrial Informatics*, *9*(1), 28–42. https://doi.org/10.1109/TII.2012.2218253

Güngör, V. C., Sahin, D., Kocak, T., Ergüt, S., Buccella, C., Cecati, C., & Hancke, G. P. (2011). Smart grid technologies: Communication technologies and standards. *IEEE Transactions on Industrial Informatics*, *7*(4), 529–539. https://doi.org/10.1109/TII.2011.2166794

Gupta, A., & Sarangi, P. K. (2012). Electrical load forecasting using genetic algorithm based back- propagation method. *ARPN Journal of Engineering and Applied Sciences*, *7*(8), 1017–1020.

Hagan, M. T., & Behr, S. M. (1987). The Time Series Approach to Short Term Load Forecasting. *IEEE Transactions on Power Systems*, *2*(3), 785–791. https://doi.org/10.1109/TPWRS.1987.4335210

Hahn, H., Meyer-Nieberg, S., & Pickl, S. (2009). Electric load forecasting methods: Tools for decision making. *European Journal of Operational Research*, *199*(3), 902–907. https://doi.org/10.1016/j.ejor.2009.01.062

Hamidi, V., Li, F., & Robinson, F. (2009). Demand response in the UK's domestic sector. *Electric Power Systems Research*, *79*(12), 1722–1726. https://doi.org/10.1016/j.epsr.2009.07.013

Hamidi, V., Smith, K. S., & Wilson, R. C. (2010). Smart Grid technology review within the Transmission and Distribution sector. *Innovative Smart Grid Technologies Conference Europe (ISGT Europe), 2010 IEEE PES*, 1–8. https://doi.org/10.1109/ISGTEUROPE.2010.5638950

Hamilton, B. A., Miller, J., & Renz, B. (2010). Understanding the Benefits of the Smart Grid. *Strategy*, *43*(9B), 6793–6798. https://doi.org/10.1143/jjap.43.6793

Hauttekeete, L., Stragier, J., Haerick, W., & De Marez, L. (2010). Smart, smarter, smartest... The consumer meets the smart electrical grid. *2010 9th Conference of Telecommunication, Media and Internet, CTTE 2010*. https://doi.org/10.1109/CTTE.2010.5557717

Hendrik C. Ferreira, Lutz Lampe, John Newbury, T. G. S. (2011). *Power line communications: Theory and applications for narrowband and broadband communications over power lines*. *John Wiley and Sons*.

Heng, E. (1998). Short term load forecasting using genetic algorithm and neural networks. *Energy Management and ...*, 576–581.

https://doi.org/10.1109/EMPD.1998.702749

Hippert, H. S., Pedreira, C. E., & Souza, R. C. (2001). Neural networks for short-term load forecasting: A review and evaluation. *IEEE Transactions on Power Systems*, *16*(1), 44–55. https://doi.org/10.1109/59.910780

Hou, T. H., Chen, S. H., Lin, T. Y., & Huang, K. M. (2006). An integrated system for setting the optimal parameters in IC chip-package wire bonding processes. *International Journal of Advanced Manufacturing Technology*, *30*(3–4), 247–253. https://doi.org/10.1007/s00170-005-0083-0

Hoverstad, B. A., Tidemann, A., Langseth, H., & Ozturk, P. (2015). Short-Term Load Forecasting With Seasonal Decomposition Using Evolution for Parameter Tuning. *IEEE Transactions on Smart Grid*, *6*(4), 1904–1913. https://doi.org/10.1109/TSG.2015.2395822

Hurtgen, M., & Maun, J. (2008). Advantages of power system state estimation using Phasor Measurement Units. *16th Power System Computation Conference (PSCC)*, 1–7. Retrieved from http://www.pscc-central.org/uploads/tx_ethpublications/pscc2008_520.pdf

Hydro Ottowa. (2018). Retrieved from https://hydroottawa.com/accounts-and-billing/residential/time-of-use

International Energy Agency. (2009). *Energy Policies of IEA Countries - Turkey*. *Review Literature And Arts Of The Americas*. https://doi.org/10.1787/9789264096431-en

International Energy Agency. (2011). Technology Roadmap - Smart Grids. *Current*, 52. https://doi.org/10.1007/SpringerReference_7300

Islam, B., Baharudin, Z., Raza, Q., & Nallagownden, P. (2014). A hybrid neural network and genetic algorithm based model for short term load forecast. *Research Journal of Applied Sciences, Engineering and Technology*, *7*(13), 2667–2673. https://doi.org/10.19026/rjaset.7.583

Joy, J., Jasmin, E. A., Rajan John, V., & Professor, A. (2013). Challenges of Smart Grid. *ISSN International Journal of Advanced Research in Electrical Electronics and Instrumentation Engineering*, *2*(3), 2320–3765. https://doi.org/10.1007/978-3-319-25391-6

Kabalci, Y., & Kabalci, E. (2017). A low cost smart metering system design for smart grid applications. *Proceedings of the 8th International Conference on Electronics, Computers and Artificial Intelligence, ECAI 2016*, 1–6.

https://doi.org/10.1109/ECAI.2016.7861078

Kapasite, E. A., & Miktar, S. P. (2018). Türkiye Elektrik Şebekesi Günlük Özet Raporu.

Karagöl, E. T., & Kavaz, I. (2017). BİLİREnerji. *SetaSiyaset,Ekonomi Ve Toplum Araştirmalari Vakfi*, *197*(197), 1–32. Retrieved from https://setav.org/assets/uploads/2017/04/YenilenebilirEnerji.pdf

Kaushal, R. (2011). Challenges of Implementing Smart Grids, 1–10.

Keyhani, A. (2011). *Design of Smart Power Grid Renewable Energy Systems*.

Khan, R. H., & Khan, J. Y. (2013). A comprehensive review of the application characteristics and traffic requirements of a smart grid communications network. *Computer Networks*, *57*(3), 825–845. https://doi.org/10.1016/j.comnet.2012.11.002

Kincay, O., & Ozturk, R. (2010). Thermal Power Plants in Turkey. *Energy Sources*, *25*(June), 135–151. https://doi.org/10.1080/00908310390142190

King, D. (2007). Short Term Load Forecasting using Multiple Linear Regression, 1192–1198.

Kılıç, N. (2006). Türkiye Elektrik Enerjisi Üretim ve Tüketimine Genel Bakış, 12–19.

Koponen, P. (1996). Adding power quality monitoring to a smart kWh motor. *Power Engineering Journal*, *10*(4), 159. https://doi.org/10.1049/pe:19960406

Kostková, K., Omelina, Ľ., Kyčina, P., & Jamrich, P. (2013). An introduction to load management. *Electric Power Systems Research*, *95*, 184–191. https://doi.org/10.1016/j.epsr.2012.09.006

Kourou K, Exarchos TP, Exarchos KP, Karamouzis MV, F. DI. (2014). Machine learning applications in cancer prognosis and prediction. *Comput Struct Biotechnol J*.

Kumar, D., Chandna, P., & Pal, M. (2018). Efficient optimization of process parameters in 2.5 D end milling using neural network and genetic algorithm. *International Journal of System Assurance Engineering and Management*, *9*(5), 1198–1205. https://doi.org/10.1007/s13198-018-0737-6

Kyriakides, E., & Polycarpou, M. (2007). Short Term Electric Load Forecasting : a Tutorial. *Sudies in Computational Intelligence*, *418*, 391–418.

https://doi.org/10.1007/978-3-540-36122-0_16

Leszczyna, R. (2018). A review of standards with cybersecurity requirements for smart grid. *Computers and Security*, *77*, 262–276. https://doi.org/10.1016/j.cose.2018.03.011

Lewis, R. P., Igic, P., & Zhou, Z. (2009). Assessment of communication methods for smart electricity metering in the U.K. *1st IEEE-PES/IAS Conference on Sustainable Alternative Energy, SAE 2009 - Proceedings*, (October). https://doi.org/10.1109/SAE.2009.5534884

Li, S., Goel, L., & Wang, P. (2016). An ensemble approach for short-term load forecasting by extreme learning machine. *Applied Energy*, *170*, 22–29. https://doi.org/10.1016/j.apenergy.2016.02.114

Liu, K., Subbarayan, S., Shoults, R. R., Manry, M. T., Kwan, C., Lewis, F. I., & Naccarino, J. (1996). Comparison of very short-term load forecasting techniques. *IEEE Transactions on Power Systems*, *11*(2), 877–882. https://doi.org/10.1109/59.496169

Lu, Z. L. Z., Lu, X. L. X., Wang, W. W. W., & Wang, C. (2010). Review and evaluation of security threats on the communication networks in the smart grid. *Military Communications Conference, 2010 - Milcom 2010*, 1830–1835. https://doi.org/10.1109/MILCOM.2010.5679551

Lund, H. (2000). Choice Awareness : The Development of Technological and Institutional Choice in the Public Debate of Danish Energy Planning, *259*(February), 249–259.

Mejia, P. D., & Marine, N. P. (2014). Optimal Location of Distributed Generators, *1*(10), 713–717.

Menghani, V. (2016). *Smart Grid for Sustainable Development Regulatory and Operational Perspective*.

Mengliang, L. I. U. (2011). Short Term Load Forecasting Based on the Particle Swarm Optimization with Simulated Annealing. *Proceedings of the 30th Chinese Control Conference*, *1*(1), 5250–5252.

Midilli, A., Ay, M., Dincer, I., & Rosen, M. A. (2005). On hydrogen and hydrogen energy strategies II : Future projections affecting global stability and unrest. *Renewable and Sustainable Energy Reviews*, *9*(3), 273–287. https://doi.org/10.1016/j.rser.2004.05.002

Miller, S. (2015). *How to Build a Neural Network (Part One)*.

Mo, Y., Kim, T. H. J., Brancik, K., Dickinson, D., Lee, H., Perrig, A., & Sinopoli, B. (2012). Cyber-physical security of a smart grid infrastructure. *Proceedings of the IEEE*, *100*(1), 195–209. https://doi.org/10.1109/JPROC.2011.2161428

Moghram, I., & Rahman, S. (1989). Analysis and Evaluation of Five Short-Term Load Forecasting Techniques. *IEEE Power Engineering Review*, *9*(11), 42–43. https://doi.org/10.1109/MPER.1989.4310383

More, B. R. (2014). Electric Load Forecasting in Smart Grid Environment and Classification of Methods, *5*(7), 49–52.

Murtaza, M., Singh, V., & Prakash, R. (2014). ANFIS: A Vision for Smart Electric Power Grid. *Ripublication.Com*, *4*(2), 145–152. Retrieved from https://www.ripublication.com/irph/ijict_spl/ijictv4n2spl_07.pdf

Nadar, A. (2016). *Introduction to Smart Grid "Conceptual Definition of Smart Grid."*

Nagasaka, K., & Mamun, M. Al. (2004). Long-term Peak Demand Prediction of 9 Japanese Power Utilities Using Radial Basis Function Networks, 1–8. https://doi.org/10.1109/PES.2004.1372805

National Energy Efficieny Action Plan (NEEAP). (2018). Retrieved from www. yegm .gov.tr

Nguyen, D., & Widrow, B. (1990). Improving the learning speed of 2-layer neural networks by choosing initial values of the adaptive weights. *1990 IJCNN International Joint Conference on Neural Networks*, 21–26 vol.3. https://doi.org/10.1109/IJCNN.1990.137819

Niu, D., & Dai, S. (2017). A short-term load forecasting model with a modified particle swarm optimization algorithm and least squares support vector machine based on the denoising method of empirical mode decomposition and grey relational analysis. *Energies*, *10*(3), 1–20. https://doi.org/10.3390/en10030408

Nuqui, R. F., & Phadke, A. G. (2005). Phasor measurement unit placement techniques for complete and incomplete observability. *IEEE Transactions on Power Delivery*, *20*(4), 2381–2388. https://doi.org/10.1109/TPWRD.2005.855457

Nyman, K. J., & Dilli, B. (2015). Turkey's Energy Transition: Milestones and Challenges, 1–177. Retrieved from http://documents.worldbank.org/curated/en/249831468189270397/Turkey-s-energy-transition-milestones-and-challenges

Oğuz, F., Akkemik, K. A., & Göksal, K. (2014). Can law impose competition? A critical discussion and evidence from the Turkish electricity generation market. *Renewable and Sustainable Energy Reviews*, *30*, 381–387. https://doi.org/10.1016/j.rser.2013.10.024

Oleg Gulich. (2010). Technological and Business Challenges of Smart Grids.

Opris, I., & Caracasian, L. (2013). On the implementation of the functionalities of smart metering systems. *2013 - 8th International Symposium on Advanced Topics in Electrical Engineering, ATEE 2013*. https://doi.org/10.1109/ATEE.2013.6563366

Osman Sevaioğlu, K. K. (2013). *DAY AHEAD MARKETS*.

Otuoze, A. O., Mustafa, M. W., & Larik, R. M. (2018). Smart grids security challenges: Classification by sources of threats. *Journal of Electrical Systems and Information Technology*, (2017), 1–16. https://doi.org/10.1016/j.jesit.2018.01.001

Özbuğday, F. C., Öğünlü, B., & Alma, H. (2016). The sustainability of Turkish electricity distributors and last-resort electricity suppliers: What did transition from vertically integrated public monopoly to regulated competition with privatized and unbundled firms bring about? *Utilities Policy*, *39*, 50–67. https://doi.org/10.1016/j.jup.2015.10.003

Pallonetto, F., Oxizidis, S., Milano, F., & Finn, D. (2016). The effect of time-of-use tariffs on the demand response flexibility of an all-electric smart-grid-ready dwelling. *Energy and Buildings*, *128*, 56–67. https://doi.org/10.1016/j.enbuild.2016.06.041

Panapakidis, I. P. (2016). Clustering based day-ahead and hour-ahead bus load forecasting models. *International Journal of Electrical Power and Energy Systems*, *80*, 171–178. https://doi.org/10.1016/j.ijepes.2016.01.035

Papalexopoulos, A. D., & Hesterberg, T. C. (1989). A RECRESSION-BASED APPROACH TO SHORT-TERM SYSTEM LOAD FORECASTING Alex D. Papalexopoulos Systems Engineering Croup Pacific Gas and Electric Company. Retrieved from ieeexplore.ieee.org/iel1/59/3139/00099410.pdf

Paudyal, S., Canizares, C. a., & Bhattacharya, K. (2011). Optimal Operation of Distribution Feeders in Smart Grids. *IEEE Transactions on Industrial Electronics*, *58*(10), 4495–4503. https://doi.org/10.1109/TIE.2011.2112314

Pekka, S., Diaz, L., Orchard, N., Vorisek, T., Rochas, C., Morch, A. Z., … Togeby, M. (2008). Definition of Smart Metering and Applications and Identification of Benefits. *European Smart Metering Alliance*, *25*(May), 1–42.

Phadke, A. G. (1983). PHAEgJ,P("t ", (5).

Phy, A. S. U. (n.d.). Dynamic and Thermodynamic, 11–13.

Platform, E. T. (n.d.). SmartGrids.

Policies, E., & Countries, I. E. A. (2016). Turkey 2016.

Publication, N. S. (2012). NIST Special Publication 1108R2 NIST Framework and Roadmap for Smart Grid Interoperability Standards , NIST Special Publication 1108R2 NIST Framework and Roadmap for Smart Grid Interoperability Standards. *Nist Special Publication*, *0*, 1–90. https://doi.org/10.6028/NIST.SP.1108r3

Ramchurn, S., Vytelingum, P., Rogers, A., & Jennings, N. R. (2012). Putting the "Smarts" into the Smart Grid: A Grand Challenge for Artificial Intelligence. *Communications of the Acm*, *55*(4), 86–97. https://doi.org/10.1145/2133806.2133825

Raza, M. Q., & Khosravi, A. (2015). A review on artificial intelligence based load demand forecasting techniques for smart grid and buildings. *Renewable and Sustainable Energy Reviews*, *50*, 1352–1372. https://doi.org/10.1016/j.rser.2015.04.065

Richardson, D. B. (2013). Electric vehicles and the electric grid: A review of modeling approaches, Impacts, and renewable energy integration. *Renewable and Sustainable Energy Reviews*, *19*, 247–254. https://doi.org/10.1016/j.rser.2012.11.042

Rihan, M., Ahmad, M., & Beg, M. S. (2011). Phasor measurement units in the Indian smart grid. *ISGT2011-India*, 261–267. https://doi.org/10.1109/ISET-India.2011.6145392

Rosen, M., & Dincer, I. (1997). Sectoral energy and exergy modeling of Turkey. *Journal of Energy Resources Technology*, *119*(September 1997), 200. https://doi.org/10.1115/1.2794990

S Chowdhury, Peter Crossley, S. P. C. (n.d.). Protection issues for Microgrids" Microgrids and Active Distribution Networks. In *2009*.

Sarle, W. S. (1994). Neural Networks and Statistical Models. *Proceedings of the Nineteenth Annual SAS Users Group International Conference, April, 1994*, 1–13. https://doi.org/10.1.1.27.699

Sauter, T., & Lobashov, M. (2011). End-to-end communication architecture for smart grids. *IEEE Transactions on Industrial Electronics*, *58*(4), 1218–1228. https://doi.org/10.1109/TIE.2010.2070771

Sevaioğlu, O. (2016a). *Başkent Prosumer Awareness in Distribution Grid Operations*.

Sevaioğlu, O. (2016b). *Daily Load Curve Customer Awareness*.

Sevaioğlu, O. (2016c). *Demand Flexibility Service For Day-ahead*.

Sevaioğlu, O. (2016d). *Power Quality Management for Grid Awareness*.

Sevaioğlu, O. (2016e). *Prosumer & Utility Scale Storage Integration*.

Sevaioğlu, Os. (2003). Ulusal ve Maliyet Esaslı Tarifeler. *Energy and Ecogeneration World Magazine*.

Sevioğlu, O. (2016). *Structure and Principles of the Micro-Grid*.

Short Term Electricity Load Forecasting With Multiple Linear Regression And Artificial Neural Network. (2012), (October), 1–50.

Silva, L. R. M., Duque, C. A., & Ribeiro, P. F. (2015). Recent developments on signal processing for smart grids. *2015 IEEE Power Energy Society General Meeting*, 1–5. https://doi.org/10.1109/PESGM.2015.7286144

Singh, A. K. (2012). Smart Grid Architceture Akash K Singh , PhD. *Ijcer*, *2*, 861–895.

Singh, A. K., Ibraheem, Khatoon, S., Muazzam, M., & Chaturvedi, D. K. (2012). Load forecasting techniques and methodologies: A review. *ICPCES 2012 - 2012 2nd International Conference on Power, Control and Embedded Systems*. https://doi.org/10.1109/ICPCES.2012.6508132

SINGH, G., BISWAS, K. K., & MAHALANABIS, A. K. (1978). Power system load forecasting using smoothing techniques. *International Journal of Systems Science*, *9*(4), 363–368. https://doi.org/10.1080/00207727808941705

Şirin, S. M. (2017). A panel data analysis on the costs of Turkish electricity distribution companies. *Energy Strategy Reviews*, *18*, 250–259. https://doi.org/10.1016/j.esr.2017.10.004

Sms Metering. (2018). Retrieved from http://www.smsmetering.co.uk/category/smart-meters/dlc-meters/

Soliman, S. (2010). *Electrical Load Forecasting*.

Soliman, S. A., Persaud, S., El-Nagar, K., & El-Hawary, M. E. (1997). Application of least absolute value parameter estimation based on linear programming to short-term load forecasting. *International Journal of Electrical Power & Energy Systems*, *19*(3), 209–216. https://doi.org/10.1016/S0142-0615(96)00048-8

Sood, V. K., Fischer, D., Eklund, J. M., & Brown, T. (2009). Developing a communication infrastructure for the smart grid. *2009 IEEE Electrical Power and Energy Conference, EPEC 2009*, (November). https://doi.org/10.1109/EPEC.2009.5420809

Sources of energy. (n.d.), 269–293.

Srinivasan, D., & Lee, M. A. (1995). Survey of Hybrid Fuzzy Neural Approaches to Electric Load Berkeley Initiative in Soft Computing. *IEEE International Conference on Intelligent Systems for the 21st Century.*, 4004–4008. https://doi.org/10.1109/ICSMC.1995.538416

Staff, P. by B.-M. (2013). *Smart Grid key to boosting power efficiency in GCC as peak demand grows*. Retrieved from http://www.bi-me.com/main.php?id=64152&t=1

Steffen, B. (2018). The importance of project finance for renewable energy projects. *Energy Economics*, *69*, 280–294. https://doi.org/10.1016/j.eneco.2017.11.006

Su, W., Eichi, H., Zeng, W., & Chow, M. Y. (2012). A survey on the electrification of transportation in a smart grid environment. *IEEE Transactions on Industrial Informatics*, *8*(1), 1–10. https://doi.org/10.1109/TII.2011.2172454

Summary for Policymakers. (n.d.).

Sun, X., Luh, P. B., Cheung, K. W., Guan, W., Michel, L. D., Venkata, S. S., & Miller, M. T. (2016). An Efficient Approach to Short-Term Load Forecasting at the Distribution Level. *IEEE Transactions on Power Systems*, *31*(4), 2526–2537. https://doi.org/10.1109/TPWRS.2015.2489679

Tayeb, E. B. M., Ali, A. T., & Emam, A. A. (2013). Electrical Energy Management and Load Forecasting in a Smart Grid, *2*(6), 98–101.

Taylor, B. J. (2006). *Methods and Procedures for the Verification and Validation of*

Artificial Neural Networks. *Institute for Scientific Research, Inc.* https://doi.org/10.1007/s13398-014-0173-7.2

Taylor, J. W., & Buizza, R. (2002). Weather Ensemble Predictions. *Power*, *17*(3), 626–632.

The University of Texas at Austin Energy Inittute. (2017). The History and Evolution of the U.S. Electricity Industry. *The Full Cost of Electricity (FCe-)*. Retrieved from http://sites.utexas.edu/energyinstitute/files/2016/09/UTAustin_FCe_History_2016.pdf%0Ahttp://energy.utexas.edu/files/2017/05/UTAustin_FCe_Exe_Summary_2017.pdf

Time of Use. (2018). Retrieved from https://hydroottawa.com/accounts-and-billing/residential/time-of-use

Torres, J. (n.d.). SMART GRID : CHALLENGES AND OPPORTUNITIES Sandia National Laboratories " Exceptional Service in the National Interest ."

Total Primary Energy Supply (TPES). (2017). Retrieved from https://www.iea.org/statistics/?country=TURKEY&year=2016&category=Key indicators&indicator=TPESbySource&mode=chart&categoryBrowse=false&dataTable=RENEWABLES&showDataTable=true

Toyoda, J., Chen, M., & Inoue, Y. (1970). An Application of State Estimation to Short-Term Load Forecasting, Part II: Implementation. *IEEE Transactions on Power Apparatus and Systems*, *PAS-89*(7), 1683–1688. https://doi.org/10.1109/TPAS.1970.292824

Tuballa, M. L., & Abundo, M. L. (2016). A review of the development of Smart Grid technologies. *Renewable and Sustainable Energy Reviews*, *59*, 710–725. https://doi.org/10.1016/j.rser.2016.01.011

Turkey Water Report. (2009), 52. Retrieved from www2.dsi.gov.tr/english/pdf_files/TurkeyWaterReport.pdf

Turkish Electricity Transmission Corporation. (2017). Retrieved from http://www.cigre-seerc.org/Images/files/documents/2017/2_4_8_2 TURKEY_TEIAS Presentation for SEERC.pdf

Türkiye Elektrik Enerjisi Talep Projeksiyonu Raporu. (2017). Retrieved from http://www.enerji.gov.tr/File/?path=ROOT%2F1%2FDocuments%2FEİGM Ana Rapor%2FTürkiye Elektrik Enerjisi Talep Projeksiyonu Raporu.pdf

Türkiye Elektrik Üretim-İletim İstatistikleri. (2017). Retrieved from https://www.teias.gov.tr/tr/turkiye-elektrik-uretim-iletim-istatistikleri

Türkiye nüfusu. (2018). Retrieved from http://www.tuik.gov.tr/PreTablo.do?alt_id=1047

Türkiye ulusal yenilenebilir enerji eylem plani. (2014).

Tzafestas, S., & Tzafestas, E. (2001). Computational intelligence techniques for short-term electric load forecasting. *Journal of Intelligent and Robotic Systems*, *31*, 7–68. https://doi.org/10.1023/A:1012402930055

U.S. Department of Energy. (2010). the SMART GRID. *Communication*, *99*, 48. https://doi.org/10.1016/B978-1-59749-570-7.00011-X

Uddin, Z., Ahmad, A., Qamar, A., & Altaf, M. (2018). Recent advances of the signal processing techniques in future smart grids. *Human-Centric Computing and Information Sciences*, *8*(1). https://doi.org/10.1186/s13673-018-0126-9

Ulusoy, A., & Oguz, F. (2007). The privatization of electricity distribution in Turkey: A legal and economic analysis. *Energy Policy*, *35*(10), 5021–5034. https://doi.org/10.1016/j.enpol.2007.04.035

US Department of Energy. (2016). Advanced Metering Infrastructure and Customer Systems. https://doi.org/10.1109/CCA.2014.6981554

Uzlu, E., Akpinar, A., & Kömürcü, M. I. (2011). Restructuring of Turkey's electricity market and the share of hydropower energy: The case of the Eastern Black Sea Basin. *Renewable Energy*, *36*(2), 676–688. https://doi.org/10.1016/j.renene.2010.08.012

Vijayapriya, T., & Kothari, D. P. (2011). Smart Grid: An Overview. *Smart Grid and Renewable Energy*, *02*(04), 305–311. https://doi.org/10.4236/sgre.2011.24035

Vineetha, C. P., & Babu, C. A. (2014). Smart grid challenges, issues and solutions. *Proceedings of 2014 International Conference on Intelligent Green Building and Smart Grid, IGBSG 2014*. https://doi.org/10.1109/IGBSG.2014.6835208

Wang, J., Zhu, S., Zhang, W., & Lu, H. (2010). Combined modeling for electric load forecasting with adaptive particle swarm optimization. *Energy*, *35*(4), 1671–1678. https://doi.org/10.1016/j.energy.2009.12.015

Yan, Y., Qian, Y., Sharif, H., & Tipper, D. (2013). A survey on smart grid communication infrastructures: Motivations, requirements and challenges. *IEEE*

Communications Surveys and Tutorials, *15*(1), 5–20. https://doi.org/10.1109/SURV.2012.021312.00034

Yang, Z., Chen, Y. X., Li, Y. F., Zio, E., & Kang, R. (2014). Smart electricity meter reliability prediction based on accelerated degradation testing and modeling. *International Journal of Electrical Power and Energy Systems*, *56*, 209–219. https://doi.org/10.1016/j.ijepes.2013.11.023

Yazhini, S. P., & Devipriya, R. (2016). Support Vector Machine with Improved Particle Swarm Optimization Model for Intrusion Detection, *7*(2), 37–42.

Yu, F., & Xu, X. (2014). A short-term load forecasting model of natural gas based on optimized genetic algorithm and improved BP neural network. *Applied Energy*, *134*, 102–113. https://doi.org/10.1016/j.apenergy.2014.07.104

Yumak, K., Tosun, G., Varlik, B., & Bağriyanik, M. (2016). Load curve classification for the evaluation of demand side management programs. *IOP Conference Series: Materials Science and Engineering*, *161*(1). https://doi.org/10.1088/1757-899X/161/1/012111

Zaballos, A., Vallejo, A., & Selga, J. (2011). Heterogeneous communication architecture for the smart grid. *IEEE Network*, *25*(5), 30–37. https://doi.org/10.1109/MNET.2011.6033033

Zafar, R., Mahmood, A., Razzaq, S., Ali, W., Naeem, U., & Shehzad, K. (2018). Prosumer based energy management and sharing in smart grid. *Renewable and Sustainable Energy Reviews*, *82*(August 2016), 1675–1684. https://doi.org/10.1016/j.rser.2017.07.018

ZHANG, P., LI, F., & BHATT, N. (2010). Next-Generation Monitoring, Analysis, and Control for the Future Smart Control Center. *Smart Grid, IEEE Transactions On*, *1*(2), 186–192. https://doi.org/10.1109/TSG.2010.2053855

Zhou, L., Xu, F. Y., & Ma, Y. N. (2010). Impact of smart metering on energy efficiency. *2010 International Conference on Machine Learning and Cybernetics, ICMLC 2010*, *6*(July), 3213–3218. https://doi.org/10.1109/ICMLC.2010.5580715