SHORT TERM ELECTRICITY PRICE FORECASTING IN TURKISH ELECTRICITY MARKET

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ABSTRACT

SHORT TERM ELECTRICITY PRICE FORECASTING IN TURKISH ELECTRICITY MARKET

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With the aim for higher economical efficiency, considerable and radical changes have occurred in the worldwide electricity sector since the beginning of 1980s. By that time, the electricity sector has been controlled by the state-owned vertically integrated monopolies which manage and control all generation, transmission, distribution and retail activities and the consumers buy electricity with a price set by these monopolies in that system. After the liberalization and restructuring of the electricity power sector, separation and privatization of these activities have been widely seen. The main purpose is to ensure competition in the market where suppliers and consumers compete with each other to sell or buy electricity from the market and the consumers buy the electricity with a price which is based on competition and determined according to sell and purchase bids given by producers and customers rather than a price set by the government.

Due to increasing competition in the electricity market, accurate electricity price forecasts have become a very vital need for all market participants. Accurate forecast of electricity price can help suppliers to derive their bidding strategy and optimally design their bilateral agreements in order to maximize their profits and hedge against risks. Consumers need accurate price forecasts for deriving their electricity usage and bidding strategy for minimizing their utilization costs.

This thesis presents the determination of system day ahead price (SGOF) at the day ahead market and system marginal price (SMF) at the balancing power market in detail and develops artificial neural network models together with multiple linear regression models to forecast these electricity prices in Turkish electricity market. Also the methods used for price forecasting in the literature are discussed and the comparisons between these methods are presented. A series of historical data from Turkish electricity market is used to understand the characteristics of the market and the necessary input factors which influence the electricity price is determined for creating ANN models for price forecasting in this market. Since the factors influencing SGOF and SMF are different, different ANN models are developed for forecasting these prices. For SGOF forecasting, historical price and load values are enough for accurate forecasting, however, for SMF forecasting the net instruction volume occurred due to real time system imbalances is needed in order to increase the forecasting accuracy.

ÖZ

TÜRKİYE ELEKTRİK PİYASASINDA KISA VADELİ ELEKTRİK FİYAT TAHMİNİ

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1980 yılından itibaren yüksek ekonomik verimlilik amacıyla tüm dünyada elektrik enerjisini sektöründe önemli ve radikal değişiklikler meydana gelmiştir. O zamana kadar, elektrik sektörü tüm üretim, iletim, dağıtım ve parekende satış faaliyetlerini yöneten ve kontrol eden devlete ait dikey entegre tekeller tarafından kontrol edilmiş ve tüketiciler elektriği bu sistemdeki tekellerin belirlediği fiyattan satın almışlardır. Elektrik enerjisi sektöründe meydana gelen liberalleşme ve yeniden yapılandırma sonrasında tüm bu aktivitelerde ayrıştırma ve özelleştirme yaygın olarak görülmüştür. Buradaki temel amaç, üretici ve tüketicilerin elektrik enerjisi satmak veya almak için birbirleriyle rekabet ettikleri ve tüketicilerin elektrik enerjisini rekabete dayalı ve devletin belirlediği fiyat yerine üretici ve tüketicilerin

teklifleri ile belirlenen fiyattan satın almaya başladıkları bir market temin etmektir.

Elektrik piyasasında rekabetin artması nedeniyle, isabetli elektrik enerjisi fiyat tahminlerinde bulunmak tüm piyasa katılımcıları için son derece hayati ihtiyaç haline gelmiştir. Elektrik enerjisi fiyatının doğru tahmini üreticilerin teklif stratejilerini belirlemesini ve karlılığı maksimum seviyeye çıkaracak ve risklere karşı koruyacak olan en uygun ikili anlaşmaları yönetmelerini sağlamaktadır. Ayrıca tüketiciler elektrik enerjisi tüketimlerini kontrol etmek ve maliyetleri en aza indirecek şekilde teklif stratejilerini belirlemek için doğru elektrik enerjisi fiyat tahminine ihtiyaç duymaktadırlar.

Bu tezde, gün öncesi piyasasında oluşan sistem gün öncesi fiyatının (SGOF) ve dengeleme güç piyasasında oluşan sistem marginal fiyatının (SMF) belirlenmesi prosedürü ayrıntılı bir şekilde anlatılmış ve bu fiyatların tahmin edilmesi için çoklu doğrusal regresyon modelleri ile birlikte yapay sinir ağı modelleri geliştirilmiştir. Ayrıca literatürde fiyat tahmini için kullanılan yöntemler açıklanmış ve bu yöntemler arasında karşılaştırmalar sunulmuştur. Türkiye elektrik piyasasından geçmiş veri serileri market karakteristiğini anlamak için kullanılmıştır ve fiyat tahmini yapacak yapay sinir ağı modelinin oluşturulması için fiyatı etkileyen faktörler belirlenmiştir. Sistem gün öncesi fiyatını ve system marjinal fiyatını etkileyen faktörler farklı olduğu için bu fiyatları tahmin etmek için farklı yapay sinir ağı modelleri oluşturulmuştur. Doğru SGOF tahmini için geçmiş fiyat ve yük değerleri yeterli olup, gerçek zamanda meydana gelen dengesizlikler sonucu oluşan net talimat hacmi bilgisi SMF tahminlerindeki performansı arttırmak için gereklidir.

To My Parents and My Wife

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LIST OF SYMBOLS AND ABBREVIATIONS

ACF	Auto correlation function
ANN	Artificial neural network
AR	Autoregressive
ARIMA	Autoregressive integrated moving average
ARMA	Autoregressive moving average
BOO	Built-Operate-Own
BOT	Built-Operate-Transfer
BSR	Balancing and settlement regulation
BSS	Balancing and settlement system
DA	Day-ahead
DAPE	Daily average percentage error
DMAPE	Daily mean absolute percentage error
DR	Dynamic regression
EMRA	Energy Market Regulatory Authority
ENTSO-E	European Network of Transmission System Operators for Electricity
EUAS	Turkish Electricity Generation Company
FDGS	Final day ahead generation/consumption schedules
FMCP	Final market clearing price (TL/MWh)
GARCH	General Autoregressive conditional heteroscedastic
HEPP	Hydroelectric power plant
MA	Moving average
MAE	Mean absolute error
MAPE	Mean absolute percentage error

MCP	Market clearing price (TL/MWh)
MFSC	Market Financial Settlement Center
MLR	Multiple linear regression
MMS	Market management system
MSE	Mean squared error
NLDC	National load dispatch center
NTH	Net instruction volume (MWh)
PACF	Partial autocorrelation function
R	Correlation coefficient
RMSE	Root mean squared error
$SAF_{t,p,u,r}$	System Purchase Price (TL/MWh) to be applied for bid “r” of market participant “p” for the settlement period “u”, for trade zone “t”
$SAM_{t,p,s,u,r}$	Actual System Purchase Volume (MWh) of market participant “p” in the related advance period "s" under its bid “r” for the settlement period “u”, for trade zone “t”
$SAT_{t,p,s}$	Amount of payable (TL) to be accrued on the market participant “p” for the purchases of the related market participant from the system in the related advance period "s", for trade zone “t”
$SATF_{t,p,u,r}$	System Purchase Bid Price (TL/MWh) for bid “r” of market participant “p” for the settlement period “u”, for trade zone “t”
SGOF	System day ahead price (TL/MWh)
SLR	Simple linear regression
SMF	System marginal price (TL/MWh)
SSE	Sum squared error
$SSF_{t,p,u,r}$	System Sales Price (TL/MWh) to be applied for bid “r” of market participant “p” for the settlement period “u”, for trade zone “t”

$SSM_{t,p,s,u,r}$	Actual System Sales Volume (MWh) of market participant "p" in the related advance period "s" under its bid "r" for the settlement period "u", for trade zone "t", determined as a result of day ahead balancing
SSR	Sum of squares regression
$SST_{t,p,s}$	Amount of receivable (TL) to be incurred on the market participant "p" for the sales to the system in the related advance period "s", for trade zone "t"
$SSTF_{t,p,u,r}$	System Sales Bid Price (TL/MWh) for bid "r" of market participant "p" for the settlement period "u", for trade zone "t"
TEAS	Turkish Electricity Generation Transmission Company
TEDAS	Turkish Electricity Distribution Company
TEIAS	Turkish Electricity Transmission Company
TEK	Turkish Electricity Administration
TETAS	Turkish Electricity Trading and Contracting Company
TOOR	Transfer of Operating Rights
UMCP	Unconstrained market clearing price (TL/MWh)
WMAE	Weekly mean absolute error
WMAPE	Weekly mean absolute percentage error
YAL	Up-regulation
$YALF_{d,u,r}$	Offer price (TL/MWh) to be applied for offer "r" of balancing entity "d" within the context of balancing power market, for the settlement period "u"
$YALM_{d,u,r}$	Accepted and fulfilled offer volume (MWh) of balancing entity "d" within the context of balancing power market, regarding the offer "r" valid for the settlement period "u"

$YALT_d$	Amount of receivable (TL) to be accrued on the related market participant regarding the offers of balancing entity “d, accepted in all settlement periods of related invoicing period” within context of balancing power market
$YALTF_{d,u,r}$	Offer Price (TL/MWh) for offer “r” of balancing entity “d” within the context of balancing power market , valid for the settlement period “u”
YAT	Down-regulation
$YATF_{d,u,r}$	Bid price (TL/MWh) to be applied for bid “r” of balancing entity “d” within the context of balancing power market, valid for the settlement period “u”
$YATM_{d,u,r}$	Accepted and fulfilled bid volume (MWh) of bid “r” of balancing entity “d” within the context of balancing power market, valid for the settlement period “u”
$YATT_d$	Amount of payable (TL) to be accrued on the related market participant for the bids of balancing entity “d” within the context of balancing power market accepted in all settlement periods of related invoicing period

CHAPTER 1

INTRODUCTION

1.1. Research Motivation

With the aim for higher economic efficiency, considerable and radical changes have occurred in the worldwide electricity sector since the beginning of 1980s. By that time, the electricity sector has been controlled by the state-owned vertically integrated monopolies which manage and control all generation, transmission, distribution and retail activities and the consumers buy electricity with a price set by these monopolies in that system. Also in that system, it was seen that the monopoly could not manage all of these activities adequately, use the resources effectively, tackle with the losses and theft and make investments profitably. After the liberalization and restructuring of the electricity power sector, separation and privatization of these activities have been widely seen. The main purpose is to ensure competition in the market where suppliers and consumers compete with each other to sell or buy electricity from the market and efficient utilization of resources for cost minimization which turns to providing the electricity to the customers in cheaper and better quality ways. With the new structure, the costumers can choose their suppliers in order to increase the competition and buy the electricity with a price which is based on competition and determined according to sell and purchase bids given by producers and customers rather than a price set by the government.

Due to increasing competition in the electricity market, accurate electricity price forecasts have become very vital need for all market participants. In a regulated electricity market, due to meet the electricity demand, generation resource scheduling was based on minimizing the costs which resulted that accurate demand forecasting was the key point [1]. After deregulation, the scheduling of generation resources such as hydro and thermal resources now turns out to be based on maximizing the profits [2] and therefore an accurate price forecast presents very important information for any decision making. Accurate forecast of electricity price can help suppliers to derive their bidding strategy and optimally design their bilateral agreements in order to maximize their profits and hedge against risks. In other words, if suppliers forecast the electricity price more accurately, they can manage the risks of over/underestimating the income earned from supplying energy to the system [3]. Also electricity price is a good indicator for making decision on investing new generation facilities for the suppliers [4]. Consumers need accurate price forecasts for deriving their electricity usage and bidding strategy for minimizing their utilization costs.

Since the electricity cannot be stored in an economic way and the supply-demand balance should be maintained in the real time, the electricity price in the electricity market is more volatile than the other markets. Price forecasting is a challenging task due to too many variables with various uncertainties that affect the price in various way. Some variables such as load, weather conditions, precipitation and natural gas price can be predicted, while generator outages, suppliers bidding strategies, spinning reserve market price and even unethical market participant behavior are either unpredictable or publicly unavailable [5].

In recent years, the electricity price forecasting has become very interested area in electrical engineering and a lot of research has been done on this issue and trying out to find the methods that estimate the prices most accurately. Since the nonlinear nature of the price, the artificial neural network method (ANN) as non-linear method is frequently used in recent times rather than linear forecasting methods. Artificial neural networks are simple but very effective tool for price forecasting because they have the ability to approximate any nonlinear function and due to their data-driven properties, they are able to solve problems where input-output relationship is neither well defined nor easily computable [6].

This thesis presents the determination of system day ahead price (SGOF) at the day ahead market and system marginal price (SMF) at the balancing power market in detail and develops artificial neural network (ANN) models together with multiple linear regression models to forecast these electricity prices. Also the methods used for price forecasting in the literature are discussed and the comparisons between these methods are presented. A series of historical data from Turkish electricity market is used to understand the characteristics of the market and develop models for price forecasting.

1.2. Objectives of the Thesis

Restructured and deregulated systems are very volatile in nature and price forecasting has emerged more challenging and nonlinear than ever before. In order to maximize the profits or minimize the costs in a competitive electricity market, the market participants need to forecast future prices more accurately with volatile aspects and several techniques and models have been developed and implemented for accurate price forecasting. The main purpose of all these techniques and models was to achieve minimum error at price forecasting. However, due to the nonlinear and complex nature of the price, most of these techniques, especially linear ones, face with many problems and challenges for achieving this goal. In this thesis, the main objectives are as follows:

- Understand the methodology used for the determination of system day ahead price (SGOF) and system marginal price (SMF) which are determined at day ahead market and balancing power market, respectively, in Turkish electricity sector and find out what the parameters used in determination of day ahead and real time system prices are and which of them play main roles and are important than others.
- Perform a literature review in this area to find out most suitable methods according to price forecasting and electricity market.
- Using the publicly available data and proposed ANN models together with multiple linear regression model developed for Turkish electricity market, forecast future day ahead prices and system marginal prices and evaluate the performance of these models by comparing the forecasted results with the actual values and also compare the forecasting performances of neural network and multiple linear regression models in Turkish electricity market.
- By the bienayme-chebycheff inequality which is frequently used in statistical studies and probability theory, forecast future SMF values together with probable lower and upper boundaries.

1.3. Outline of the Thesis

This thesis is organized in five chapters. Research motivation, objectives of the thesis and outline are presented in the first chapter.

In Chapter 2, the overview of the current electricity sector in Turkey is presented and a brief history of deregulation and privatization process in Turkish electricity market is described. Also the balancing activities which consist of day ahead balancing in day ahead market and real-time balancing in balancing power market are studied together with the determination process of system day ahead price and system marginal price.

In Chapter 3, general review to the time series techniques are given and especially artificial neural networks and multiple linear regression methodology are explained in detail with error minimization process.

In Chapter 4, the methodology to select the optimum ANN architecture that provides the minimum daily mean absolute percentage error (DMAPE) for system day-ahead price and system marginal price forecasting problem in Turkish electricity market is studied in detail. The determination of training and transfer functions, the quantity of training vectors, hidden neurons and the training data that significantly affect the electricity price is shown with the MAPE results. Also the performances of proposed ANN model for SGOF forecasting are compared with the results of MLR model. The proposed ANN model is modified with using volatility analysis and bienayme-chebycheff inequality in order to forecast SMF values more accurately together with probable lower and upper boundaries which is useful for market participants to derive bidding strategy and hedge against volatility risks.

Finally Chapter 5 represents the summary of the study and conclusions based on the forecast results. Moreover, it suggests recommendations for the future investigation.

CHAPTER 2

OVERVIEW OF THE TURKISH ELECTRICITY SECTOR

2.1. Turkish Electricity Market at a Glance

Turkish electricity market which has an average annual growth of 9-10% is one of the fastest growing electricity markets in the world [23]. The considerable increase in the consumption due to rapid urbanization, economical developments and population rise force the sector to increase generation and transmission capability in order to supply the electricity to the end users in a continuous, quality and low cost manner.

By the end of 2011, the installed capacity in Turkish electricity system has reached 52,911 MW and it has shown 3387 MW increase corresponding to 6.8% annual rate of increase in installed capacity compared to the previous year 2010. The increases of installed capacity through different resources such as thermal power plants, hydraulic power plants, wind power and geothermal power plant have been provided as 1652.6 MW, 1305.9 MW and 428.5 MW respectively [7].

The electricity production in 2011 has reached 229.3 billion kWh with an increase of 8.6% compared to the previous year 2010. The share of EÜAŞ at this total production was 46.1% at 2009, 45.2% at 2010 and 40.4% at 2011 whereas private sector provided the rest of 59.6% production at 2011. In terms of resources, 45.4% of total electricity production was obtained by natural gas whereas 28.9% by coal, 22.8% by hydraulic sources, 2.4% by geothermal and wind, 0.6% by liquid fuels and waste [7]. In comparison with the year 2010, especially the utilization rate of imported coal and wind power increased while notably liquid fuels (LPG, naphtha, fuel oil) and natural gas rates has been observed to decrease.

According to Electricity Energy Market and Supply Security Strategy Paper, Published on 18.05.2009, some targets have been set for electricity generation such that utilizing all domestic ignite, hard coal resources and hydraulic potential, increasing of installed wind and geothermal capacity up to 20,000MW and 600 MW respectively, reducing the share of natural gas in electricity production down to 30% by 2023 and providing 5% of electricity generation from nuclear energy by 2023 [8].

TEIAS, Transmission System Operator and the only transmission facility in Turkish electricity sector, has undertaken such tasks as operation and maintenance of all transmission facilities, managing the transmission system, planning of load dispatch, developing investments for renewing and expansion of transmission system, preparing generation capacity projection and executing international interconnection studies and operating the mainly financial electricity energy market. TEIAS, which is the 5th biggest facility of European Interconnected System (ENTSO-E) with its 229 billion kWh consumption per year and 104,658 MVA installed transformer capacity and 49,403.5 km length of transmission line, has been working synchronous parallel with ENTSO-E since 18.09.2010.

The electricity consumption annual rate of increase which was 8.5% in 1990s, decreased to 5.1% in 2000s due to economic crisis. The yearly electricity demand and peak demand annual rate of increase from 1980 to 2009 is presented at Figure 3. The electricity consumption annual rate of increase is found as 7.18% in 2000s when we ignore 2001 and 2009 which are the years that the impacts of global crisis most felt. The electricity consumption in 2011 was increased by 9.5% compared to the previous year and occurred as 230.306 million kWh. Peak demand in 2011 was increased by 8.18% compared to the previous year and the peak demand of 2011 occurred as 36.122 MW on 28 July Thursday at 14:30 whereas the lowest demand occurred as 20.241 MW on 6 October Tuesday at 18:30 which was 1st day of Ramadan. According to 10-year production capacity projection study prepared by TEIAS, the peak demand will rise to 46.800 MW by 2015-end and 66.845 MW by 2020-end with an average annual increase rate of 7.19% whereas the consumption will rise to 303140 million kWh by 2015-end and 433900 by 2020-end with an average annual increase rate of 7.51%.

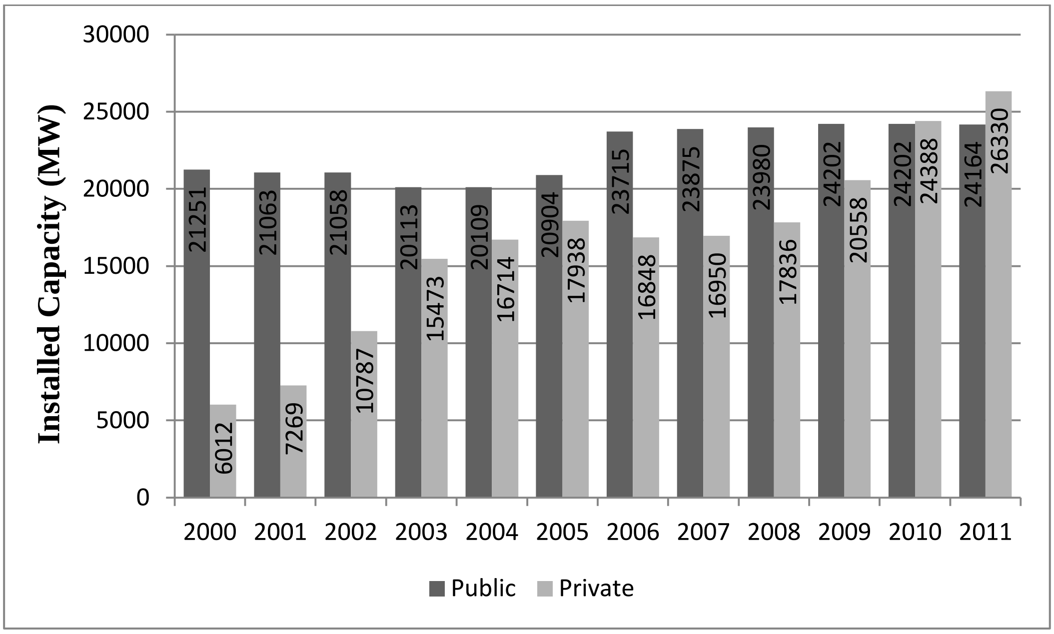

Figure 1 Installed capacity development in Turkey from 2000 to 2011 [16]

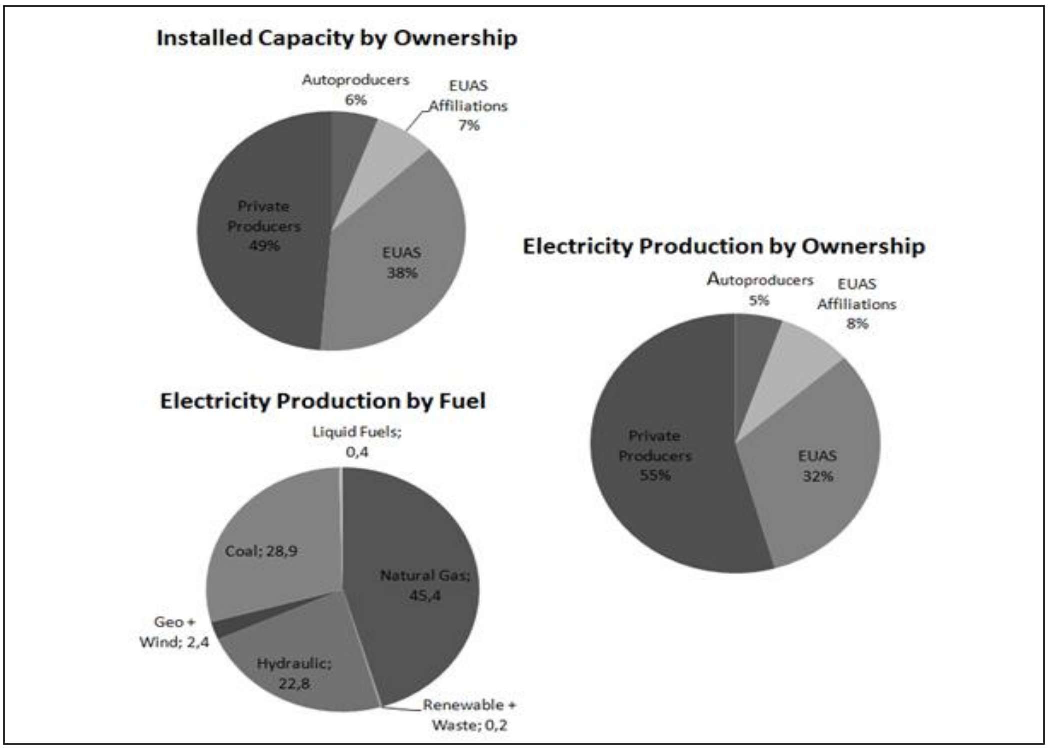

Figure 2 Installed capacity and electricity production by ownership and fuel types in 2011 in Turkey [7]

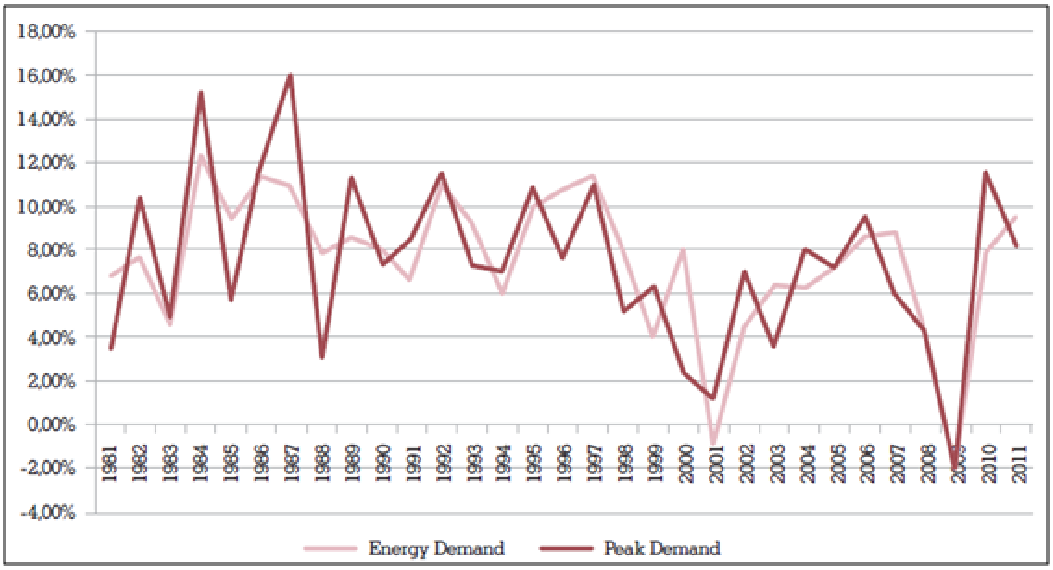

Figure 3 Annual demand increase from 1981 to 2011 [15]

2.2. Liberalization in Turkish Electricity Sector

In Turkey, Turkish Electricity Administration (TEK) was established in 1970, and it engaged in activities such as generation, transmission, distribution and sales. In the early 1980s, TEK, state-owned vertically integrated company was the main company in the Turkish electricity sector. After 1984, the participation of private sector was observed, where construction of the generation plants and sale of produced electricity to TEK under different models, such as Built-Operate-Transfer (BOT), Built-Operate-Own (BOO), Transfer of Operating Rights (TOOR) was allowed (Law No. 3096). With this Law, the legal basis for private participation through Build Operate and Transfer (BOT) contracts for new generation facilities, Transfer of Operating Rights (TOOR) contracts for existing generation and distribution assets, and the auto producer system for companies (to produce their own electricity) has been formed. BOT concession brought a private company possibility to build and operate a plant for up to 99 years (subsequently reduced to 49 years) and after that to transfer it to the state at no cost. Under a TOOR, the private enterprise would through a lease-type arrangement operate, with rehabilitation where necessary, the existing government-owned facility. In 1997 the additional law called Build Operate and Own (BOO) Law (No. 4283) was enacted for private sector participation in the construction and operation of new power plants, together with guarantees provided by the Undersecretariat of Treasury [9].

TEK was demerged into two state-owned companies named Turkish Electricity Generation Transmission Company (TEAS) and Turkish Electricity Distribution Company (TEDAS) in 1993. In March 2001, for the purpose of privatization and liberalization of Turkish electricity market, TEAS was unbundled into three separate state owned entities Electricity Generation Company (EUAS), Turkish Electricity Transmission Company (TEIAS) and Turkish Electricity Trading and

Contracting Company (TETAS) with the Electricity Market Law [10]. In accordance with the new law, distribution activities would be performed by TEDAS that was privatized into 21 regional distribution companies, and Energy Market Regulatory Authority (EMRA) was established and authorized for independent regulation and control of electricity, natural gas, oil and liquefied petroleum gas (LPG). For that reason, in Turkey a major electricity market reform program has started, and this program has the aim to establish independent state owned companies that would perform electricity generation, transmission, distribution and trading activities, and finally in the frame of restructuring and privatization of the electricity market for free computation, the privatization of state owned electricity companies, except for transmission facilities, would be done [23]. Also, in 2004 Turkish High Planning Council issued the Electricity Sector Strategy Paper that serves as an important milestone in electricity sector reforms, and creates the roadmap of electricity sector reform up to 2012, indicating the distribution entities and the privatization of the generation plants.

This strategy paper enabled the first privatization in electricity generation sector, which was done by Privatization Administration, and Zorlu Energy won the tender of Ankara Electricity Generation Company (ADUAS), consisting of a portfolio of hydro, geothermal and thermal power plants with an installed capacity of 141 MW. In the same way, 52 small hydroelectric power plants (HEPP) of EUAS were privatized through the method of Transfer of Operation Rights. Privatization High Council decision brought in August 2010 has approved the privatization of 18 groups. Additionally, 9 portfolio groups of EUAS were to be privatized, however there are 4 power plants (Hamitabat, Kangal, Seyitömer and Soma A-B), to be priorized in the privatization. When we look at the distribution side, Turkey has 21 electricity distribution areas, 13 of which are currently operated by the private sector, whereas privatization of 8 area has continued.

Seventeen hydropower plants (with total capacity of 7055 MW), the transmission system and market operator, TEIAS, is to remain in state ownership [9].

2.3. Balancing and Settlement System in Turkey

Electricity Sector Strategy Paper issued by Turkish High Planning Council in 2004 stated that Turkish liberal electricity market structure was to be composed of bilateral contracts between buyers and sellers. In also stated that the market structure would be complemented by a balancing and settlement mechanism to ensure advanced liberalization of electricity market. In order to carry on to a final close the objectives and principles of this strategy, it is very important that the balancing and settlement regime acts as a market, where the uncontracted generation can be bought and sold, and where the application increases security of supply by facilitating inclusion of independent and small generators. The mechanism of balancing and settlement will involve the target for formation of a spot market and signals for attraction of new investments. As referred in Strategy Paper of March 2004, one of the major components of this reform process is the "balancing and settlement system" (BSS). This system consists of activities related to; real-time balancing the demand and supply through acceptance of bids and offers, financial settlement of payables and receivables that come up from energy supplied to or withdrawn from the system. On November 3rd, 2004 after being published Turkish Official Gazette under No. 25632 based on Electricity Market Law No. 4628 BSS was put into practice. This regulation has the objective to determine the procedure and principles for the balancing of electricity demand and supply and settlement. Furthermore, it includes duties, competences and responsibilities of the involved parties in the balancing and settlement system, and principles and procedures applicable to the electricity supply and demand balancing, as well as the financial settlement of the receivables and payables of licensed legal entities that arise from participation of balancing and settlement system. Nevertheless, on August 1st 2006, upon **EMRA** decision (dated July 20th, 2006, No.831) and following 21-month of virtual implementation period the actual implementation of the system started on. Currently, 27.5% of the total energy consumption is sold through balancing market (i.e., day ahead and balancing power market), and the remaining part is sold through bilateral agreements.

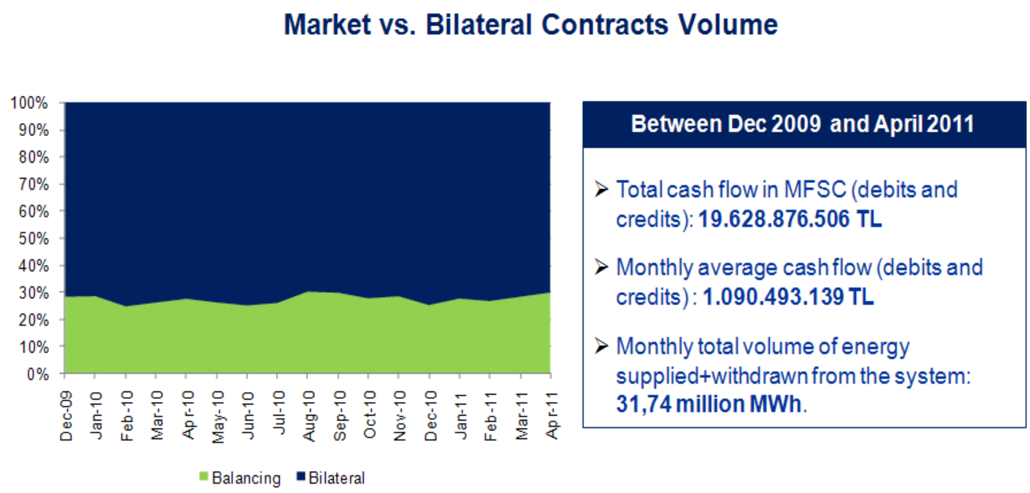

Figure 4 Balancing market vs. bilateral agreements volume comparison together with cash flow through market [16]

The balancing and settlement system consists of two components: the day ahead balancing market and the real time balancing market. On one hand, the day ahead balancing includes activities that intend to balance the supply and demand in the system executed through the day ahead market and ensure contractual obligations and generation and/or consumption plans of market participants. On the other hand, the real time balancing involves the balancing power market and ancillary services. The balancing power market intends to provide the System Operator with reserves that can be activated within 15 minutes for real time balancing. Ancillary Services provide frequency control and demand control services.

Market Financial Settlement Center (MFSC) operates the day ahead market which is TEIAS body unit. MFSC in the role of the Market Operator, one day before the real time and on the basis of settlement period, operates and manages the day ahead balancing, with the aim to maintain the supply and demand balance in line with the following goals [11];

- Evaluation of the offers and bids submitted to the day ahead balancing is done on a non-discriminatory basis amongst day ahead market participants,
- Determination of the prices applied for the settlement of day ahead balancing are done on the basis of marginal pricing or market clearing price setting principle by taking into consideration the bids and offers submitted to day ahead balancing,
- Giving opportunity to the market participants to balance their generation and consumption needs and contractual obligation in the day ahead,
- Determination of electricity reference price,
- Provide System Operator a balanced system in the day ahead,
- Provide System operator the ability to manage congestion in the day ahead,
- Provide market participants the opportunity to sell or buy electricity for the following day together with their bilateral contracts.

National Load Dispatch Center (NLDC), one of the TEIAS bodies operates the real time balancing market. Real time balancing is performed with the following general principles in order to ensure supply of sufficient and good quality of electricity energy to consumers with low-cost continuous manner [11];

- Real time balancing is done with the principles of supply quality and operational condition criteria, with the purpose of balancing supply and demand at the real time in tune by preserving the operational security and system integrity,
- Evaluation of the offers and bids submitted to the balancing power market for real time is done on a non-discriminatory basis amongst market participants, by taking into consideration the data regarding bid and offer and their balancing eligibility,
- Real time balancing activities are performed through consideration of the system security in a way that minimizes the balancing costs for System Operator.

Today, the market participants consist of licensed legal entities that supply electricity energy to the system or draw electricity energy from the system by taking part at the day ahead market and balancing power market. The market participants include above mentioned legal entities [11]:

- Generation licensee
- Auto producer licensee
- Auto producer group licensee
- Wholesale licensee
- Retail licensee

Through the Market Management System (MMS) the Market Operator declares demand forecast and transmission capacity to the market participants at the day ahead market. Furthermore, market participants submit their bids to the day ahead market until 11:30 each day. Day ahead market bids consist of single hour, and/or block and/or flexible bids for the following day concerning the sale or purchase of active electricity energy. Each purchase or sales bid that is submitted to day ahead market for each of purchase and sale directions contains 32 different price and quantity levels. Market Operator by the evaluation in line with criteria mentioned at BSR confirms or rejects each submitted bid until 12:00. Day ahead market bids submitted to MMS are taken into account without considering the transmission constraints for day ahead price determination whose process is executed between 12:00 – 13:00 each day for each hour of the following day and the consists of the following methods:

a. "All the hourly sale bids submitted to day ahead market for the relevant hour are listed in an increasing order of price starting from the price-quantity pair with lowest price until the price-quantity pair with highest price and combined into one bid. Supply curve is formed by combining each price-quantity pair with the consequent price-quantity pair in the direction of increasing price, utilizing linear interpolation method. When summation of the quantities in all validated hourly sale bids are zero, supply curve occurs between minimum and maximum prices with a quantity zero at all points.
b. All the hourly purchase bids submitted to day ahead market for the relevant hour are listed in a decreasing order of price starting from the price-quantity pair with highest price until the price-quantity pair with lowest price and combined into one bid. Demand curve is formed by combining each price-quantity pair with the consequent price-quantity pair in the direction of decreasing price, utilizing linear interpolation method. When summation of the quantities in all validated hourly purchase bids are zero, demand curve occurs between minimum and maximum prices with a quantity zero at all points.
c. By intersecting the demand and supply curves formed for every hour according to items (a) and (b), the intersection point, where purchased

and sold electricity energy quantities and transferred energy price are equal, and the price that corresponds to the intersection point are determined. When demand and supply curves are intersected on a segment corresponds to a unique quantity but an interval of price, the price that corresponds to intersection point is calculated by arithmetic average of maximum and minimum points of the price interval" [11].

d. The price determined here is called System Day Ahead Price (SGOF).

Price, TL/MWh	0	100	110	120	130	140	150	160	300.01	500
Participant A, lot	-300	-300	-300	-300	-300	-300	-300	-300	-300	-300
Participant B, lot	4000	4000	2500	0	0	0	-1000	-1300	-1700	-1700
Participant C, lot	800	800	800	800	300	300	-3000	-300	-300	-300
Participant D, lot	900	900	900	900	900	900	600	300	300	300
Participant E, lot	1200	1200	1000	1000	1000	1000	1000	1000	1000	1000
Total Purchase (lot)	**6900**	**6900**	**5200**	**2700**	**2200**	**2200**	**1600**	**1300**	**1300**	**1300**
Total Sales (lot)	**-300**	**-300**	**-300**	**-300**	**-300**	**-300**	**-1600**	**-1900**	**-2300**	**-2300**

* 1 lot = 0,1 MWh

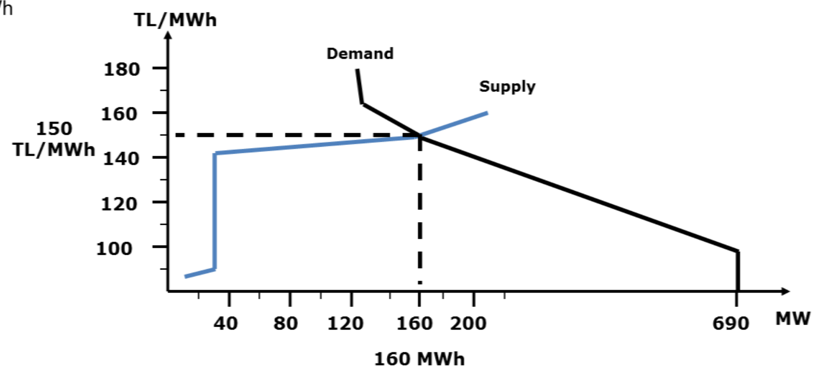

Figure 5 Determination of System Day Ahead Price (SGOF) at Day Ahead Market

For the settlement of day ahead balancing activities, amount of receivables to be incurred on the market participant due to sales to the system is calculated as follows:

$$SST_{t,p,s} = \sum_{u=1}^{a}\left(\sum_{r=1}^{n}(SSF_{t,p,s,u,r} \times SSM_{t,p,s,u,r})\right) \tag{1}$$

The system sales prices (SSF) which are applied to the actual system sales of the each market participants regarding its bids submitted to the day ahead market are calculated as follows:

If $SSTF_{t,p,u,r} \leq SGOF_{t,u}$, then $SSF_{t,p,u,r} = SGOF_{t,u}$ *(2a)*

If $SSTF_{t,p,u,r} > SGOF_{t,u}$, then $SSF_{t,p,u,r} = SSTF_{t,p,u,r}$ *(2b)*

According to settlement of day ahead balancing activities, amount of payable to be incurred on the market participant due to purchases from the system is calculated as follows:

$$SAT_{t,p,s} = \sum_{u=1}^{a}\left(\sum_{r=1}^{n}(SAF_{t,p,s,u,r} \times SAM_{t,p,s,u,r})\right) \tag{3}$$

The system purchase prices (SAF) which are applied to the actual system purchases of the each market participants regarding its bids submitted to the day ahead market are calculated as follows:

if $SATF_{t,p,u,r} \geq SGOF_{t,u}$, then $SAF_{t,p,u,r} = SGOF_{t,u}$ *(4a)*

if $SATF_{t,p,u,r} < SGOF_{t,u}$, then $SAF_{t,p,u,r} = SATF_{t,p,u,r}$ *(4b)*

Being that the day ahead market has an aim to serve a market to the System Operator creating the balance between supply and demand, in the real time system there may exist some deviations. As an example, a large consumption plant may start/stop operating suddenly, a generation outage may emerge, deviations of the load forecast plan may deteriorate the system balance due to variable whether condition, or a transmission system may have the technical problem. System Operator uses the presented proposals in order to avoid system shortages in such cases and to compensate the system balance, which has to be realized within 15 minutes in case of a request at the balancing power market. Actually, the balancing power market serves to balance the system in real time instead of trading electricity, because trading is very risky at balancing power market and the day ahead market is the right place for the electricity trading.

Each day, when the day ahead balancing process is completed and market participants notify their final day ahead generation/consumption schedules (FDGS) containing next day hourly generation or consumption values which are finalized by the instructions taken at day ahead market together with available capacities and the offers and bids related to generation/consumption increases or decreases regarding balancing power market to the System Operator via MMS, the balancing power market process begins at 14:00. The System Operator is in charge of controlling FDGS, its offers and bids, and if any error is caught at the notifications, the System Operator is in charge of contacting the relevant market participant to make sure that until 17:00 the required corrections are done. After the offers and bids are ranked according to their prices, the System Operator evaluates them and notifies the instruction for the accepted offers and bids to the market participants. The aim is to prevent the existing and possible energy deficit or surplus in the following day system, avoiding system accumulation or reserving capacity by subservient services. The System Operator notifies to the market participants tag value 0 for real time balancing instructions that must be realized within 15 minutes, tag value 1 for removing transmission congestion and tag value 2 for subservient services. Balancing power market system marginal price

(SMF) for each hour is determined in the two hours after the related hour and notification to the market participants.

Offers and bids are submitted to the balancing power market by the market participants at 15 levels of volumes, including that all offer prices shall be equal or higher than the system day ahead price (SGOF) determined for the related hour, and all bids prices shall be equal or smaller than the SGOF for the related hour. The aim is to ensure the system security and minimize the balance costs by taking into consideration transmission congestion, technical constraint of market participants' balancing entities and supply reliability and quality, and evaluation of all offers and bids serves to that purpose.

Marginal prices of the system are determined in the following way:

a. If there is energy deficit in the system at hour 't', starting from the lowest up-regulation offer price, SMF for hour 't' equals to the maximum accepted hourly offer price, corresponding to the net instruction volume applied to up-regulated balancing entities to correct the energy deficit.
b. If there is energy surplus in the system at hour 't', starting from the highest down-regulation bid price, SMF for hour 't' equals to the minimum accepted hourly bid price corresponds to net instruction volume applied to down-regulated balancing entities to correct the energy surplus.
c. In case the system is in balance at hour 't', SMF for hour 't' equals to SGOF determined at the day ahead market.
d. Instruction of the offers or bids is not required while taking into account determining system marginal price.

The system direction (i.e., energy deficit, energy surplus or energy balance) based on the settlement period is determined as follows:

$$\text{If} \quad \sum_{d=1}^{k}\sum_{r=1}^{m} YALM_{d,u,r} > \sum_{d=1}^{k}\sum_{r=1}^{n} YATM_{d,u,r} \tag{5a}$$

For the relevant settlement period and trade zone, there is energy deficit in the system.

$$\text{If} \quad \sum_{d=1}^{k}\sum_{r=1}^{m} YALM_{d,u,r} < \sum_{d=1}^{k}\sum_{r=1}^{n} YATM_{d,u,r} \tag{5b}$$

For the relevant settlement period and trade zone, there is energy surplus in the system.

$$\text{If} \quad \sum_{d=1}^{k}\sum_{r=1}^{m} YALM_{d,u,r} = \sum_{d=1}^{k}\sum_{r=1}^{n} YATM_{d,u,r} \tag{5c}$$

For the relevant settlement period, system is at balance.

The net instruction volume is:

$$NTH_u = \left| \sum_{d=1}^{k}\sum_{r=1}^{m} YALM_{d,u,r} - \sum_{d=1}^{k}\sum_{r=1}^{n} YATM_{d,u,r} \right| \tag{6}$$

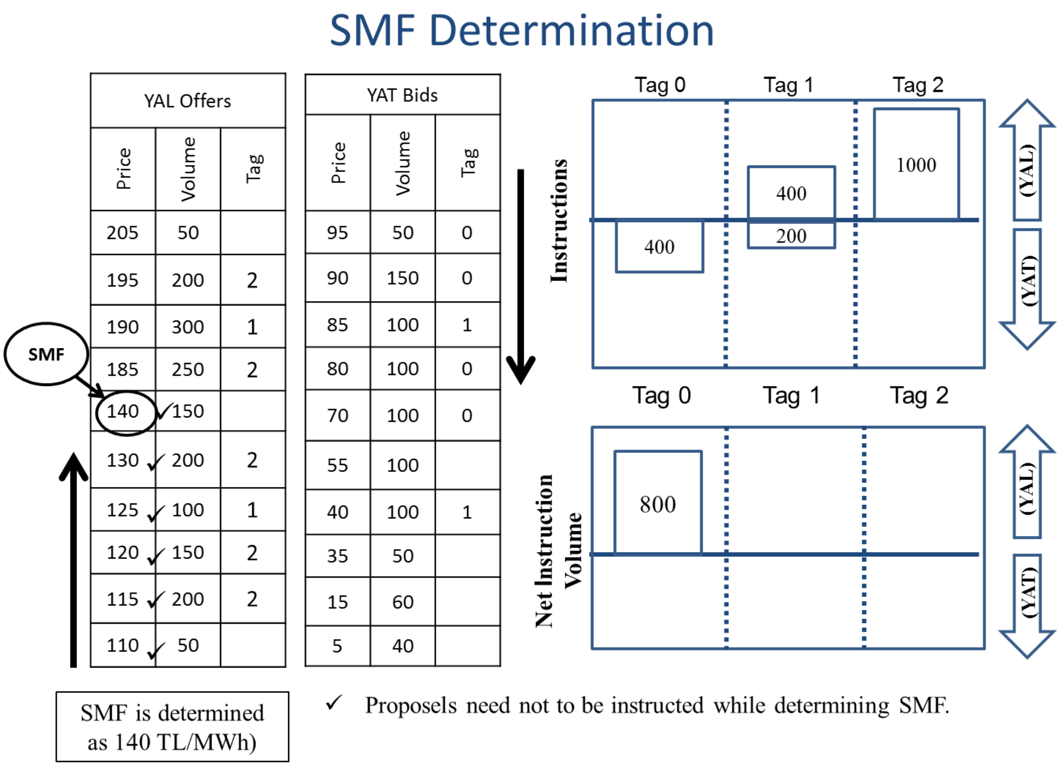

Figure 6 Determination of system marginal price (SMF) at balancing power market

For the settlement of balancing power market activities, amount of receivables to be incurred on the market participant due to up-regulation instructions (YAL instructions) given to the each balancing entity is calculated as follows:

$$YALT_d = \sum_{u=1}^{m}\left(\sum_{r=1}^{n}(YALM_{d,u,r} \times YALF_{d,u,r})\right) \tag{7}$$

The offer prices (YALF) which are applied to offer instructions of the each market participants regarding its offers submitted to the balancing power market are calculated as follows:

- When there is energy deficit in the price zone where the related balancing entity is located;

If $YALTF_{d,u,r} \leq SMF_{d,u,t,}$, then $YALF_{d,u,r} = SMF_{d,u,t}$ *(8a)*

If $YALTF_{d,u,r} > SMF_{d,u,t}$, then $YALF_{d,u,r} = YALTF_{d,u,r}$ *(8b)*

- When the price zone where the related balancing entity is located is in balance and/or there is energy surplus in the price zone,

$$YALF_{d,u,r}=YALTF_{d,u,r} \qquad (8c)$$

For the settlement of balancing power market activities, amount of payable to be incurred on the market participant due to down-regulation instructions (YAT instructions) given to the each balancing entity is calculated as follows:

$$YATT_d = \sum_{u=1}^{m} \left(\sum_{r=1}^{n} (YATM_{d,u,r} \times YATF_{d,u,r}) \right) \qquad (9)$$

CHAPTER 3

ELECTRICITY PRICE FORECASTING WITH TIME SERIES MODELS

3.1. Autoregressive (AR) Models

One of the most important approaches in price forecasting is time series modeling. Autoregressive models are a part of time series analysis. In this model, present value is defined in terms of previous values. If model consists only one previous value, then this model called as AR (1) model. For p previous values, present time value y_t is defined with AR(p) model as;

$$y_t = \theta_1 y_{t-1} + \theta_2 y_{t-2} + \cdots + \theta_p y_{t-p} + e_t + \mathrm{C} \tag{10}$$

where;

$\theta_1, \theta_2, \theta_p$	coefficients
p	model degree
e_t	random error term with zero average and constant variance
C	constant.

Above equation can be defined as sum of previous terms.

$$y_t = C + \sum_{i=1}^{p} \theta_i y_{t-i} + e_t \quad (11)$$

3.2. Moving Average (MA) Models

Moving average models are based on taking average of previous observed values. Present time value y_t may be defined in terms of average value of previous observation errors. Error terms added to average for every new observation value. The name “moving” comes from changing average value with every new observation. For q previous values, MA(q) is given as;

$$y_t = e_t + \sum_{j=1}^{q} \theta_j e_{t-j} \quad (12)$$

where;

e_t	error term
θ_j	coefficients.

3.3. ARMA/ARIMA Models

ARMA models are simply combination of autoregressive models and moving average models. ARMA models can be expressed as;

$$y_t = C + \sum_{i=1}^{p} \theta_i y_{t-i} + e_t + \sum_{j=1}^{q} \theta_j e_{t-j} \quad (13)$$

ARMA models can be applied to stationary functions. A stationary function is a function that has a constant mean and variance. But in practice, most of the time series are non-stationary. In order to fit a model to non-stationary time series,

series must be differentiated until the non-stationary factor is removed. Differentiated model expressed as ARIMA (p,d,q) model where p, q are numbers of past terms used in AR and MA models and d is the degree of differentiation.

To define a time series is stationary or non- stationary, two functions must be examined. Autocorrelation (ACF) function is a function that defines the statistical relationship between two time series term with delay k.

$$R_k = \frac{\sum_{t=b}^{n-k}(z_t-\bar{z})(z_{t+k}-\bar{z})}{\sum_{t=b}^{n}(z_t-\bar{z})^2} \tag{14}$$

where, the mean of the series given below.

$$\bar{z} = \frac{\sum_{t=b}^{n} z_t}{n-b+1} \tag{15}$$

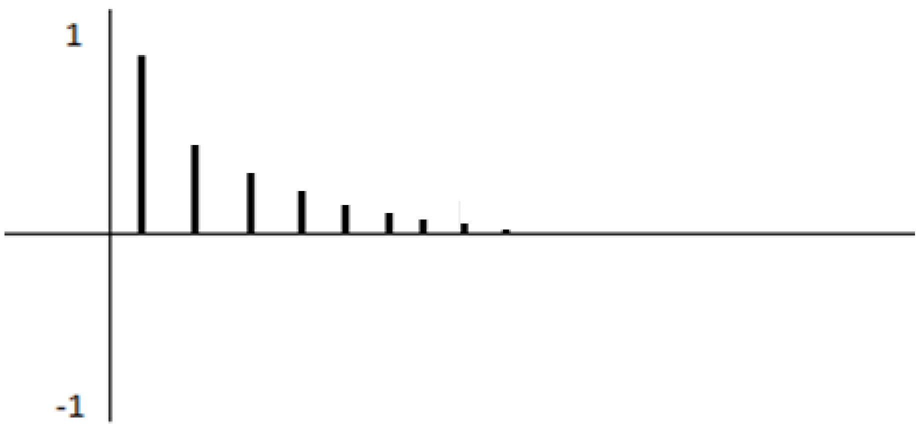

Figure 7 Fast dying ACF

If the time series has a fast dying ACF, the series is stationary. Time series must be differentiated to make the series stationary.

Partial Autocorrelation (PACF) function, is a function that defines the statistical relationship between two error term with delay k.

$$r_{kk} = r_1 \qquad k=1$$

$$r_{kk} = \frac{r_k - \sum_{j=1}^{k-1} r_{k-1\,k-1,j} r_{k-j}}{1 - \sum_{j=1} r_{k-1\,,j} r_j} \qquad k=2\backslash 3\backslash 4\ldots \tag{16}$$

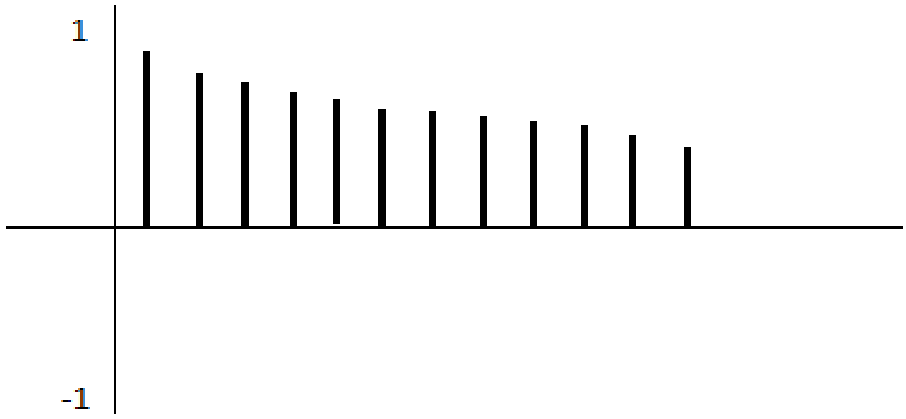

Figure 8 Slow dying ACF

3.4. Transfer Function (TF) Models

While forecasting with time series analysis, main difficulty is to have stationary series. Mostly used method to convert a non-stationary time series into stationary is differencing as mentioned above. When differencing method is insufficient, transfer function models are used to obtain stationary series. Transfer function models need two time series that are statistically correlated.

Price at time t is denoted by p_t and demand at time t is denoted by d_t. If demand and price series are non stationary, these functions are transformed as given below.

$$x_t = f(d_t) \text{ and } y_t = f(p_t)$$
$$y_t = C + v(B)f(d_t) + e_t \tag{17}$$

where B is backshift operator, $Bz_t=z_{t-1}$, $B^2z_t=z_{t-2}$, $B^nz_t=z_{t-n}$.

$$v(B) = v_0C + v_1B + \cdots + v_kB^k \tag{18}$$

v_k are the coefficients describe the relationship between two series.

3.5. Dynamic Regression (DR) Models

Dynamic regression models are used when the sampled data are not linear or cannot be linearized by taking logarithm. The expression for a dynamic regression model with a disturbance N is given below. In this study, related data points are linear.

$$y_t = C + f\left(x_{t,1}, x_{t,2}, \dots x_{t,n}\right) + N_t \tag{19}$$

3.6. Simple/Multiple Linear Regression (SLR/MLR) Models

Regression method based on fitting the best curve to sampled data points. If fitted curve is a first degree polynomial, then the model called as a simple linear regression model.

$$y_t = c + ax_t + t \tag{20}$$

where;

e_t	error term,
x_t, y_t	variables,
c, a	constants.

In price forecasting studies, X axis is used for the time and Y axis is used for the price corresponding to the specified time value.

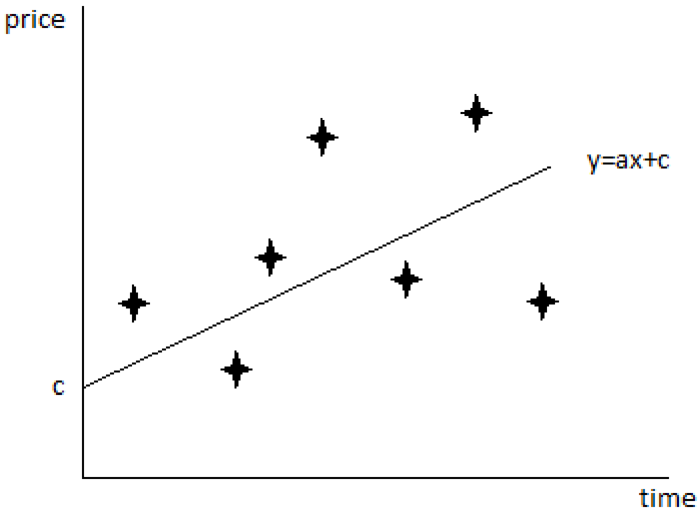

Figure 9 Best fitting curve at simple linear regression

In this model, error term for each data point is described as the distance from the best fitting curve. Sum of all error terms (e_t) for best fitting curve must be zero.

$$E(e_t) = 0 \tag{21}$$

Standard deviation of y_t and e_t must be same. Variance σ^2 described as the square of standard deviation.

$$\sigma^2(y_t) = \sigma^2(e_t) = \sigma^2 \tag{22}$$

To find the best fitting curve, if the data sample points show non linear characteristics, sum of error terms will be different than zero and this method comes insufficient. In most cases, to find the best fitting curve, square of each error terms are taken to eliminate negative sign and added. This term is called as sum of square errors (SSE). The polynomial giving the minimum SSE is the best fitting curve for linear regression.

$$\sum[y_t - (a + bx_t)]^2 = Q \tag{23}$$

For Q minimum;

$$b = [(x_t - x_m)(y_t - y_m)]/[\sum(x_t - x_m)^2]$$

$$a = y_m - bx_t$$

$$x_m = (\sum x_t)/t \tag{24}$$

$$y_m = (\sum y_t)/t$$

Then, the fitted curve for forecasting will be;

$$y' = a + bx \tag{25}$$

If data points show an exponential behavior, then taking logarithm will be an efficient way for linearization.

For more precise results, more than one variable can be used for forecasting. This method called as multiple linear regression.

$$y_t = a + bx_{t1} + cx_{t2} + dx_{t3} + \cdots + e_t \tag{26}$$

To define the relationship between variables, correlation between each variable must be defined separately. For two independent variable equation, correlation matrix is given below.

$$\begin{array}{c} \\ x1 \\ x2 \\ y \end{array} \begin{array}{c} \begin{array}{ccc} x1 & x2 & y \end{array} \\ \begin{bmatrix} 1 & R_{12} & R_{y1} \\ R_{12} & 1 & R_{y2} \\ R_{y1} & R_{y2} & 1 \end{bmatrix} \end{array}$$

Sum of square errors (SSE) term must be minimum.

$$\sum e_t{}^2 = \sum (y_t - y'_t)^2 \tag{27}$$

Partial differentiation of SSE will be zero. By differentiating SSE by means of each coefficient, equation system below obtained.

$$\frac{\partial(SSE)}{\partial a} = \frac{\partial(SSE)}{\partial b} = \frac{\partial(SSE)}{\partial c} = 0 \tag{28}$$

Then;

$$\sum y_t = na + b\sum x_{t1} + c\sum x_{t2}$$

$$\sum x_{t1}y_t = a\sum x_{t1} + b\sum x_{t1}^2 + c\sum x_{t1}x_{t2} \tag{29}$$
$$\sum x_{t2}y_t = a\sum x_{t2} + b\sum x_{t1}x_{t2} + c\sum x_{t2}^2$$

Solving these equations will give a,b,c coefficients. Basic terms for multiple linear regression are given below:

- Sum of all squares (SSTO);

$$\sum(y_t - y_m)^2 \tag{30}$$

- Sum of squares error (SSE);

$$\sum {e_t}^2 = \sum(y_t - {y'}_t)^2 \tag{31}$$

- Sum of squares regression (SSR);

$$SSTO - SSE = \sum({y'}_t - y_m)^2 \tag{32}$$

- Multiple correlation coefficient(R);

$$R = \sqrt{SSR/SSTO} \tag{33}$$

3.7. GARCH Models

General Auto Regressive Conditional Heteroscedastic (GARCH) models are used when the sampled data points have spikes. Normal ARIMA models assume these spikes as statistically meaningless. ARIMA models have constant variance and covariance functions and expected value of the error term is assumed to be zero. However, electricity values may vary too much if time series build on hourly, daily or weekly periods. In this case, for more precise solutions, GARCH models preferred instead of ARIMA models. GARCH models basically treats error term as AR time series. General form of GARCH model is given below.

$$y_t = C + \sum_{i=1}^{p} \theta_i y_{t-i} + \sum_{j=1}^{q} \theta_j u_{t-j}^2 \tag{34}$$

where u_t is white noise.

3.8. Artificial Neural Networks (ANN) Model

Artificial neural network, inspired by human brain, is a parallel and distributed information processing system consisting of weighted links through the processing elements connected to each other and each of them has its own memory structures. In other words, artificial neural network is a computer program that mimics biological neural networks. Basic element of the human brain is the neuron and there are approximately 10^{11} neurons at the cortex of the human brain. Those neurons are interconnected with each other and each neuron has 10000 connections through synapses. A typical neuron consists of four parts as cell body or soma, axon, dendrite and synapses as shown in Figure 10.

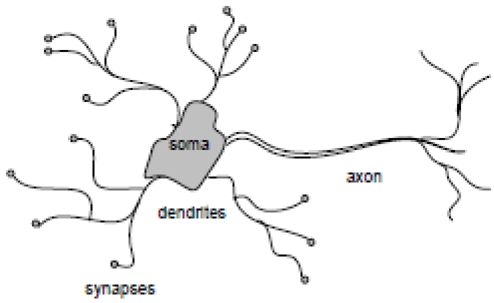

Figure 10 Biological neuron structure [14]

Communication between cells occurs as a result of electrochemical reactions. Dendrites collect the input signals from other cells together with the weights given to signals by synapses. The weight is either excitatory or inhibitory which means that potential of input signal is increased by excitatory weight while the potential of signal is decreased by inhibitory weight. Those signals are processed and summed inside the soma and when the sum goes beyond a certain threshold, the soma will fire an action potential through an axon which transfers the potential to other neurons by synapses. After firing the action potential, the soma will reset the voltage to the resting potential, and it has to wait some time until it can fire another potential.

Artificial neural networks can be modeled as a mathematical form of a biological neuron which is shown in Figure 11. Input vector works as a dendrite and collect information from outside. The weight vector gives weight to the information as synapses. The summing element represented as a soma sums all of the information and the transfer function fires the potential when the threshold value is exceeded and finally output vector gives the result as axon of the neuron.

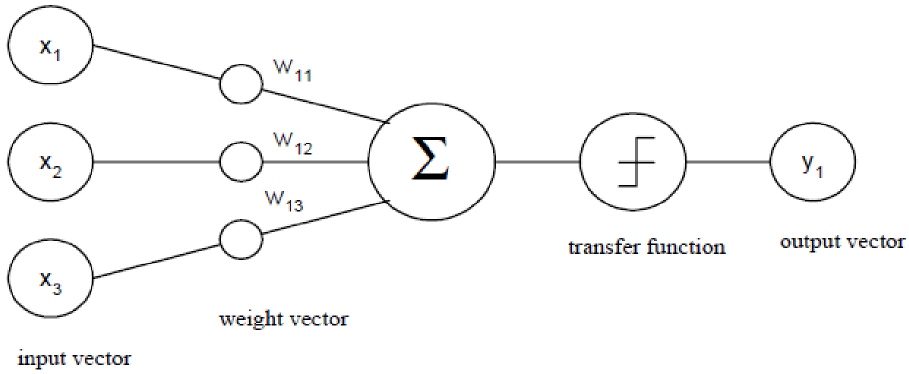

Figure 11 Mathematical model of a neuron

The neuron receives information through an input vector containing R elements and x_1, x_2, ... x_R are the input elements. The inputs are multiplied by a weight vector corresponding to the individual input elements and here denoted by w_1 , w_2, ... w_R . The dot product of the inputs with corresponding weights are summed with a single bias value b and the output of the summer is then fed to the transfer function φ . The output y is calculated through the transfer function and the mathematical explanation of the output is shown in the following equation:

$$y = \varphi(b + \sum_{i=1}^{R} x_i \bullet w_i) \tag{35}$$

The transfer function φ may be linear or nonlinear function and it is a mathematical representation in terms of spatial or temporal frequency of the relation between the input and output [17]. Some of the transfer functions used frequently in artificial neural network is shown in Figure 12. Generally, transfer functions squeeze the output of neural networks into a certain range and this range is usually between 0 to 1 or -1 to 1. Hard-limit transfer function (step function), multistep transfer function and sigmoid function are the three major functions used in neural networks. In step function, the output is 1 when the summed input is equal or greater than threshold value and the output is 0 when the summed input is smaller than threshold value. Let φ be the transfer function and x be input. The hard-limit transfer function is represented as follows:

$$\varphi\ (\mathrm{x}) = \begin{cases} 1 & if\ x \geq 0 \\ 0 & if\ x < 0 \end{cases} \tag{36}$$

In multistep transfer function, the output is 1 or 0 at both threshold values and when the summed input is between these two threshold values, the output is a semi-linear function. The multistep transfer function is represented as follows:

$$\varphi(x) = \begin{Bmatrix} 1 & x \geq \theta_2 \\ (x-\theta_1)/(\theta_2-\theta_1) & \theta_2 \geq x \geq \theta_1 \\ 0 & x \leq \theta_1 \end{Bmatrix} \tag{37}$$

Although there are several advantages of using above functions such as high speed of calculation and easy realization in the hardware, these functions are not suitable for neural networks when the backpropagation technique is preferred because these functions have discontinuous derivatives which prevent the gradient based error minimization procedures. Sigmoid transfer functions are the most frequently nonlinear transfer functions used in neural networks because it is easily differentiable thus permitting the evaluation of weight increments via the chain rule for partial derivatives which is used for gradient based error minimization in backpropagation procedures. All sigmoid transfer functions have the common *S* shape that is essentially linear in the center and nonlinear toward their bounds that are approached asymptotically [18]. The most popular sigmoid functions are the logistic sigmoid function and the hyperbolic tangent function. The logistic sigmoid function, shown in Eq. (38) takes the input that varies between plus and minus infinity and squashes the output into the range 0 to 1. The hyperbolic tangent function, shown in Eq. (39) squashes the output into the range -1 to 1.

$$\varphi(x) = \frac{1}{1+e^{-x}} \tag{38}$$

$$\varphi(x) = \tanh(x) = \frac{2}{1+e^{-2x}} - 1 \tag{39}$$

Although there are different kinds of ANN structures used in the literature such as single layer network, Hopfield network and Kohonen network, multilayer perceptron is most common and widely used kind of ANN architecture. This architecture is feedforward, i.e., information flows from input to output (in one direction) and there is no loop in this architecture. The multilayer perceptron consists of one input layer, one or more hidden layer and an output layer. Determination of the number of hidden layer and neurons for each layer is based on tradeoffs and there is still no best method to find these values. According to the literature, for time series modeling and price forecasting applications, three-layered feedforward neural network is the simplest and most widely used kind of ANN architecture shown in Figure 13 [13].

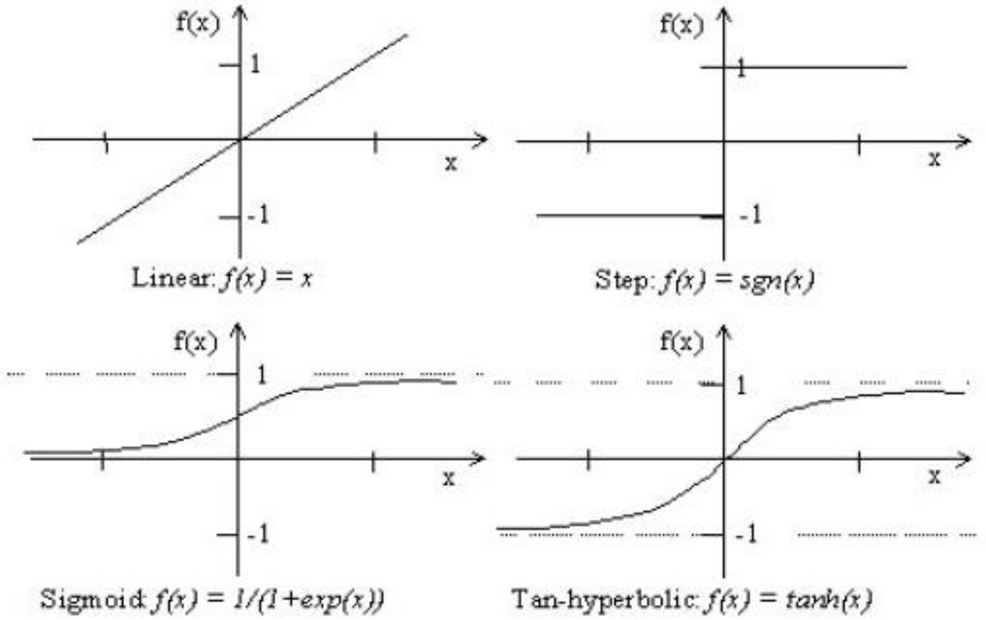

Figure 12 Common transfer functions used in artificial neural networks

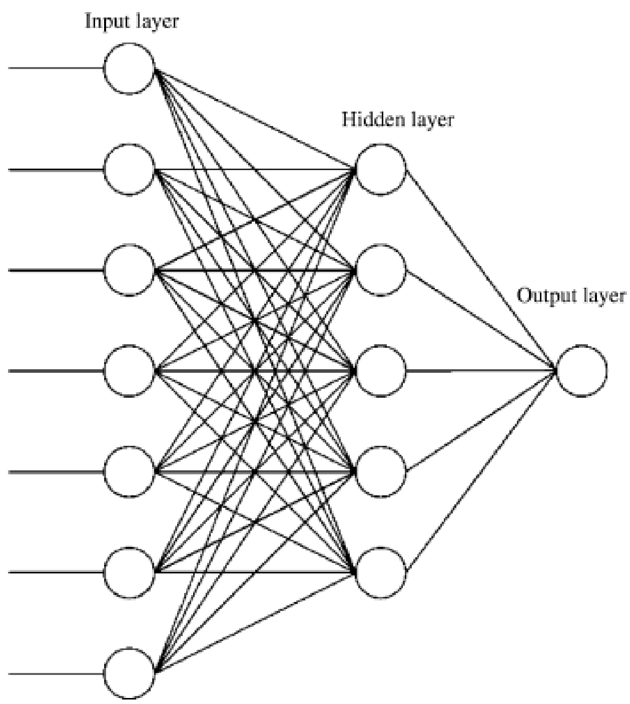

Figure 13 Example of a three layer feedforward neural network model

In the three-layered feedforward neural network, each input neuron in the input layer is connected to all hidden neurons in the hidden layer and each hidden neuron is connected to output neuron in the output layer. As mentioned at the beginning of this part, the signals taken by input neurons are multiplied by corresponding weights and summed at the hidden layer. Then they are activated by transfer functions. Let *i, j and k* refers to input, hidden and output layers respectively, x_i refers to input, w_{ji} refers to weight between input and hidden layer, v_j refers to summed signal in the hidden layer and φ_j refers to transfer function in the hidden layer. The summed signal v_j can be expressed as:

$$v_j(n) = \sum_{i=1}^{n} x_i(n) w_{ji}(n) \tag{40}$$

where n is the number of input neurons. The activated sum x_j through the transfer function in the hidden layer can be expressed as:

$$x_j = \varphi_j(v_j) + b_j \tag{41}$$

where b_j is the threshold value in the hidden layer. Usually logistic or hyperbolic tangent sigmoid transfer functions are utilized in the hidden layer.

The activated sum x_j in the hidden layer is multiplied by weight w_{kj} between hidden and output layers and summed at the output layer. These summed signals are activated by transfer function in the output layer. Let v_k refers to summed signal at the output layer, φ_k refers to transfer function and y_k refers to the output signal. The summed signal v_k at the output layer can be expressed as:

$$v_k(m) = \sum_{j=1}^{m} x_j(m) w_{kj}(m) \tag{42}$$

where m is the number of hidden neurons in the hidden layer. The output signal y_k at the output layer through the transfer function can be expressed as:

$$y_k = \varphi_k(v_k) + b_k \tag{43}$$

where b_k is the threshold value at the output layer. Usually linear function is utilized as a transfer function in the output layer.

The main advantage of using ANN in forecasting applications is its ability to learn. Forecasting applications with artificial neural networks consist of two steps: training and testing. In the training process, a training data containing both inputs and corresponding outputs (targets), i.e., $[x_1, t_1]$, $[x_2, t_2]$, …$[x_r, t_r]$ where X_r is the input vector and T_r is the target vector, is applied to the neural network. The success of the ANN training is highly dependent on the proper selection of training data. Once the training data is applied, the output produced by transfer functions of the neural network at the output layer is compared with the targeted output and the error is calculated. At each iteration, the neural network adjusts its weights and biases in order to minimize this error until an acceptable error value is achieved which means that the neural network learns to training data. Therefore, the training is an optimization process and it begins with random weights and biases and the goal is to adjust them so that the error will be minimal.

In the testing process, the trained neural network is tested by applying new data (testing data) that the network has never seen in the training process and the purpose of testing is to check the generalization ability and forecasting accuracy of the neural network for this unseen data [13]. Generally, 85% of the data is used for the training process whereas 15% for the testing process. Overtraining of the neural network should be avoided because too much or wrong information in the training process results the neural network being confused and poor generalization ability of the new data outside the training set.

The most popular and widely used training algorithm is the backpropagation algorithm. In this algorithm, the input is multiplied with the corresponding weights and summed at the hidden layer and passed through the transfer function in order to find the network output, which is then compared to the actual output to calculate the error. This error is propagated back and the network adjusts its weights and biases at each layer in order to minimize the error until the convergence criteria are achieved. Backpropagation is done by gradient descent technique which is discussed below:

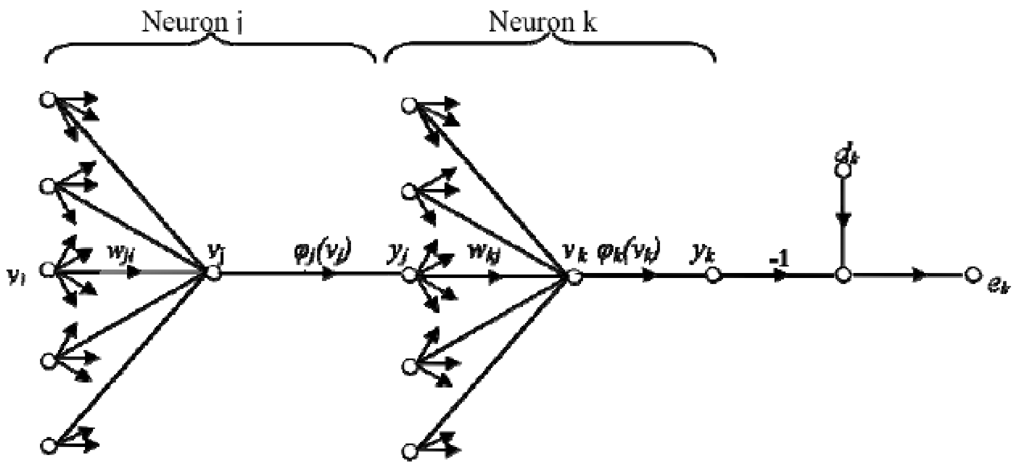

Figure 14 Signal flow diagram inside neural network

The error at the output neuron k is defined as:

$$e_k = y_k - d_k \tag{44}$$

The sum-squared error in the network is given by Eq. (45). Here the error is squared because the magnitude of the error instead of its sign is important.

$$E = \frac{1}{2}\sum_{k=1}^{p}(y_k - d_k)^2 \tag{45}$$

where p is the total number of the neuron at the output layer. The output of neuron k is:

$$y_k = \varphi_k(v_k) = \varphi_k(\sum w_{kj} y_j) \tag{46}$$

where φ_k is the activation function at the output layer. Generally pure linear (purelin) transfer function is used in the output layer as follows:

$$y_k = \varphi_k(v_k) = v_k \tag{47}$$

Since the goal is to minimize the error with adjusting the weights, we need to find the derivative of E with respect to w_{kj}. The adjustment of each weight using the method of gradient descendent at neuron k is:

$$\Delta w_{kj} = -\eta \frac{\partial E}{\partial w_{kj}} \tag{48}$$

where η is a constant that denotes the learning rate.

By chain rule, $\partial E / \partial w_{kj}$ can be expressed as:

$$\frac{\partial E}{\partial w_{kj}} = \frac{\partial E}{\partial y_k}\frac{\partial y_k}{\partial v_k}\frac{\partial v_k}{\partial w_{kj}} \tag{49}$$

Differencing Eq. (45) w.r.t y_k

$$\frac{\partial E}{\partial y_k} = (y_k - d_k) = e_k \tag{50}$$

Differencing Eq. (47) w.r.t v_k

$$\frac{\partial y_k}{\partial v_k} = 1 \tag{51}$$

Derivative of v_k w.r.t w_{kj} is:

$$\frac{\partial v_k}{\partial w_{kj}} = \frac{\partial(\sum w_{kj} y_j)}{\partial w_{kj}} = y_j \tag{52}$$

Thus, using equations (50) to (52), Eq. (49) can be expressed as:

$$\frac{\partial E}{\partial w_{kj}} = (y_k - d_k).1.y_j = (y_k - d_k)y_j \tag{53}$$

The adjustment Δw_{kj} applied to w_{kj} is:

$$\Delta w_{kj} = -\eta(y_k - d_k)y_j = -\eta\delta_k y_j \tag{54}$$

where δ_k denotes local gradient at layer k.

The next step is to determine the weight adjustment for layer j, i.e., Δw_{kj} :

$$\Delta w_{ji} = -\eta \frac{\partial E}{\partial w_{ji}} = -\eta (\sum_k \frac{\partial E}{\partial y_k} \frac{\partial y_k}{\partial v_k} \frac{\partial v_k}{\partial y_j}) \frac{\partial y_j}{\partial v_j} \frac{\partial v_j}{\partial w_{ji}} \tag{55}$$

The output of neuron j is:

$$y_j = \varphi_j(v_j) = \varphi_j(\sum w_{ji} x_i) \tag{56}$$

where φ_j is the activation function at the hidden layer. Generally logistic sigmoid (logsig) transfer function is used in the hidden layer, thus:

$$y_j = \varphi_j(v_j) = \frac{1}{1+e^{-v_j}} \tag{57}$$

Derivative of y_j w.r.t v_j is:

$$\frac{\partial y_j}{\partial v_j} = \frac{e^{-v_k}}{(1+e^{-v_k})^2} = y_j(1-y_j) \tag{58}$$

Derivative of v_j w.r.t wji

$$\frac{\partial v_j}{\partial w_{ji}} = \frac{\partial(\sum w_{ji} x_i)}{\partial w_{ji}} = x_i \tag{59}$$

Now substituting previous results back into Eq. (55) we have:

$$
\begin{aligned}
\Delta w_{ji} &= -\eta \frac{\partial E}{\partial w_{ji}} = -\eta (\sum_k (y_k - d_k) w_{kj}) y_j (1 - y_j) x_i \\
&= -\eta (\sum_k \partial_k w_{kj}) y_j (1 - y_j) x_i \\
\Delta w_{ji} &= -\eta \partial_j x_i
\end{aligned}
\tag{60}
$$

where local gradient ∂_j at the hidden layer j can be defined as:

$$\partial_j = \sum_k \partial_k w_{kj}) y_j (1 - y_j) \tag{61}$$

3.9. Electricity Price Forecasting Evaluation

To evaluate the accuracy of various models in price forecasting, different indicators are used in the literature. The most popular and widely used ones are mean absolute error (MAE), mean squared error (MSE), daily and weekly mean absolute percentage error (DMAPE and WMAPE), root mean squared error (RMSE), sum squared error (SSE). The formulae of all of these performance indicators are as follows:

$$MAE = \frac{1}{n} \sum_{t=1}^{n} \left| (a_t - f_t) \right| \tag{62}$$

$$MAPE = \frac{1}{n}\sum_{t=1}^{n}\frac{|a_t - f_t|}{\frac{1}{n}\sum_{t=1}^{n} a_t} x100\% \tag{63}$$

$$DMAPE = \frac{1}{24}\sum_{t=1}^{24}\frac{|a_t - f_t|}{\frac{1}{24}\sum_{t=1}^{24} a_t} x100\% \tag{64}$$

$$WMAPE = \frac{1}{168}\sum_{t=1}^{168}\frac{|a_t - f_t|}{\frac{1}{168}\sum_{t=1}^{168} a_t} x100\% \tag{65}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{t=1}^{n}(a_t - f_t)^2} \tag{66}$$

$$SSE = \sum_{t=1}^{n}(a_t - f_t)^2 \tag{67}$$

where;

a_t : Actual price at time t

f_t : Forecasted price at time t

The forecasting performance of the time series models in different electricity markets are shown in Table 1.

Table 1 Forecasting performance comparison of time series models

Reference No	Model Type	Data Used (days)	Predicted Period	Level of Accuracy	Time Horizon
[24]	AR, ARMA	442	45 days	WMAE 3-7%	1-7 DA
[25]	AR, ARMA	272	4 weeks	WMAPE 3-11.1%	1 DA
[26]	GARCH	147,105	12 months	WMAPE 9-11%	1 DA
[27]	DR, TF	81,135,92	2 weeks, 1 week	DMAPE 3-5%	1 DA
[28]	ARIMA	145,85,73, 92	3 and 11 weeks	WMAPE 8-20% (Ave. 11%)	1 DA
[29]	ARIMA	48	4 weeks of 4 seasons	WMAPE 5-27%	1 DA
[30]	Multivariate ARMA	27	1 week	DAPE min 0.1-5.3% DAPE max 52.2-98.7%	1 DA
[31]	MLR	28	4 weeks of 4 seasons	WMAPE 7-18.5%	1 DA
[32]	ANN	14/28	1 day, 30 days	DMAPE 20-38%	1 DA
[33]	ANN	77	1 week	DMAPE 11.57-12.86%	1DA
[34]	ANN	28	2 weeks	MAPE 8.44-15.87%	1 DA
[35]	ANN	90	1 week, 1 month	WMAPE 10.69-25.77%	1-6h ahead
[36]	ANN	7-56	1 week	WMAPE 11-13%	Short term

Table 1 (cont'd)

[37]	ANN	-	1 week	DMAPE 10-20%	1 DA
[38]	ANN	-	1 week	WMAPE 15.5%	1 DA
[39]	ANN	48	4 weeks of 4 seasons	Av. WMAPE 7.5%	1 DA

CHAPTER 4

ANN BASED SGOF AND SMF FORECASTING IN TURKISH ELECTRICITY MARKET

4.1. Proposed ANN Model

Introduction of restructuring in the electric power industry made electricity price forecasting very important activity for all market participants in the electricity markets. On one hand, while precise short-term price forecasting in the spot market assists the power suppliers build their bidding strategies to achieve the maximum profit; on the other hand, in order to maximize their utilities consumers can derive a plan by using the electricity purchased from the pool, or through usage of self-production capability to protect themselves against high prices. Traditional generation scheduling of energy resources in the regulated framework was based on cost minimization [1]. In the new deregulated framework, since generation scheduling of energy resources, such as hydro resources [12], is now based on profit maximization, forecasting of the electricity prices has become essential for development of negotiation skills for achievement of better profits. For the same reasons as producers, consumers as well need short-term electricity prices forecast.

Among the tools for forecasting, neural networks are simple, but powerful and flexible forecasting tools, if there is enough data for training, an adequate selection of the input–output samples, an appropriate number of hidden units and enough computational resources provided. Also, due to the reason that neural networks are data-driven [6], they have the approximation ability advantages of any nonlinear function and solving the problems where the input–output relationship is neither well defined nor easily computable. According to the literature, single hidden layer feed forward network [13] is most popular model for time series modeling and forecasting. This type of network used in the literature for price forecasting [12] has the sigmoid functions for hidden layers and linear functions for output layers.

Data selection and model structure development are the first stage in developing an ANN model, and are very essential and time consuming process. This is a necessary step for the ANN to model the input-output relationship. This stage of data selection and preprocessing includes extraction of the unnecessary information from the input data set and determination of the necessary input factors which influence the electricity price. If there is unnecessary information, ANN would become over fitted and will have poor performance on one hand, and on the other hand, if the input data is not enough, the network will inflexible to model the input-output relationship [6]. It is known that many physical factors influence the electricity price, where some factors have more dominant effects than the others. Being that the weather factors effect are included in the demand information, as well as some factors that influence the price such as; generator outages and bidding strategies, information are not publicly available, so generally the historical price, historical load and forecasted load are considered as input parameters of the ANN.

This part will study the methodology to select the optimum ANN architecture that for day-ahead price forecasting problem can provide the minimum daily mean absolute percentage error (DMAPE). Definition of the training and transfer function, quantity of input parameters, quantity of training vectors, impact of data-preprocessing and quantity of hidden neurons will be done through selection of the optimum ANN architecture. In this study 01/01/2011 to 31/12/2011 data of the Turkish electricity market including system hourly loads and SGOF are used. Load and price curves of the whole year are showed on Figures 15. A typical low and a high demand days are selected as the target forecasting days for assessing the performance of the proposed ANN architecture. These are 20/02/2011 and 28/07/2011, respectively. In order to better understand the correlation between load and price, whole year load and price graph is more closely examined and Figure 16 is given as an example that shows load and price curve between 18/07/2011 and 31/07/2011, i.e., 2 weeks. As seen from Figure 16 that load and price shows positive correlation with each other and when load decreased, price decreased and when load increased, price increased and on weekends, especially on Sundays, load and price values are lower than those of the other days.

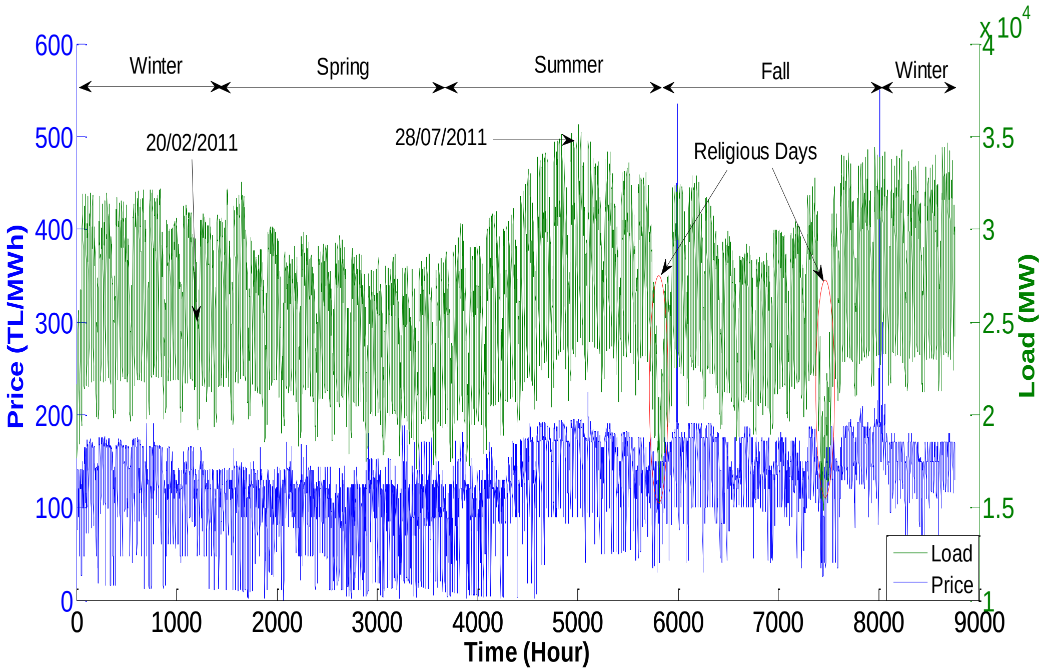

Figure 15 Load and price curve of Turkish electricity market from 01/01/2011 to 31/12/2011

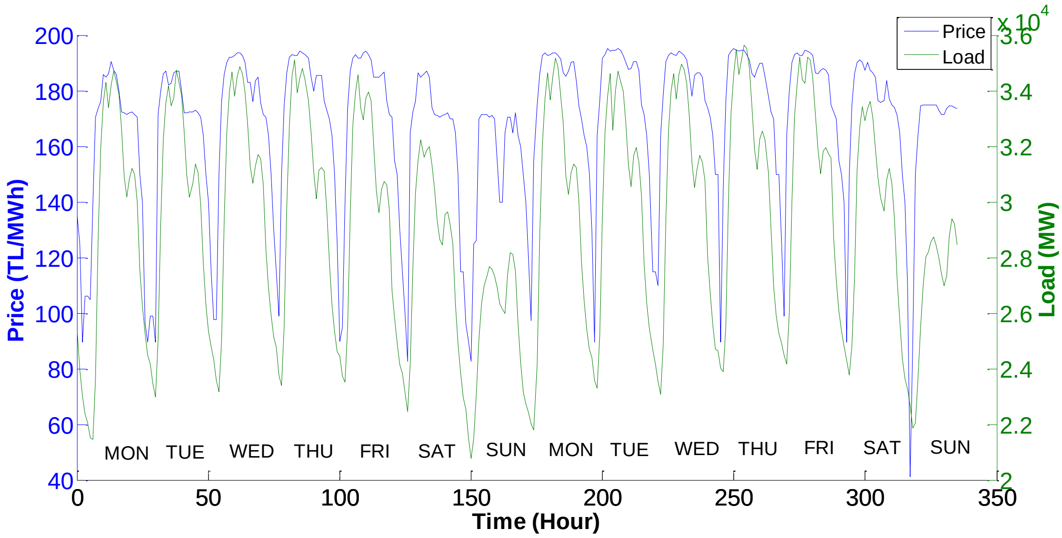

Figure 16 Load and price curve of Turkish electricity market from 18/07/2011 to 31/07/2011

4.1.1 Training and Transfer Function Selection

For selection of the most suitable training and transfer functions of the ANN for the Turkish electricity market day-ahead price forecasting, and in order to achieve minimum daily MAPE for the test sets, the combinations of the training functions given in Table 2 and transfer functions 'logsig' and 'tansig' of the MATLAB neural network toolbox are considered. As mentioned before, due to its easily differentiable property which is permitting the evaluation of weight increments via the chain rule for partial derivatives that is used for gradient based error minimization in backpropagation procedures [18], 'logsig' and 'tansig', which are the most widely used transfer functions in the literature, are used for the transfer functions of the ANN in this study.

Since the weights of ANN are initialized randomly, in every train and test of the ANN, different result can be achieved. So, In order to not to depend on the single training process, the training and testing procedure is repeated ten times for each case with the average results shown in Figures 17-18**.**

Table 2 Training functions of MATLAB neural network toolbox

Name	Description
traingda	Gradient descent with adaptive learning rate backpropagation
trainlm	Levenberg-Marquardt backpropagation
traingdx	Gradient descent with momentum and adaptive learning rate backpropagation
trainrp	Resilient backpropagation
traincgb	Conjugate gradient backpropagation with Powell-Beale restarts
trainscg	Scaled conjugate gradient backpropagation

Figures 17-18 presents performances of various combinations of training and transfer functions. These figures show that the most suitable combination is *traincgb* as training function and *logsig* as transfer function, i.e., MAPE of 8.88% for 20/02/2011 and MAPE of 3.09% for 28/07/2011. *Traincgb* is a network training function that updates weight and bias values according to the conjugate gradient back propagation with Powell-Beale restarts and the *logsig* is the log sigmoid transfer function. According to the results, it can be seen that the MAPE of 28/07/2011 (3.09%) is much smaller than the MAPE of 20/02/2011 (8.88%). The reasons behind is that in order to forecast hourly day ahead price, we use previous day same hour and previous week same hour information as input to the proposed ANN model which is given in Figure 25 and when we analyze the correlation of 20/02/2011 and 28/07/2011 with their previous day and previous week inputs, we can see that 28/07/2011 have stronger correlation (R^2=0.8598) than 20/02/2011 (R^2=0.5759) and therefore the forecasting performance of 28/07/2011 is better than the forecasting performance of 20/02/2011.

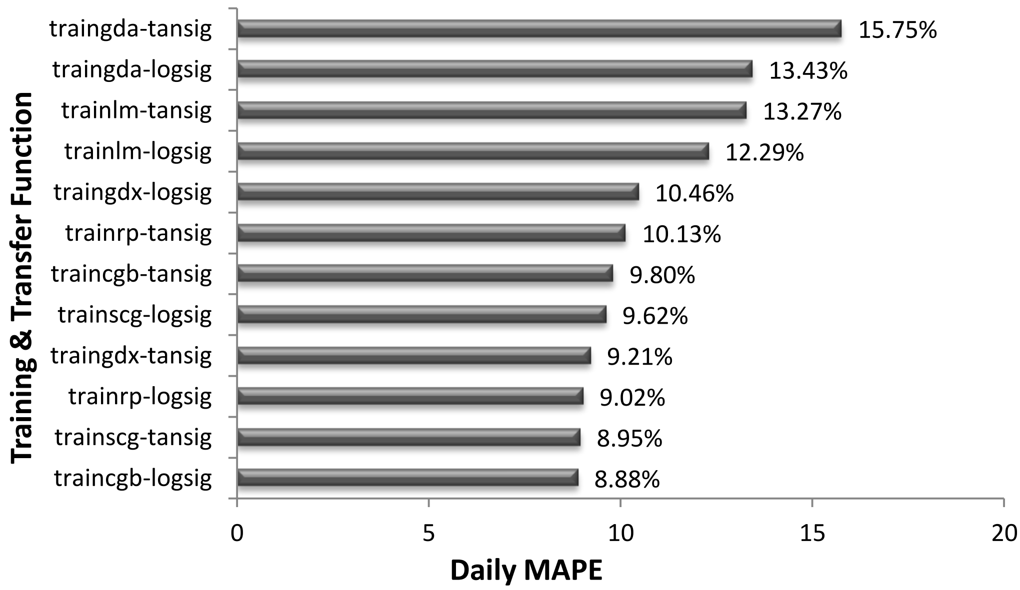

Figure 17 ANN based MAPE values of training and transfer function combinations for 20/02/2011

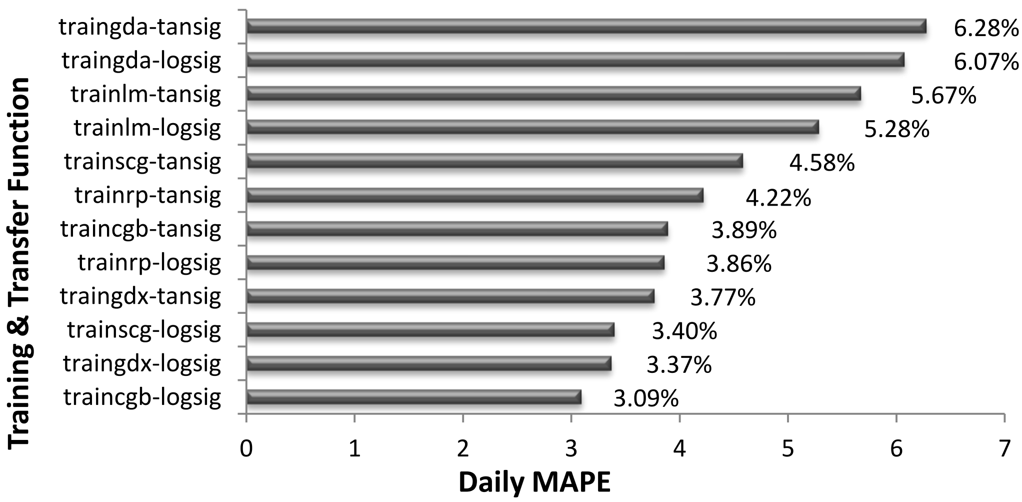

Figure 18 ANN based MAPE values of training and transfer function combinations for 28/07/2011

Figure 19 presents load and price relationship for 20/02/2011 together with 19/02/2011 (previous day) and 13/02/2011 (previous week same day). Figure 20 presents load and price relationship for 28/07/2011 together with 27/07/2011 (previous day) and 21/07/2011 (previous week same day). Figure 19-20 also shows the fitting curves and correlation coefficients.

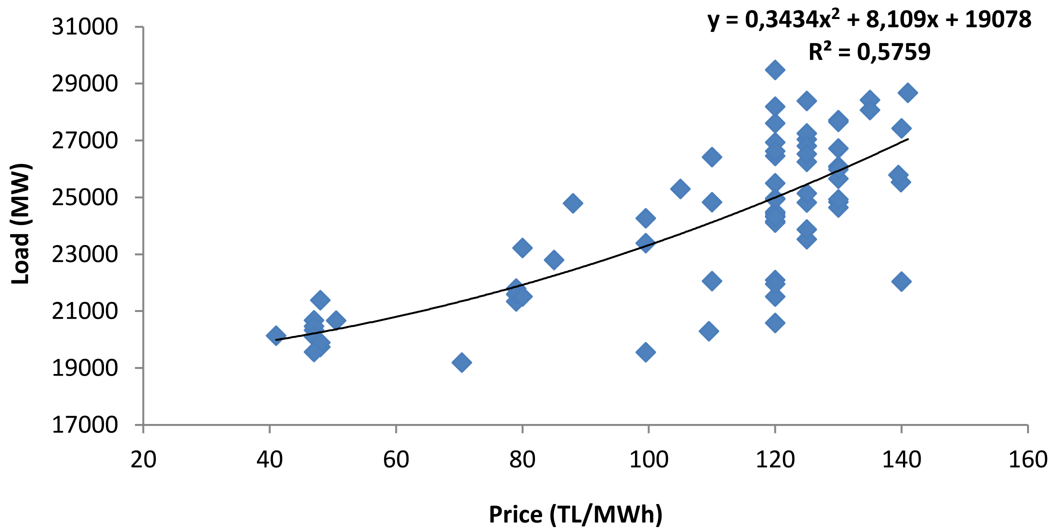

Figure 19 Load and price relationship for 20/02/2011, 19/02/2011 and 13/02/2011

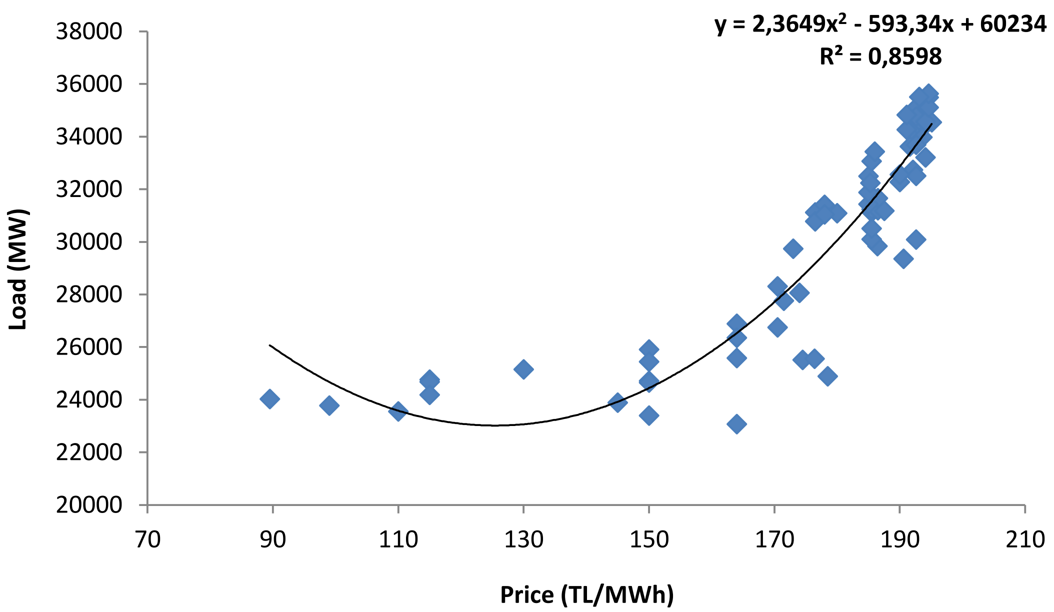

Figure 20 Load and price relationship for 28/07/2011, 27/07/2011 and 21/07/2011

4.1.2 Selection of Input Parameters and the Number of Training Vectors

This section will study the impact of the number of training vectors and types of input parameters on forecasting performance. For prediction of the 24 hourly prices for 20/02/2011 and 28/07/2011, selection of the appropriate numbers of training vectors and input parameters are needed.

In Table 3 three models with the factors that are considered in studying the impact of input vectors are presented. Historical information includes previous day same hour, previous week same hour and previous 24 hours average load and price information. Forecasted information includes the hourly load values for the forecasted day. In Table 4**,** the training period start from 02/01 to 19/02 and 20/02 is the test day. It is important to emphasize that the training period can vary from two weeks to seven weeks as indicated in column 1 of Table 4**,** where case numbers show the number of weeks of training. In Case 1, the training period starts from 06/02 to 19/02 (lasting for 2 weeks), this means 2 weeks before the forecast day. In Case 2, the training period starts from 30/01 to 19/02 (lasting for 3 weeks). In Case 6, the training period starts from 02/01 to 19/02 (lasting for 7 weeks). The training periods of the remaining cases for predicting SGOF of 28/07 and also the cases given in Table 5 are defined in the similar way. The procedure of training and testing is repeated ten times for each model type and training periods that present the average DMAPE results.

Table 3 Input factors considered in different model types

Factors	Model 1	Model 2	Model 3
Historical Price	√	√	√
Historical Load		√	√
Forecasted Load			√

Table 4 Forecasting performance of different models for 20/02/2011

Case No	Training vectors	Training period	Testing average daily MAPE (%)		
			Model 1	Model 2	Model 3
1	2 week	06/02 - 19/02	17.674	14.263	13.279
2	3 week	30/01 - 19/02	13.971	10.177	9.34
3	4week	23/01 - 19/02	13.208	9.99	9.336
4	5week	16/01 - 19/02	13.878	10.75	***7.6***
5	6 week	09/01 - 19/02	12.264	10.313	10.987
6	7 week	02/01 - 19/02	12.35	9.823	8.239

Table 5 Forecasting performance of different models for 28/07/2011

Case No	Training vectors	Training period	Testing average daily MAPE (%)		
			Model 1	Model 2	Model 3
1	2 week	14/07 - 27/07	4.359	3.627	3.703
2	3 week	07/07 - 27/07	3.831	3.695	3.6121
3	4week	30/06 - 27/07	4.666	3.675	3.5127
4	5week	23/06 - 27/07	4.052	3.703	***3.468***
5	6 week	16/06 - 27/07	4.188	3.704	3.67
6	7 week	09/06 - 27/07	4.572	3.774	3.582
7	8 week	02/06 - 27/07	4.298	3.976	4.022

As Figure 21 and Figure 22 show, the worst forecasting performance is obtained if historical price is only considered as input to the ANN (i.e., Model 1). Also, better forecasting performance than that of Model 1 can be obtained if additional historical load information is considered as input to the ANN (i.e., Model 2). Furthermore, the forecasting performance improves if the forecasted load is considered as input (i.e., Model 3), and this gives the best result. Since both the previous and forecasted load and historical price information affect the price forecasting performance the result is reasonable. Because of the impact of number of training vectors on price forecasting performance of 20/02/2011 and 28/07/2011, the testing MAPEs with an increase in training vectors (from Case 1 to Case 4) would first decrease, then as the number of training vectors increases (from Case 4 to Case 7) general increase would take place. There are a number of reasons for this occurrence.

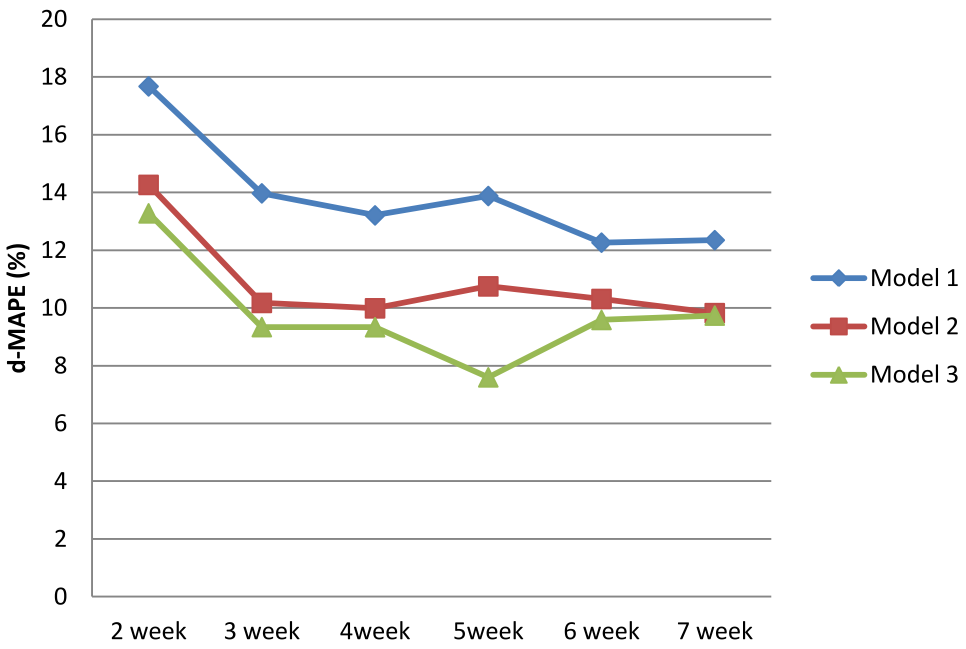

Figure 21 Impact of the number of training vectors and different models on DMAPE for 20/02/2011

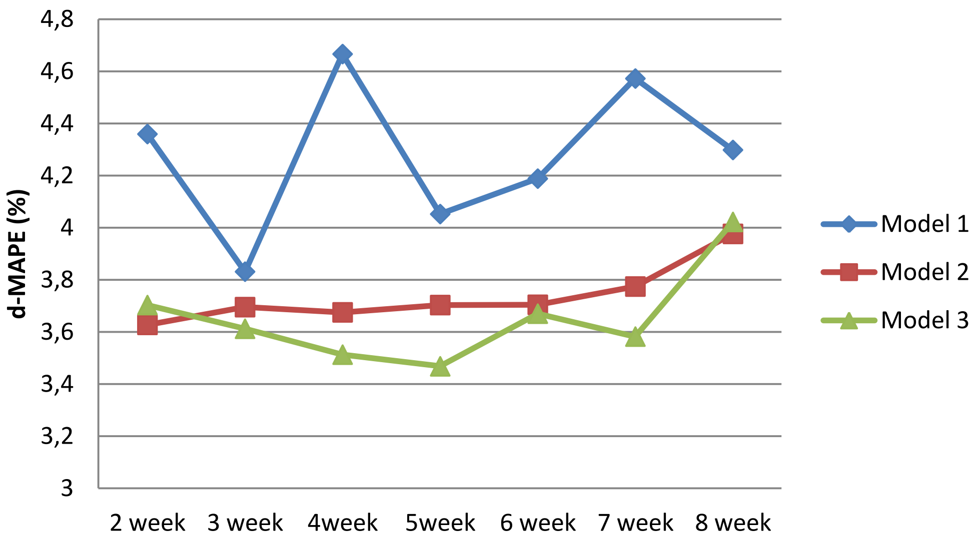

Figure 22 Impact of the number of training vectors and different models on DMAPE for 28/07/2011

First of all, by introduction of more training vectors, more diverse set of training samples are presented that will encourage more general input-output mapping. So, as measured by the testing MAPE the forecasting performance improves. Through further increase of the number of training vectors, ANN could become over-trained. This means that ANN has to adjust its weights in order to accommodate the input-output mapping of a large number of training vectors that to a large extent may not be similar to the testing data. This could worsen the forecasting performance due to further increase in the number of training vectors.

From this analysis it can be concluded that the minimum daily MAPEs such as 3.468% for 20/02/2011 and 7.6% for 28/07/2011 are obtained when using historical price, historical load and forecasted load information as input parameters and 5 weeks training periods for training ANN.

4.1.3 Selection of Number of Hidden Neurons

This section will study the impact of the number of the hidden neurons on price forecasting performance. During the 5 weeks training period, and based on the preceding analysis, the Model 3 is used as input parameters and the ANN is trained by traincgb as training function and logsig as transfer function. Figure 23 and Figure 24 show the testing MAPEs for 20/01/2011 and 28/07/2011 respectively. As Figure 23 and Figure 24 show that increasing the number of hidden neurons improves the forecasting performance because if the number of hidden neuron is too small, the network cannot find the complex relationship between input and output and may have difficulty in convergence during training. However, if we further increase the number of hidden neurons, the forecasting performance tends to decrease because a large number of hidden neurons harm the capability of network due to complicated interconnection structure and huge number of synaptic weights which results the ANN overfitted [14]. The minimum

MAPE for 20/02/2011 is achieved when ANN model has 15 hidden neurons and the minimum MAPE for 28/07/2011 is achieved when ANN model has 10 hidden neurons.

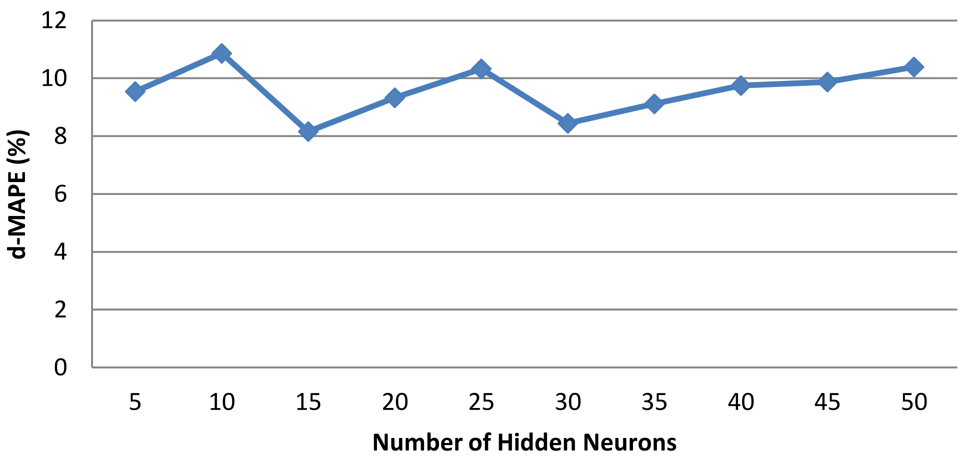

Figure 23 Impact of the number of hidden neurons on DMAPE for 20/02/2011

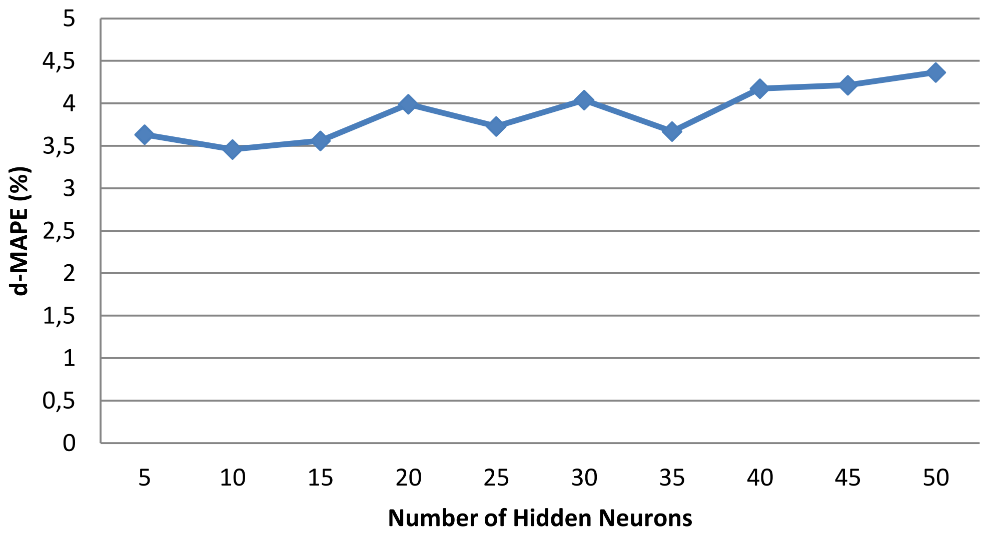

Figure 24 Impact of the number of hidden neurons on DMAPE for 28/07/2011

As mentioned at Figure 19 and Figure 20 that load and price relationship for 28/07/2011 has much stronger correlation than that of 20/02/2011 and therefore only 10 hidden neurons is enough for mapping input-output relationship for 28/07/2011. However, more hidden neurons are needed for mapping the input-output relationship for 20/02/2011 because of its lower correlation. Since the MAPE values of 10 and 15 hidden neurons for 28/07/2011 are close to each other, we can assume that the optimum ANN architecture for day ahead SGOF forecasting for Turkish electricity market has 15 hidden neurons.

4.1.4 Optimum ANN Architecture for Day-Ahead Price Forecasting

The architecture of the ANN is considered to be a three-layered feedforward that has 10-15-1 structure, meaning that the ANN consists of 10 input neurons, 15 neurons at the hidden layer and one output layer as discussed in Section 3.8 above. Figure 25 shows the ANN model implemented. 5 weeks or 35 days before the forecast day are the optimum number of training vectors. The optimum training and transfer function combination is “traincgb-logsig”.

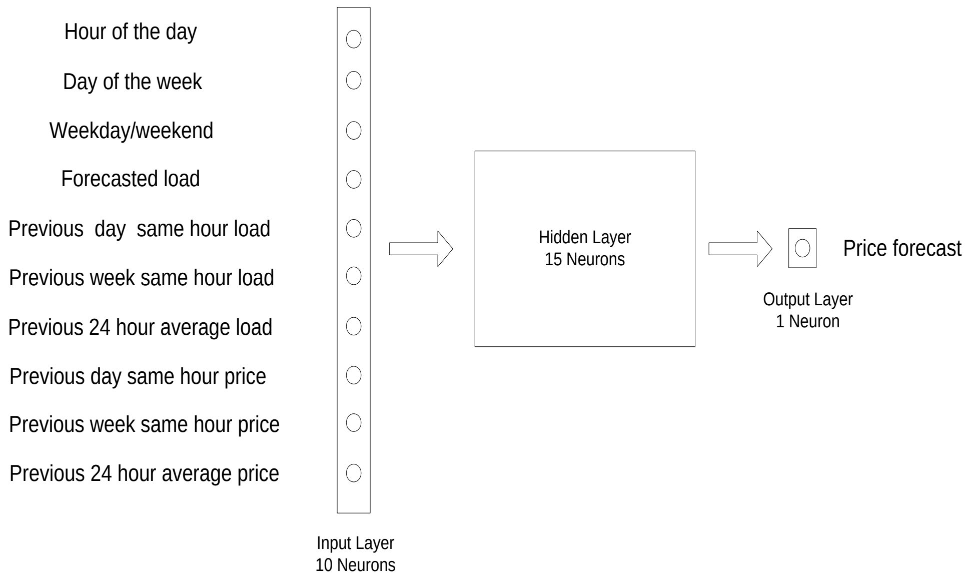

Figure 25 Proposed ANN model for SGOF forecasting

Table 6 Optimum ANN architecture for SGOF forecasting

Parameter	Value
Number of Input Neurons	10
Number of Hidden Neurons	15
Number of Output Neurons	1
Number of Training Vectors (weeks)	5
Training Function	Traincgb
Transfer Function	Logsig

Figure 26 and Figure 27 present the price forecasting results of 20/02/2011 and 28/08/2011 and the optimum ANN is trained through usage of the parameters of Table 6.

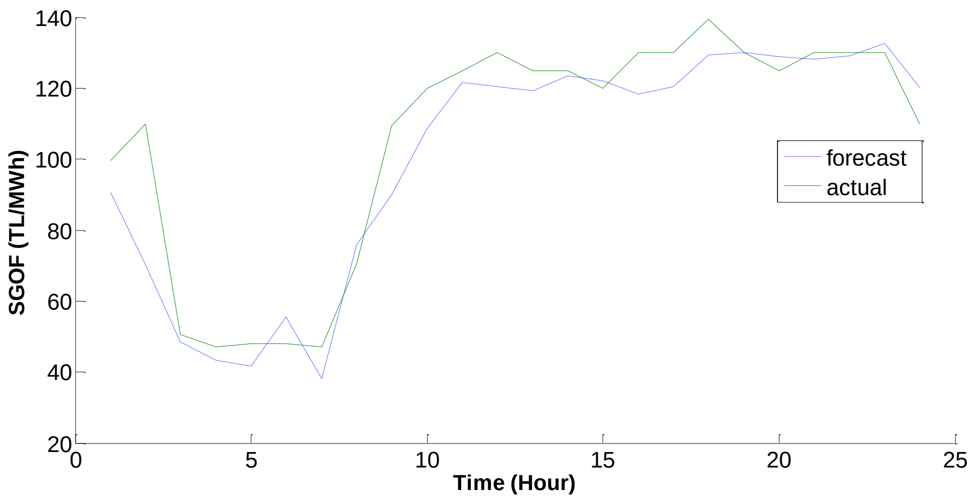

Figure 26 SGOF forecast for 20/02/2011

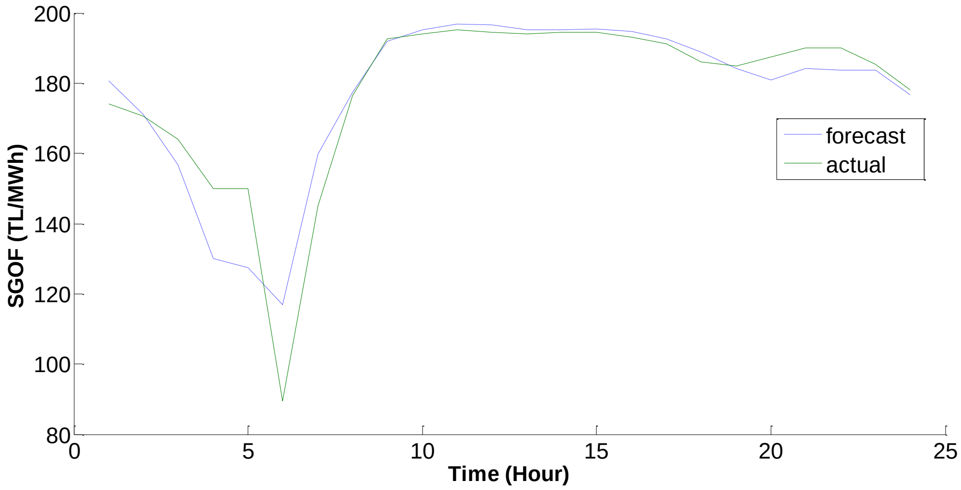

Figure 27 SGOF forecast for 28/07/2011

4.2 Application of the Proposed ANN Model

The proposed neural network approach is applied to forecast SGOF of the Turkish electricity market under many different cases, such as week-ahead price forecasting during different seasons (winter, spring, summer and autumn) of the year, weekdays and weekend days prediction, forecasting periods after price spikes (price truncation). The comparison of the MAPEs determined with the MLR is also made in Section 4.2.2.

4.2.1 Weekdays and Weekends

Time of day and type of day affect the price and load patterns because electricity price and loads show different patterns at different hours during the day and different characteristics at weekdays and weekends [19]. Some authors differentiate the data set between the type of day as weekdays and weekends for generating different models for each data set [20], [21], [22]. However, type of day information is used as input to the ANN model in this study instead of division of data set into weekdays and weekends.

Table 7 represents two different models with the factor that is whether considered or not in studying the impact of weekend and weekdays differences. In Case 1, the information about "type of day" (i.e., weekdays or weekends information) is not used as an input of the proposed ANN model. In Case 2, the "type of day" information is used as an input. According to Table 7, including the "type of day" information into the ANN model improves the forecasting performance, especially for Friday and weekends.

Table 7 Impact of the "type of day" information on average MAPE of weekdays and weekend

Testing	Training	Average MAPE (%)		Improvement
		Case 1	Case 2	
08/08, Mon	04/07 - 07/08	9.09	8.53	6.16%
09/08, Tues	05/07 - 08/08	5.27	5.00	5.40%
10/08 , Wed	06/07 - 09/08	3.57	3.26	8.68%
11/08, Thurs	07/07 - 10/08	11.97	11.66	2.63%
12/08, Fri	08/07 - 11/08	6.97	6.03	13.48%
13/08 & 14/08 Weekend	09/07 - 07/08	10.93	9.72	11.7%

4.2.2 Seasons

The performance of the proposed neural network model is checked for typical weeks of the four seasons, i.e., winter, spring, summer and autumn. The winter week is from 21/01 to 27/01, 2011 (testing set); the hourly data used to forecast this winter week are from 01/01 to 20/01, 2011 (training set). The spring week is from 06/04 to 12/04, 2011; the hourly data used to forecast this spring week are from 03/03 to 05/04, 2011. The summer week is from 25/07 to 31/07, 2011; the hourly data used to forecast this summer week are from 20/06 to 24/07, 2011. The fall week is from 13/09 to 19/09, 2011; the hourly data used to forecast this spring week are from 09/08 to 12/09, 2011. In all four different cases, type of day information is used as input to the ANN and training and testing process is repeated 10 times and minimum, maximum and average MAPEs are obtained.

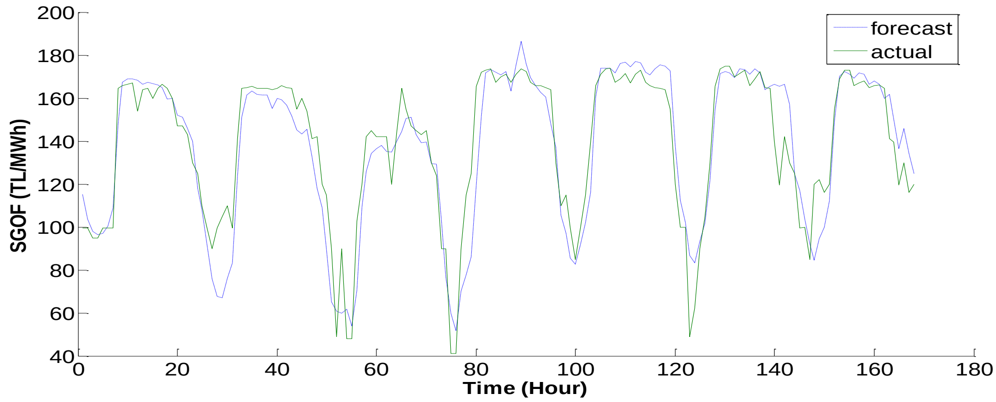

Figure 28 ANN based SGOF forecast for a winter week (from 21/1/2011 to 27/1/2011)

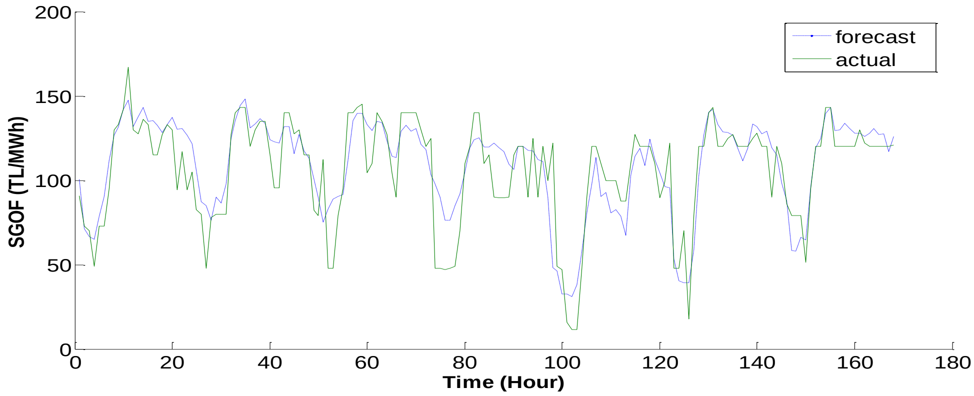

Figure 29 ANN based SGOF forecast for a spring week (from 6/4/2011 to 12/4/2011)

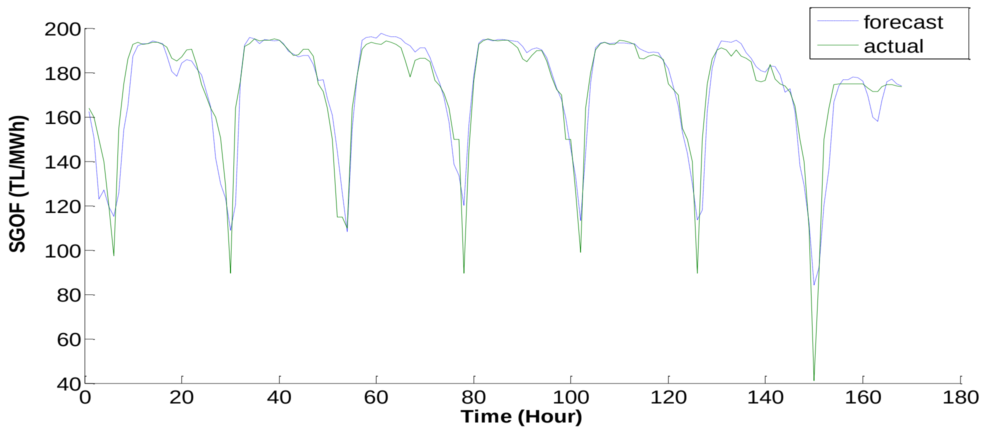

Figure 30 ANN based SGOF forecast for a summer week (from 25/7/2011 to 31/7/2011)

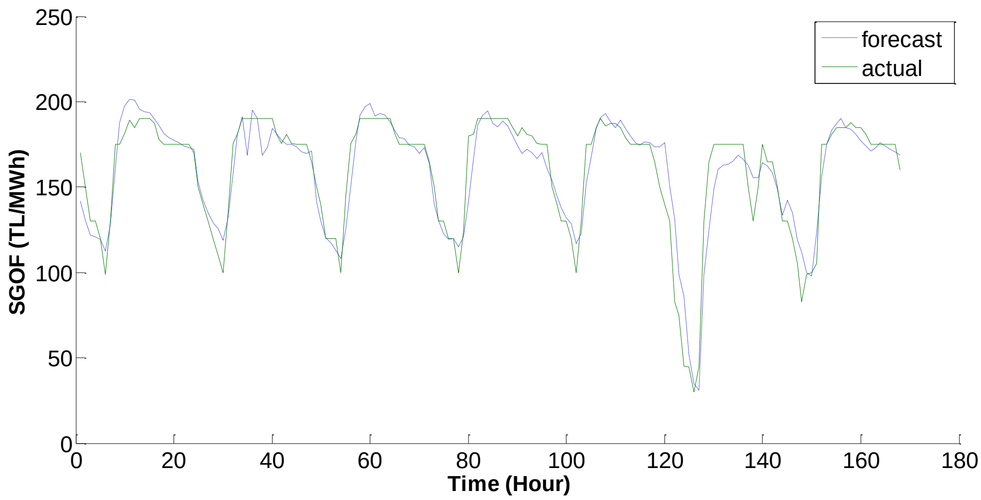

Figure 31 ANN based SGOF forecast for a fall week (from 13/9/2011 to 19/9/2011)

Figures 28-31 show the results with the proposed ANN approach for the four weeks studied. Each figure shows the forecasted prices, dashed line, together with actual prices, solid line.

As seen from Figures 28-31, the proposed ANN model can forecast week ahead prices accurately for the winter, summer and fall weeks; however, the forecasting performance for the spring week is not at the desired level. When we examine the load and price relationship of 2011 which is given in Figure 15, we can realize that the load level started to decrease at the spring and the prices showed considerable fluctuation at this period. The load and price relationship shows poor correlation for the training period (from 02/03/2011 to 05/04/2011) and testing period (from 06/04/2011 to 12/04/2011) for the spring week, i.e., poor correlation with R^2=0.467 shown in Figure 32.

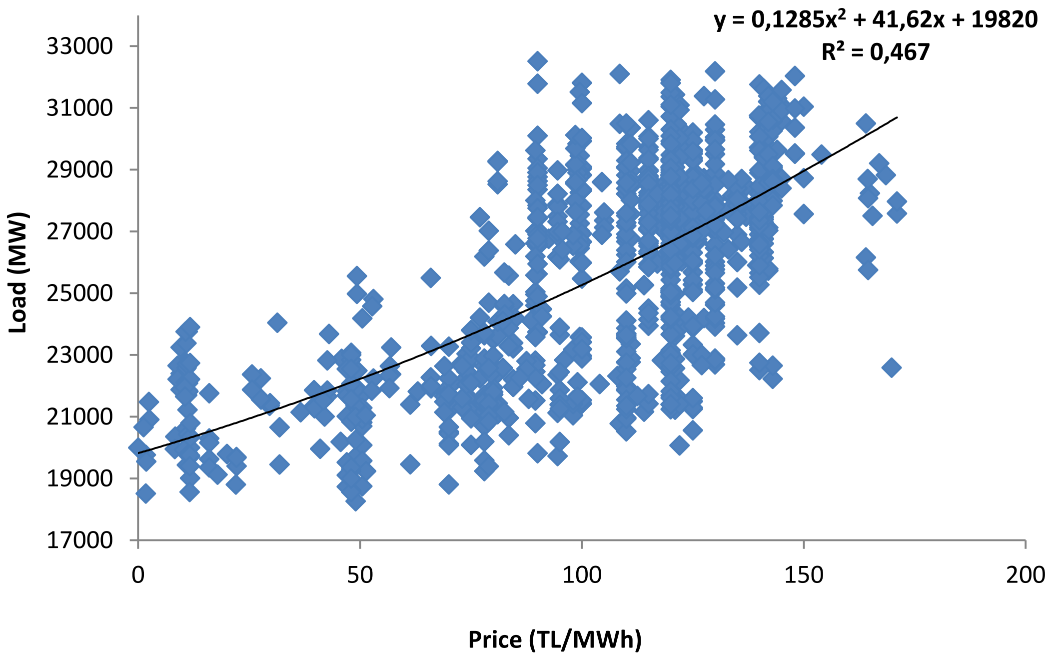

Figure 32 Load and price relationship from 02/03/2011 to 12/04/2011

Table 8 presents the minimum, maximum and average weekly MAPE values of the ANN based week ahead SGOF forecasting and MLR based SGOF forecasting of the four weeks in different seasons. According to forecasting results given in Table 8 that forecasting performance of the ANN model is better than that of MLR for all of the seasonal weeks and this result is actually expected since the

ANN develops more accurate input-output relationships than MLR due to its ability to capture nonlinear input-output mapping.

Table 8 Weekly MAPEs for the week ahead SGOF forecasting of four weeks in different seasons

Test Week (2011)	Training period	Weekly MAPE (%)			
		ANN			MLR
		Minimum	Maximum	Average	Average
Winter 21/01-27/01	01/01-20/01	7.1	9.13	**8.12**	9.14
Spring 06/04-12/04	02/03-05/04	11.76	14.22	**12.08**	12.88
Summer 25/07-31/07	20/06-24/07	4.22	5.57	**4.77**	5.32
Fall 13/09-19/09	09/08-12/09	5.29	9.17	**7.69**	7.82

4.2.3 Mitigating the Negative Effects of Price Spikes in the Training Data Set

The proposed price forecast method in its original form has not been designed for price spike forecasting. However, we add a preprocessor and postprocessor before and after the proposed price forecast method, respectively, in order to limit the price spike effects [14].

Figure 33 presents the actual prices from 13/01 to 01/03 with price spikes 19/01, 20/01, 21/01, 23/01, 02/02, 03/02, 04/02, 06/02, 08/02, 09/02, 10/02, 11/02, 13/02, 16/02, 17/02 and 24/02. In order to check the performance of the preprocessor and postprocessor techniques with the proposed ANN model, two weeks ensuing the intense price spike period are forecasted. The first week is from 17/02 to 23/02; the hourly data used to forecast this week is from 13/01 to 16/02. Without any preprocessing, the average weekly MAPE for this week is 58.44%. The second week is from 24/02 to 01/03; the hourly data used to forecast this week is from 20/01 to 23/02. Without any preprocessing, the average weekly MAPE for this week is 32.44%. Figure 34-35 present the week ahead SGOF forecasting results for these two weeks without preprocessing techniques.

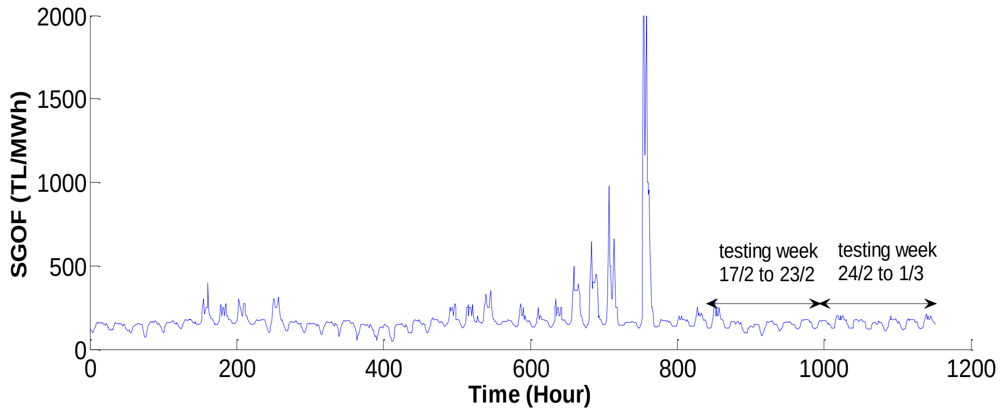

Figure 33 SGOF curve from 13/01/2012 to 01/03/2012 (without preprocessing)

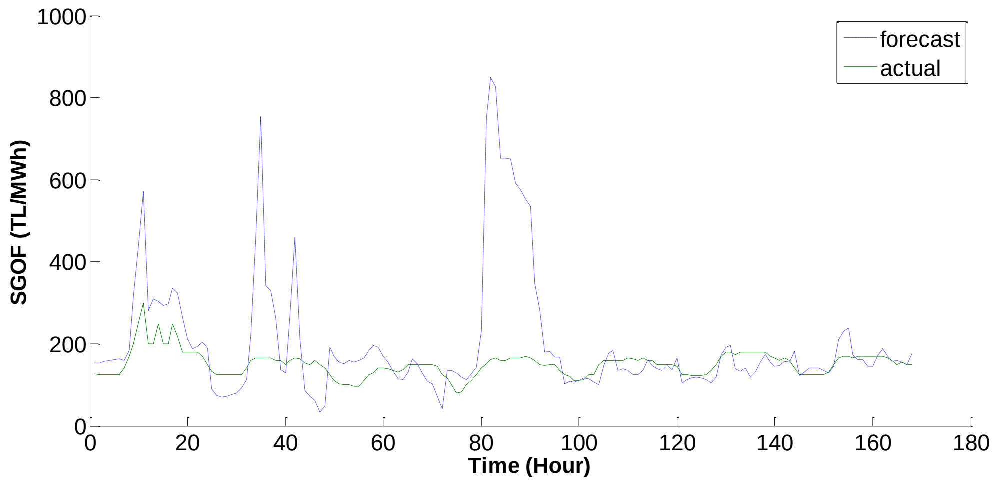

Figure 34 ANN based week ahead SGOF forecasting from 17/02/2012 to 23/02/2012 without preprocessing

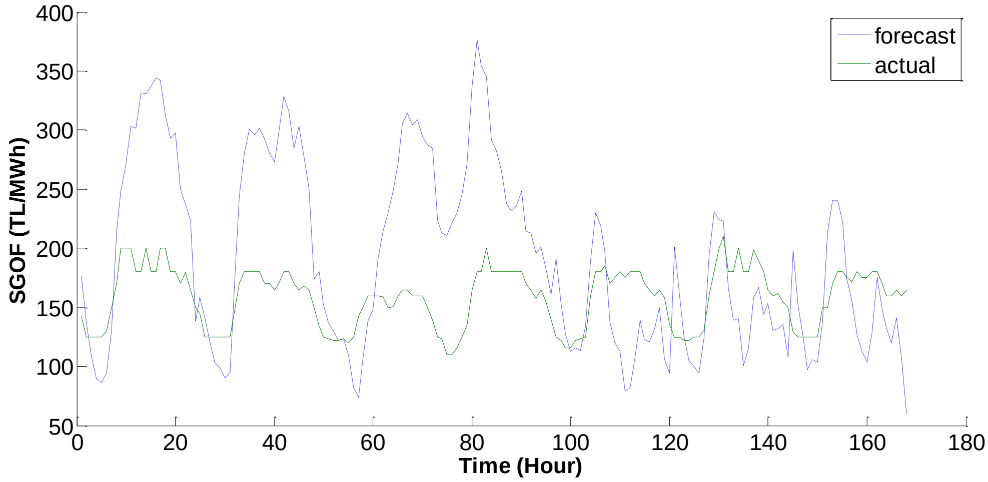

Figure 35 ANN based week ahead SGOF forecasting from 24/02/2012 to 01/03/2012 without preprocessing

Two data preprocessing techniques for limiting the price spike effects are considered:

In Case 1, the upper limit (UL) on price is determined. In preprocessing, if the prices at the training set are higher than UL, it will be set to UL. 200 TL/MWh is determined as UL and the prices higher than 200 TL/MWh is set to 200 TL/MWh. Figure 36 shows the price curve with preprocessing. For the first test week, the average weekly MAPE is 6.43%; for the second test week, the average weekly MAPE is 4.17%. The forecasting performances of the both weeks are significantly improved. Figure 37-38 present the week ahead SGOF forecasting results for these two weeks with preprocessing (Case 1).

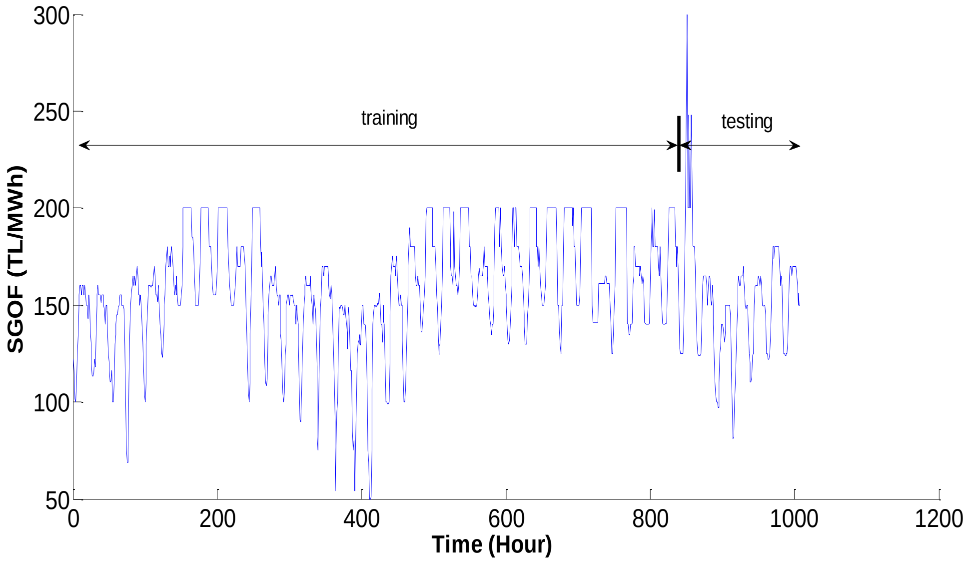

Figure 36 SGOF curve from 13/01/2012 to 23/02/2011 with preprocessing (Case 1)

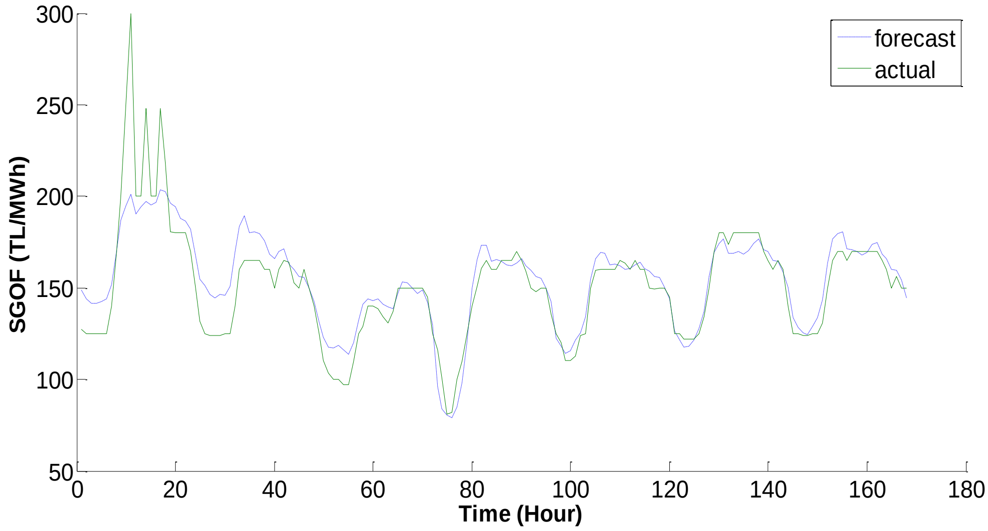

Figure 37 ANN based week ahead SGOF forecasting from 17/02/2012 to 23/02/2012 with Case 1

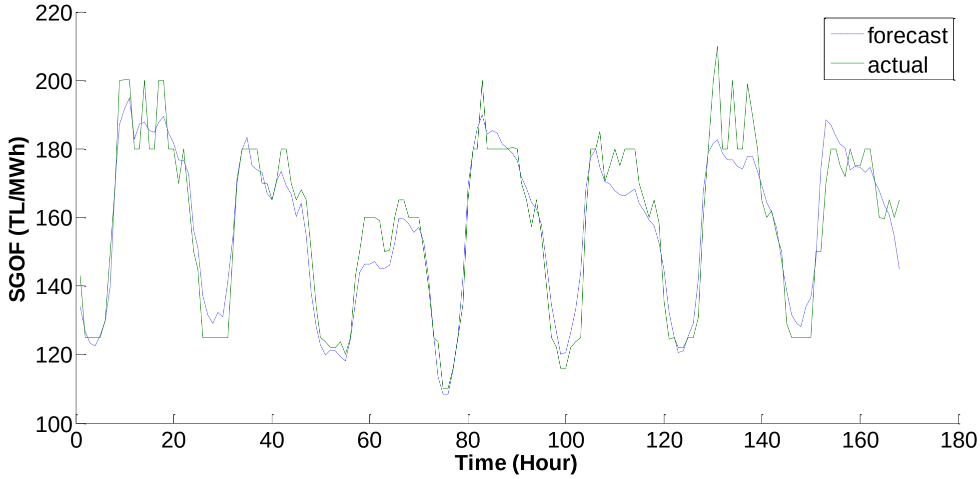

Figure 38 ANN based week ahead SGOF forecasting from 24/02/2012 to 01/03/2012 with Case 1

In Case 2, we set an upper limit of price, UL, and the preprocessor converts prices as follows:

$$P' = \begin{cases} P & P < UL \\ UL + UL\log(\frac{P}{UL}) & P \geq 0 \end{cases} \tag{68}$$

In (69), P and P' are the original price and its processed value, respectively. If a price is higher than UL, its processed value is UL plus UL times the logarithm (base 10) of the ratio of price to UL. Figure 39 presents the price curve from 13/01 to 23/02 after this preprocessing method. The postprocessor performs the inverse transform as follows:

$$K = \begin{cases} K' & K' < UL \\ UL10^{\frac{K'-UL}{UL}} & K' \geq UL \end{cases} \tag{69}$$

where K' and K are the forecasted price and modified forecasted price (after postprocessor). Accordingly, the average weekly MAPE is 8.85% for the first test week from 17/02 to 23/02; the average weekly MAPE is 6.24% for the second test week from 24/02 to 01/03. The forecasting performances of the both weeks are improved again; however, the performance at Case 1 is better than the performance at Case 2. Figure 40-41 present the week ahead SGOF forecasting results for these two weeks with preprocessing (Case 2). Table 9 shows the performances of the different preprocessing and postprocessing techniques.

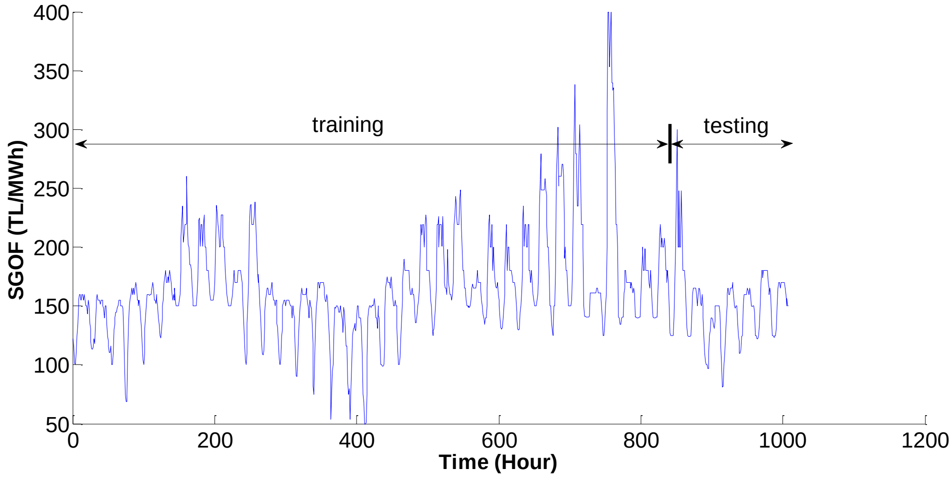

Figure 39 SGOF curve from 13/01/2012 to 23/02/2011 with preprocessing (Case 2)

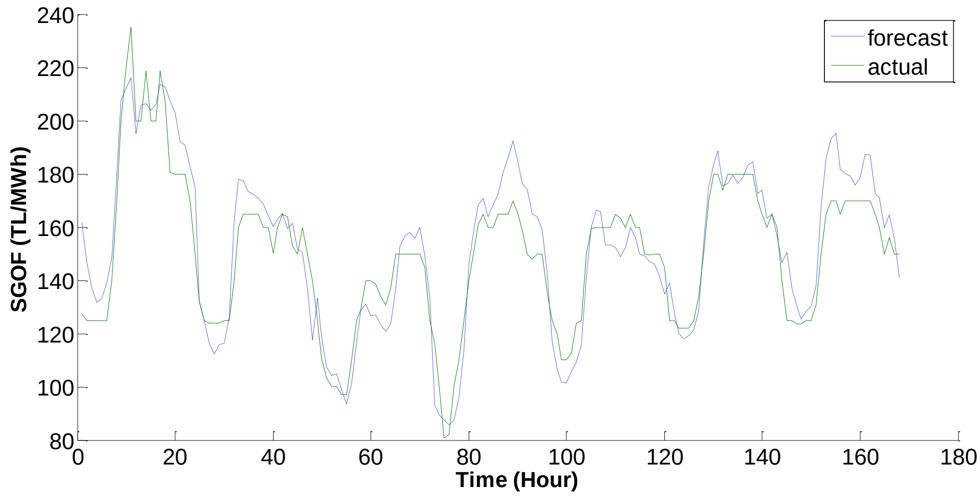

Figure 40 ANN based week ahead SGOF forecasting from 17/02/2012 to 23/02/2012 with Case 2

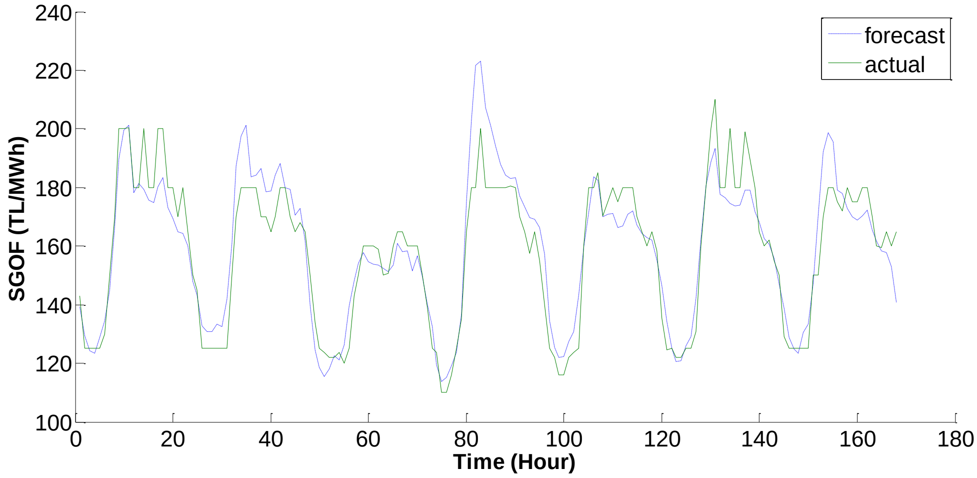

Figure 41 ANN based week ahead SGOF forecasting from 24/02/2012 to 01/03/2012 with Case 2

Table 9 The impact of the preprocessing & postprocessing techniques on weekly MAPEs

Test Week	Training period	Weekly MAPE (%)		
		No processing	Case 1	Case 2
17/02 – 23/02, 2012	13/01 – 16/02, 2012	58.44	6.43	8.85
24/02 – 01/03, 2012	20/01 – 23/02, 2012	32.44	4.17	6.24

As Table 9 indicates that limiting the magnitude of the price spikes in the training data set significantly improves the forecasting performances of the test weeks and the weekly MAPE of Case 1 is less than the weekly MAPE of Case 2 because the magnitude of price spike of Case 1 is less than that of Case 2 as described above. Also removing the price spikes completely from the training data set could be a method for mitigating the negative effect of price spikes on forecasting performances, however, the price spikes are the indicative of system abnormalities and therefore we intend to limit the magnitude of spikes rather than to remove them completely.

4.3 ANN-Based System Marginal Price (SMF) Forecasting

In this section, we study the forecasting process for SMF compared with the SGOF. The computation of SMF is much more complicated than SGOF, since SMF is related to real-time balancing of supply and demand in the entire system, therefore it depends on random variables such as congestion and generation outages which are effecting the evaluation of the system marginal price. As described before, it is not easy to consider the effect of congestion or generator outages on system marginal price forecasting because very little public information is available. However, some information such as YALM, YATM, and system direction are published on MFSC website, which can be used for SMF forecasting.

Since Electricity Market Balancing and Settlement Regulation and therefore the methodology for determination of system marginal price (SMF) at the Balancing Power Market was revised at December 2011, the data from 01/12/2011 to 20/06/2012 is used for short term SMF calculation. Three weeks were selected in three seasons in order to forecast week ahead SMF values. The winter week is from 07/01 to 13/01, 2012 (testing set); the hourly data used to forecast this winter week are from 07/12/2011 to 06/01/2012 (training set). The spring week is from 11/05 to 17/05, 2012; the hourly data used to forecast this spring week are from 06/04 to 10/05, 2012. The summer week is from 11/06 to 17/06, 2012; the hourly data used to forecast this summer week are from 07/05 to 10/06, 2012.

The same proposed model developed for SGOF forecasting which are given in Figure 25 is used for both SGOF and SMF forecasting for these three weeks. Figures 42-47 show the results with the proposed approach for the three weeks studied. Each figure shows the forecasted prices, dashed line, together with actual prices, solid line. Table 10 presents the average weekly MAPE values of the week ahead SGOF and SMF forecasting of the three weeks in different seasons.

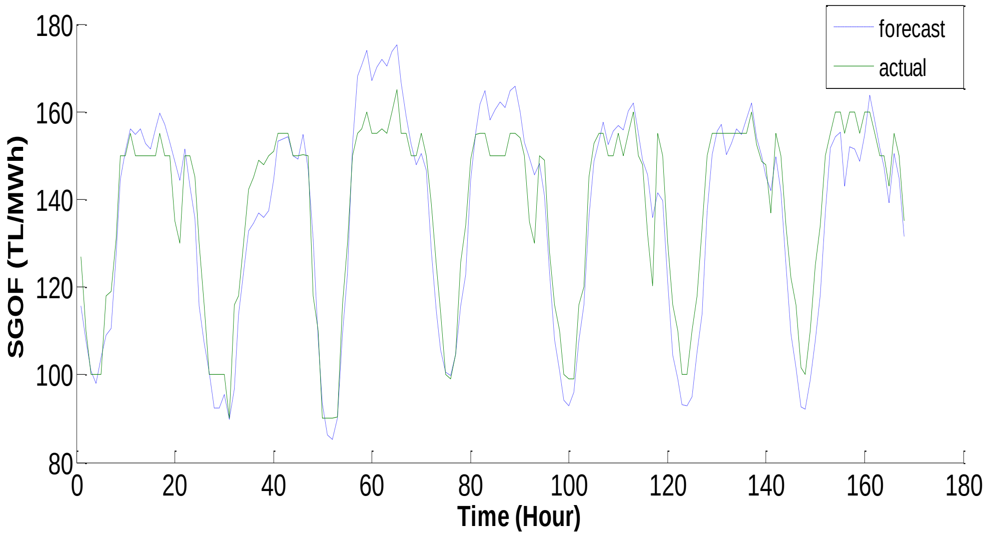

Figure 42 ANN based SGOF forecast for winter week (from 07/01/2012 to 13/01/2012)

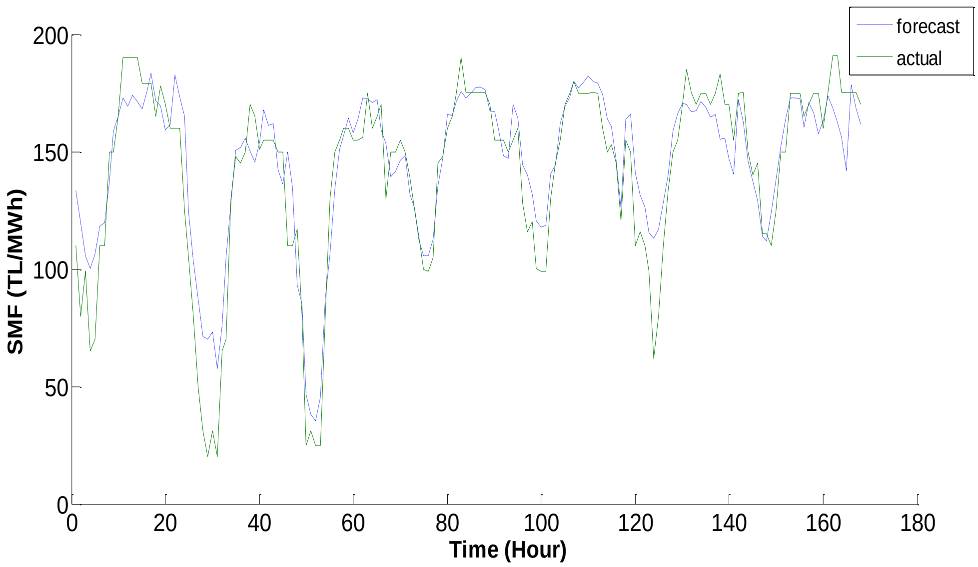

Figure 43 ANN based SMF forecast for winter week (from 07/01/2012 to 13/01/2012)

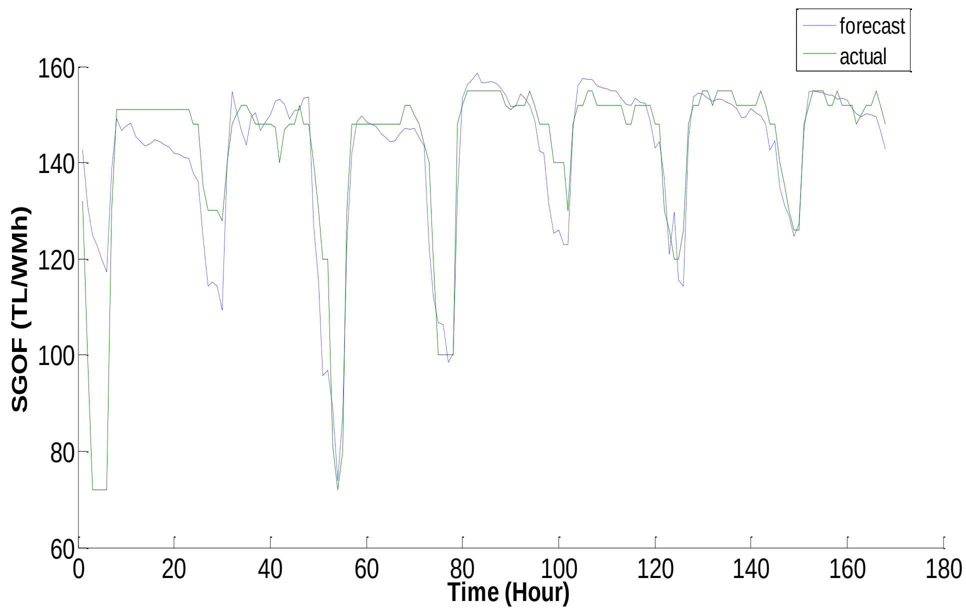

Figure 44 ANN based SGOF forecast for spring week (from 11/05/2012 to 17/05/2012)

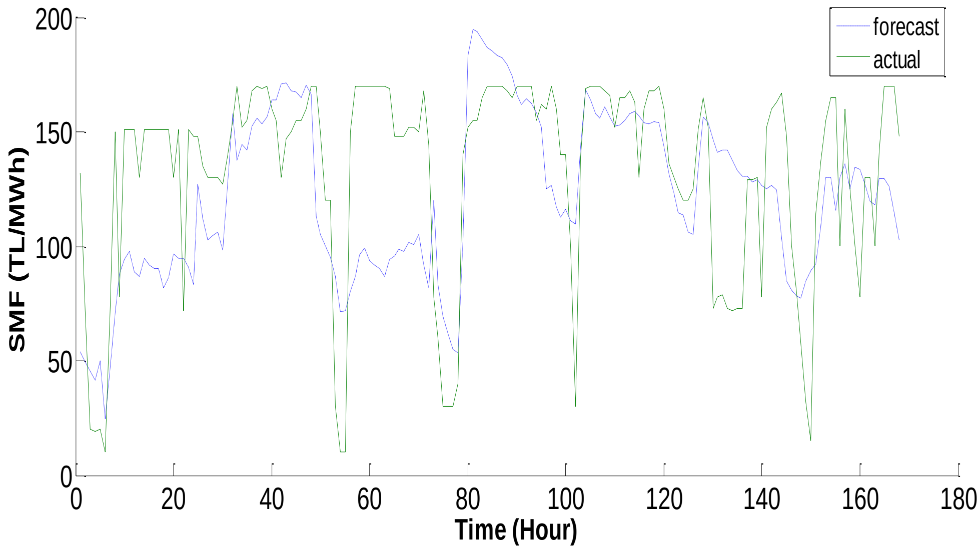

Figure 45 ANN based SMF forecast for spring week (from 11/05/2012 to 17/05/2012)

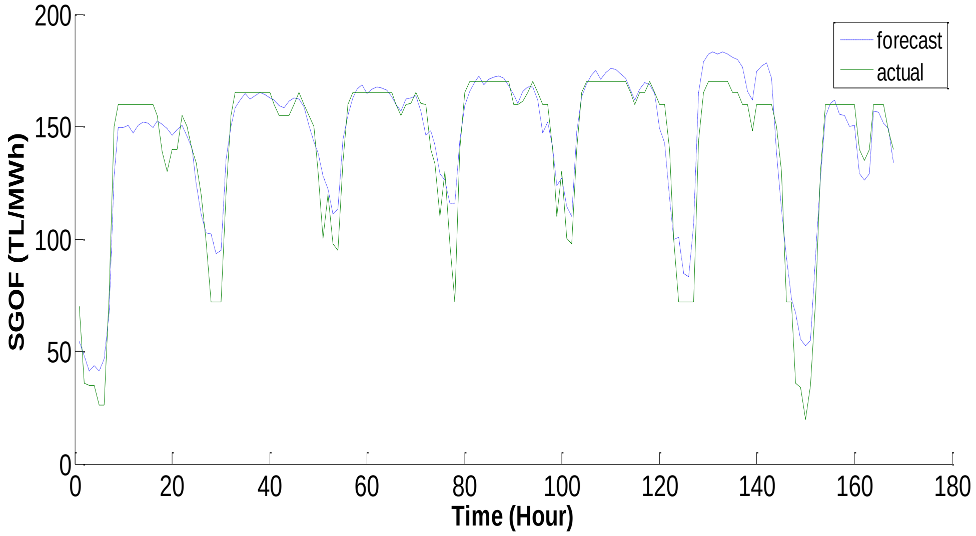

Figure 46 ANN based SGOF forecast for summer week (from 11/06/2012 to 17/06/2012)

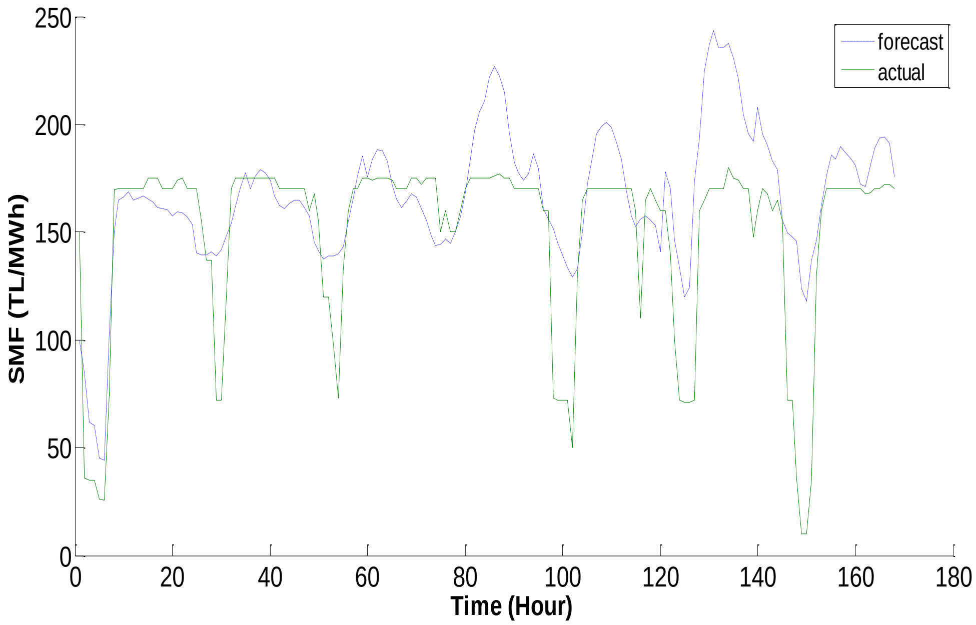

Figure 47 ANN based SMF forecast for summer week (from 11/06/2012 to 17/06/2012)

Table 10 Weekly MAPEs for the week ahead SGOF and SMF forecasting of three weeks in different seasons

Test Week	Training Period	Average Weekly MAPE (%)	
		SGOF	SMF
Winter 07/01/2012 - 13/01/2012	03/12/2011 – 06/01/2012	6.13	9.77
Spring 11/05/2012 – 17/05/2012	06/04/2012 – 10/05/2012	5.96	21.81
Summer 11/06/2012- 17/06/2012	07/05/2012 – 10/06/2012	7.97	16.31

As seen from the above results that the performances of the SGOF forecasting for different seasons of 2012 are below 8%; however, the proposed model is not suitable for SMF forecasting because the weekly MAPE values are quite higher compared with those of SGOF forecasting. Essentially, the proposed neural network model that is developed for SGOF forecasting should be revised according to SMF forecasting and new input parameters should be added to the proposed model in order to improve the forecasting performances. The determination of SMF is described in detail in Chapter 2 and since SMF is related to real-time balancing of supply and demand in the entire system, therefore it depends on the occurrence of system imbalances, in other words, if there exists any energy deficit in the system, generators starting from the lowest YAL offers increase their generation and SMF become greater than SGOF. If there exists energy surplus in the system, generators starting from highest YAT offers decrease their generation and SMF become lower than SGOF. If there is not any energy deficit or surplus and therefore the system is balanced, the SMF is equal to

SGOF which is determined at day ahead market. Therefore, we can assume that SMF depend on SGOF, system direction and the amount of imbalances which is known as NTH. Since NTH information includes the system direction information (i.e., positive NTH value means system direction with energy deficit, negative NTH value means system direction with energy surplus and zero NTH value means system balance), system direction information is not used as input parameters of ANN due to simplification.

4.3.1 Selection of Input Parameters for SMF Forecasting

In order to develop the proper ANN model for SMF forecasting, the appropriate numbers of input parameters have to be selected. Table 11 presents four models with the factors that are considered in studying the impact of input vectors. Historical information includes previous day same hour, previous week same hour and previous 24 hours average information and forecasted information includes the data for the day which is wanted to be forecasted.

Table 11 Input factors considered in different model types for SMF forecasting

Factors	Model 1	Model 2	Model 3	Model 4
Historical Load	√	√	√	√
Forecasted Load	√	√	√	√
Historical SMF	√	√	√	√
Historical SGOF		√	√	√
Forecasted SGOF	√	√	√	√
Historical NTH			√	√
Forecasted NTH				√

These four ANN models are used for week ahead SMF forecasting for the three weeks of different seasons given in Table 10. The forecasting performances are shown at Table 12.

Table 12 Weekly MAPEs for the week-ahead SMF forecasting of different models for three weeks in different seasons

Test Week	Average Weekly MAPE (%)			
	Model 1	Model 2	Model 3	Model 4
Winter 07/01/2012 - 13/01/2012	10.09	9.46	9.21	**7.07**
Spring 11/05/2012 – 17/05/2012	19.73	18.97	18.6	**12.00**
Summer 11/06/2012- 17/06/2012	17.11	14.13	13.71	**10.48**

As Table 12 shows, the worst forecasting performance is obtained when Model 1 is used for SMF forecasting. If additional historical SGOF information is considered as input to the ANN (i.e., Model 2), the better forecasting performance than that of Model 1 is obtained. Moreover, the historical NTH information is further considered as input (i.e., Model 3), the forecasting performance improves and the better result is obtained. The best result is obtained when additional forecasted day NTH information is considered as input to the ANN. This result is very reasonable since SMF highly depends on the amount of NTH as mentioned before and using the forecasted day NTH information improves the price forecasting performance. When we compare the forecasting performance of Model 4 with the SMF forecasting results shown in Table 10 which is obtained by using the proposed model developed for SGOF forecasting, we can see that we can achieve significant improvements at the MAPE values when using Model 4 for SMF forecasting, i.e., 27% decrease for the winter week, 45% decrease for the spring week and 35% decrease for the summer week. The proposed ANN model (Model 4) developed for SMF forecasting is depicted in Figure 48.

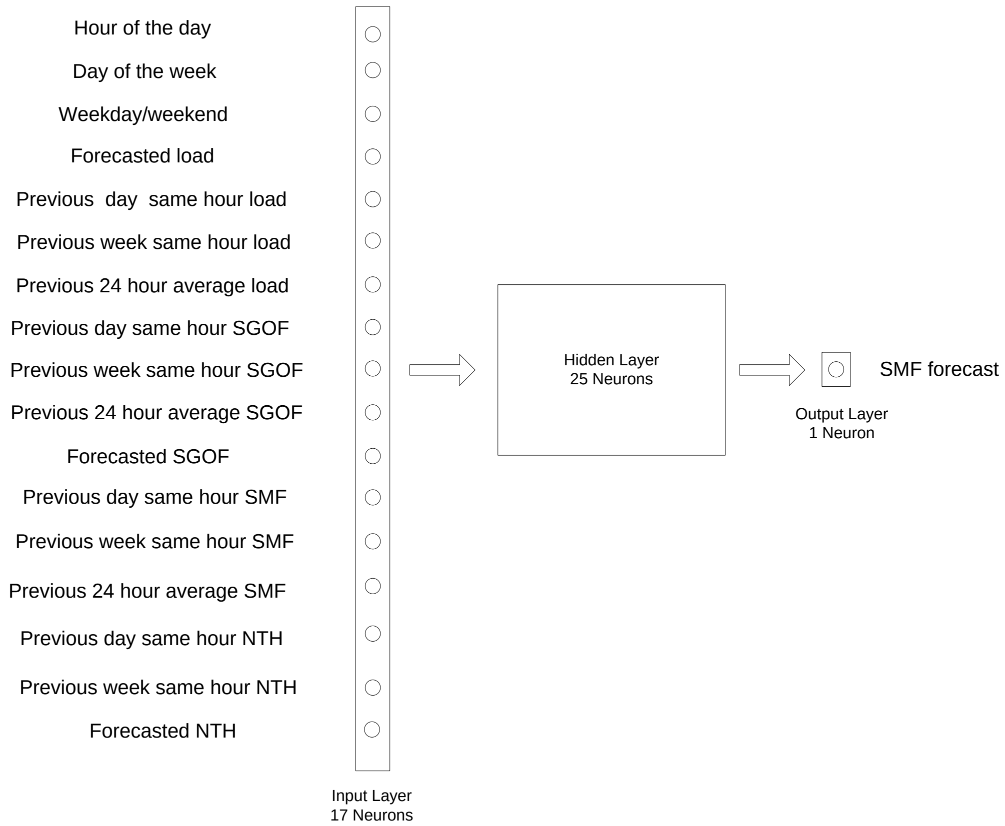

Figure 48 Proposed ANN model for SMF forecasting

Despite significant improvements, there exists a problem that has to be answered: How exactly can we predict the forecasted day NTH values? Regarding the availability of the forecasted day input parameters of Model 4, the forecasted day SGOF information is announced by the Market Operator and the forecasted day load information can be forecasted very accurately at nowadays, however, there is no available information about either the forecasted NTH value or the proposed methodology to forecast the forecasted day NTH value. Therefore, in order to forecast SMF, an ANN model for NTH forecasting has to be developed.

4.3.2 Development of ANN Model for NTH Forecasting

To predict future NTH values and develop an ANN model, the appropriate input parameters on which the value of NTH depends have to be selected. Since NTH can be explained as unexpected system imbalances at the real time system operation and occurs in case of any of the imbalances such as energy deficit, energy surplus, congestion or generation outages, we can infer that NTH forecasting is a challenging task and the complexity of NTH forecasting is due to the number of influential random factors and the lack of information on some of these factors. Although various uncertainties influence the NTH value in an intricate way, the effect of available information such as load, SGOF, SMF and historical NTH to NTH forecasting has to be studied.

Correlation coefficient method is used in order to understand the relationship between variables. The correlation coefficient is a measure of the strength and the direction of the relationship between two variables x and y, and correlation coefficient R is given by:

$$R = \frac{n\sum xy - \left(\sum x\right)\left(\sum y\right)}{\sqrt{n\left(\sum x^2\right) - \left(\sum x\right)^2}\sqrt{n\left(\sum y^2\right) - \left(\sum y\right)^2}} \tag{70}$$

where; n is the number of pairs of data.

The value of correlation coefficient R is range from -1 to 1 which is a measure for determining how certain predictions can be made from a certain model/graph. If x and y have strong positive correlation, R is close to 1. Positive correlation shows a relationship between x and y such that if x values increase, y values also increase. If x and y have strong negative correlation, R is close to -1 which means that if values of x increase, values of y decrease. If there is no or week correlation between x and y, R is close to 0. A correlation coefficient close to zero means that there is a random relationship between two variables. A correlation less than 0.5 is generally described as weak. The correlation coefficients between NTH and other variables are shown in Table 13.

Table 13 Correlation coefficients between NTH and the other variables

Correlation pairs		Correlation Coefficient (R)
NTH	Load	0,61
	SGOF	0,36
	SMF	0,67
	Delta[1]	0,74
	System Direction	0,75

According to above results, it can be concluded that NTH is poorly correlated with the day ahead price (SGOF) while there exist strong correlation between NTH and the other variables. This result is reasonable because NTH is related with the real-time system balancing so that the value of SGOF does not have significant effects on NTH value. However, the variables such as SMF, delta and system direction occur at the real time balancing market and the values of these

[1] Delta = SMF - SGOF

variable shows strong enough correlation with the NTH values. The positive system direction (energy deficit in the system) means positive NTH values while negative system direction (energy surplus in the system) means negative NTH values. SMF values greater than SGOF (positive delta value) occur when the energy deficits exist in the system and the YALM is greater than the YATM which returns as positive NTH values occurs in the system. Also the higher the delta values mean the higher the NTH values.

As a result, the factors that have effects on or show significant clues about NTH values are used as input parameters to the ANN. The input parameters include historical and forecasted day load, historical SMF, historical delta and historical system direction data. Proposed ANN model for NTH forecasting is depicted in Figure 49. Figures 50-52 present week ahead NTH forecasting for the three weeks of different seasons given in Table 10.

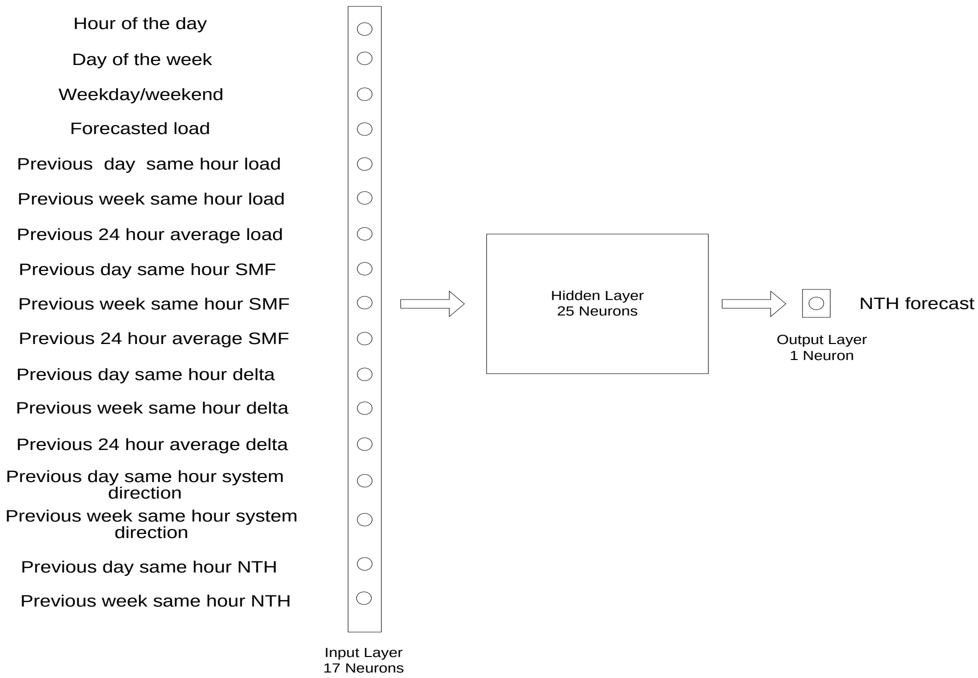

Figure 49 Proposed ANN model for NTH forecasting

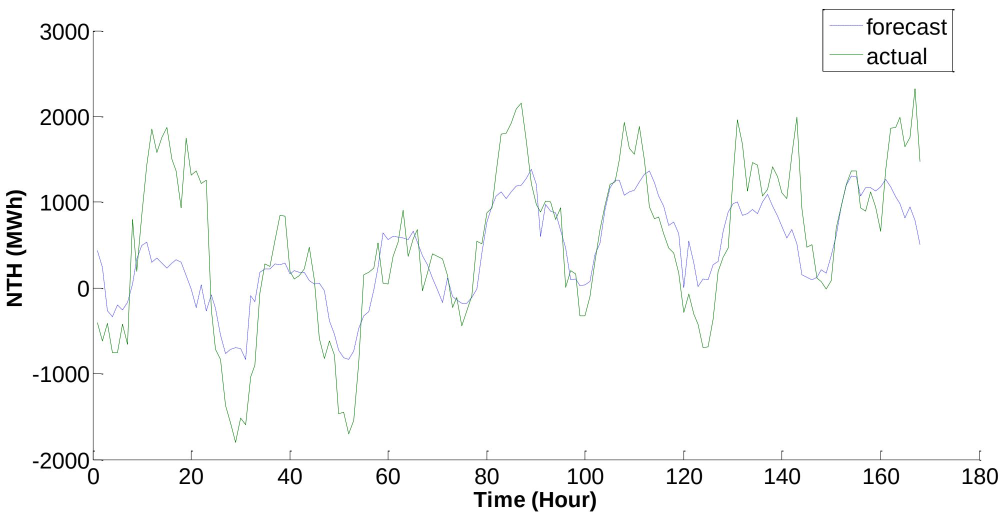

Figure 50 ANN based NTH forecast for winter week (from 07/01/2012 to 13/01/2012)

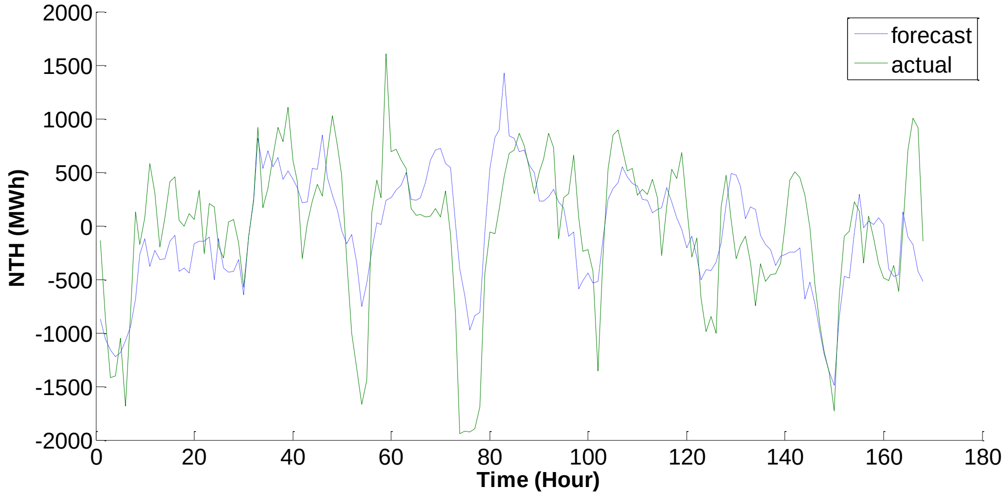

Figure 51 ANN based NTH forecast for spring week (from 11/05/2012 to 17/05/2012)

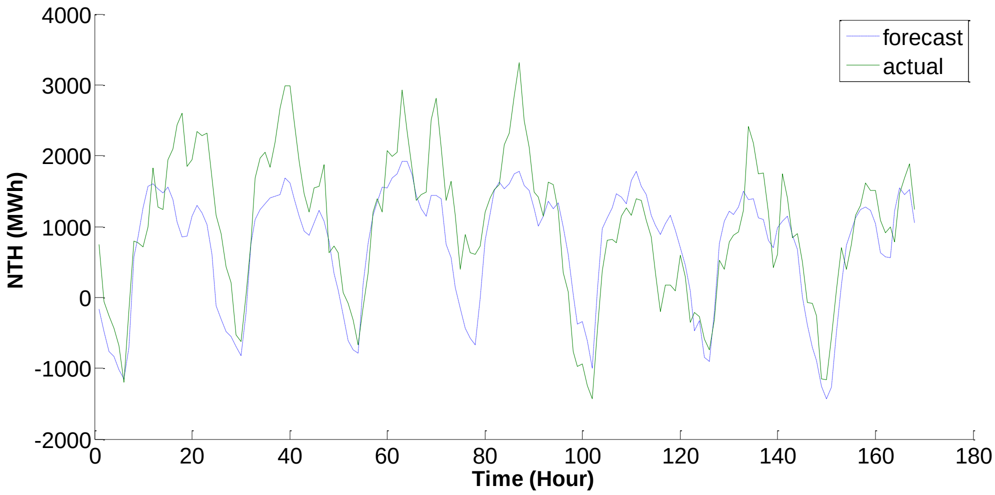

Figure 52 ANN based NTH forecast for summer week (from 11/06/2012 to 17/06/2012)

As mentioned before, using the forecasted day NTH information as input to the ANN significantly improves the SMF forecasting performance and the results are given in Table 12. We use the forecasted NTH values of the three weeks of different seasons shown at Figures 50-52 as input to the proposed ANN model for SMF forecasting and Figure 53-55 present the SMF forecasting results for the three weeks studied. Each figure shows the forecasted prices as dashed line, together with actual prices as solid line. Table 14 presents the average weekly MAPE values of the week ahead SMF forecasting of the three weeks in different seasons.

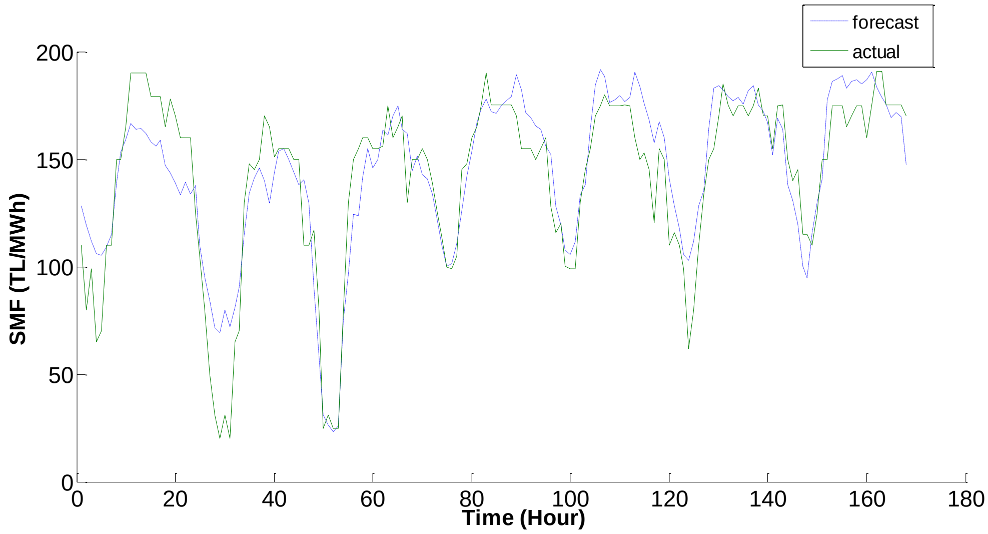

Figure 53 ANN based SMF forecast for winter week (from 07/01/2012 to 13/01/2012)

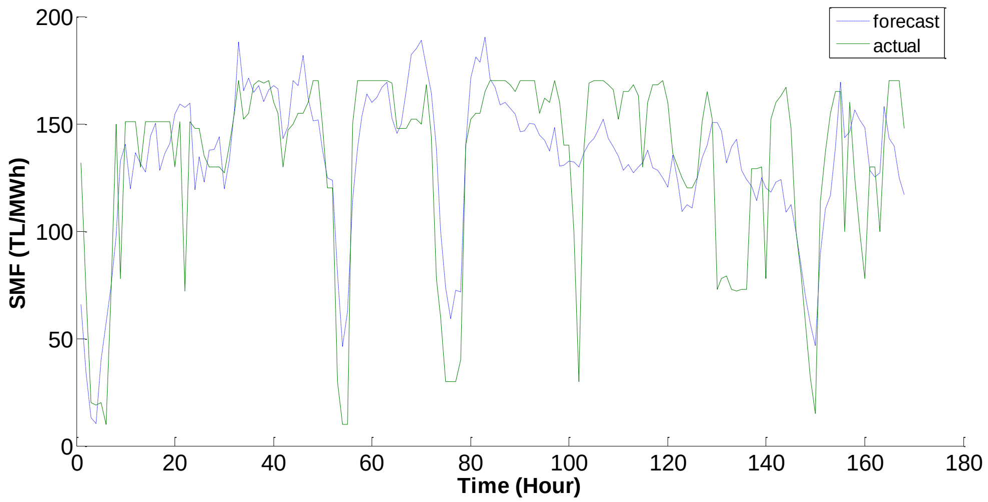

Figure 54 ANN based SMF forecast for spring week (from 11/05/2012 to 17/05/2012)

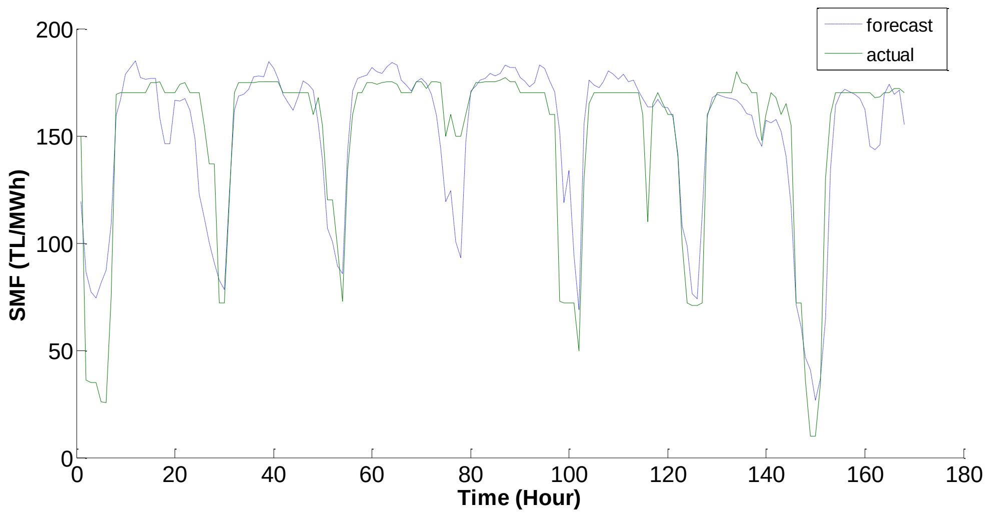

Figure 55 ANN based SMF forecast for summer week (from 11/06/2012 to 17/06/2012)

Table 14 Weekly MAPEs for the week ahead SMF forecasting of three weeks in different seasons

Test Week	Training Period	Average Weekly MAPE (%)
		SMF
Winter 07/01/2012 - 13/01/2012	03/12/2011 – 06/01/2012	9.77
Spring 11/05/2012 – 17/05/2012	06/04/2012 – 10/05/2012	21.81
Summer 11/06/2012- 17/06/2012	07/05/2012 – 10/06/2012	16.31

As seen from Table 14, the obtained SMF forecasting results are not at the desired level. The reason behind is that knowing forecasted day NTH information would significantly improve the SMF forecasting performances however this information is not available and NTH values are hard to predict because NTH is related to real time system imbalances and therefore it depends on some random events such as energy deficit, energy surplus, congestion or generation outages in the real time balancing system.

4.3.3 Probabilistic NTH Forecasting by Volatility Analysis

In order to better understand the NTH variations over a period and predict the future NTH values with probabilistic assumptions, volatility analysis is used. By this analysis, we can estimate the probability of the future NTH values falling within a predefined range, taking into account previous volatility values. After finding the future probable NTH range, we use these range as input to the proposed ANN model developed for SMF forecasting in order to forecast future probable SMF range instead of single SMF value forecasting, which is actually more reasonable for forecasting and risk analysis applications.

Volatility refers to the amount of unpredictable fluctuations of variables over a specified time interval. In economics and finance, volatility is basically a criterion to study the risks associated with holding assets when there is an uncertainty associated with the future value of the assets [4]. A high volatility means the value of a variable have changed drastically over a period of time in either direction of increase or decrease. On the contrary, low volatility refers that the value of a variable have not showed significant changes over a period of time and the variations have been quite small.

We can define e_k variables as:

$$e_k = NTH_k - NTH_{k,\exp} \tag{71}$$

where;

NTH_k : real NTH value of an hour k

$NTH_{k,\exp}$: expected NTH value of the same hour k

e_k : error at hour k

Historical volatility is defined as the standard deviation of e_k and it can be estimated by using the e_k variables as follows:

$$\sigma = \sqrt{\frac{\sum_{i=1}^{N}(e_i - \bar{e})^2}{N-1}} \tag{72}$$

where σ is the estimated value of historical volatility and $\bar{e}$ is the mean of e_i's.

In volatility analysis studies, time periods are selected according to the needs for observing variable fluctuation over a period of time. At our case, we choose 2 weeks observation for historical NTH fluctuation and therefore we define two-week volatility as follows:

$$\sigma_{k,336} = \sqrt{\frac{\sum_{i=k}^{k+335}(e_i - \bar{e})^2}{335}} \tag{73}$$

where historical volatility (σ) is calculate over a two weeks period (i.e., 336 hours) starting from time k.

In order to calculate historical two weeks volatility for the studied three weeks of different seasons shown in Figures 50-52, firstly we have to forecast the NTH values of the two weeks that are preceding the test weeks, i.e., from 24/12/2011 to 06/01/2012 for the winter, from 27/04/2012 to 10/05/2012 for the spring week and from 28/05/2012 to 10/06/2012 for the summer week. The ANN model used for NTH forecasting earlier is also used for these two weeks of different seasons forecasting. The forecasting results are shown at Figures 56-58 and each figure shows the forecasted NTH as solid blue line, actual NTH as solid green line together with the error values (e_k = actual – forecast) as dashed red line.

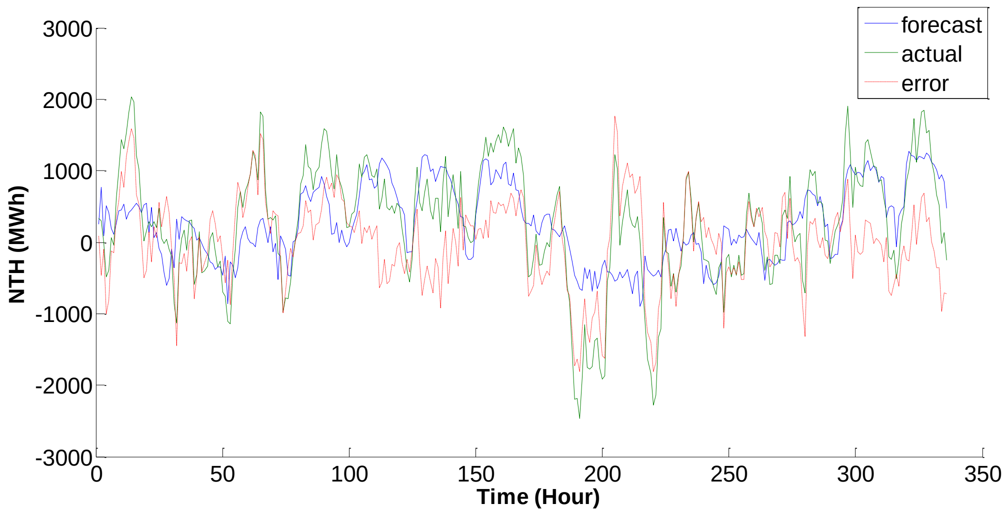

Figure 56 ANN based NTH forecast for two weeks of winter (from 24/12/2011 to 06/01/2012)

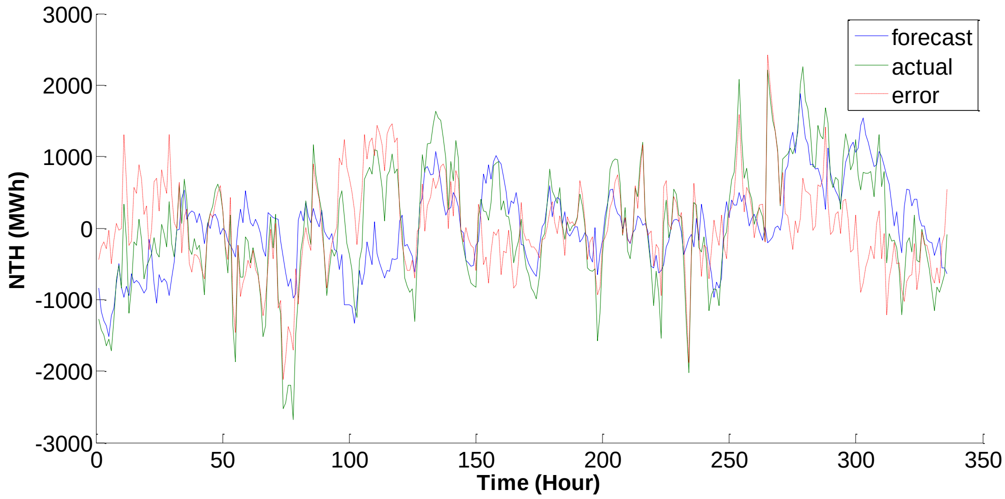

Figure 57 ANN based NTH forecast for two weeks of spring (from 27/04/2012 to 10/05/2012)

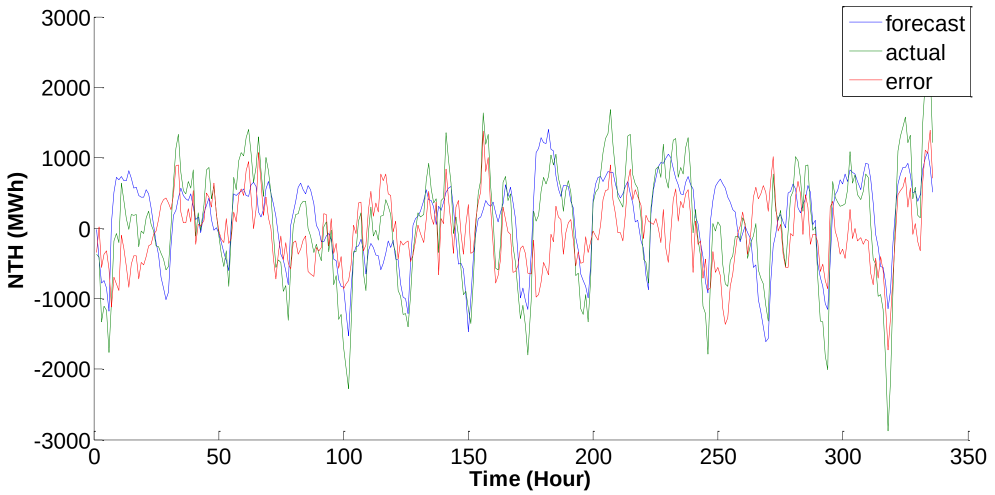

Figure 58 ANN based NTH forecast for two weeks of spring (from 28/05/2012 to 10/06/2012)

After forecasting two weeks NTH values for different seasons, we can find two weeks historical volatility using Eq. (73). The historical volatility values are given in Table 15.

Table 15 Two weeks historical volatility for different seasons

Test Week	Mean of e_k	Two weeks historical volatility (Std dev. $\sigma_{k,336}$)
Winter 24/12/2011 - 06/01/2012	22.87	548.61
Spring 27/04/2012 – 10/05/2012	-67.54	650.3
Summer 28/05/2012- 10/06/2012	-51.83	465.33

Taking into account historical volatility values, we can estimate the future NTH values falling within a predefined range by using Bienayme-Chebycheff inequality which is frequently used in statistical studies and probability theory. Bienayme-Chebycheff inequality states that in any data sample or probability distribution, the probability that a random variable differs from its mean by more than n times standard deviations is less than or equal to $1/n^2$. According to this inequality, the probability that a value will be more than two standard deviations from the mean (n=2) cannot exceed 25% ($1/n^2$ = ¼ = 25%).

Let x_i be a random variable with finite expected mean value μ and finite standard deviation σ. Then for any chosen n^2, the Bienayme-Chebycheff inequality is as follows:

$$\Pr\left(-n < x_i - \mu < +n\right) \geq 1 - \frac{\sigma^2}{n^2} \tag{74}$$

Using (74) in our case and replacing x_i with e_k and μ with $\bar{e}$, then the inequality becomes as:

$$\Pr\left(-n < e_k - \bar{e} < +n\right) \geq 1 - \frac{\sigma^2}{n^2} \tag{75}$$

Using equation (71) for e_k variables and after arrangements at Eq. (75), the inequality becomes as follows:

$$\Pr\left(NTH_{k,\exp} + \bar{e} - n < NTH_k < NTH_{k,\exp} + \bar{e} + n\right) \geq 1 - \frac{{\sigma_{k,336}}^2}{n^2} \tag{76}$$

where $\sigma_{k,336}$ is two weeks volatility as defined in Eq. (73).

The last two weeks volatility value calculated for the winter week is 548.61 MWh which was given in Table 15. If we apply this value to Eq. (76) and if we assume that in order to forecast the NTH interval with the probability of 80%, we obtain:

$$\Pr\left(NTH_{k,\exp} + \bar{e} - n < NTH_k < NTH_{k,\exp} + \bar{e} + n\right) \geq 1 - \frac{548.61^2}{n^2} = 0.8$$

From above equation, the n value is found as 1227 MWh. This means that real NTH values of the winter week, from 07/01/2012 to 13/01/2012, fall within the interval $NTH_{\exp} + \bar{e} \pm n$ with the probability of 80%, i.e.,:

$$\Pr\left(NTH_{k,\exp} + 22.87 - 1227 < NTH_k < NTH_{k,\exp} + 22.87 + 1227\right) \geq 1 - \frac{548.61^2}{1227^2} = 0{,}8$$

The expected and real NTH values for the winter week were given in Figure 50 and when we use this information together with the above NTH interval, we can obtain the following result shown in Figure 59 which shows the forecasted NTH values as red line, actual NTH values as blue line together with the interval as dashed lines. As seen from Figure 59, nearly all the real NTH values are within the found interval.

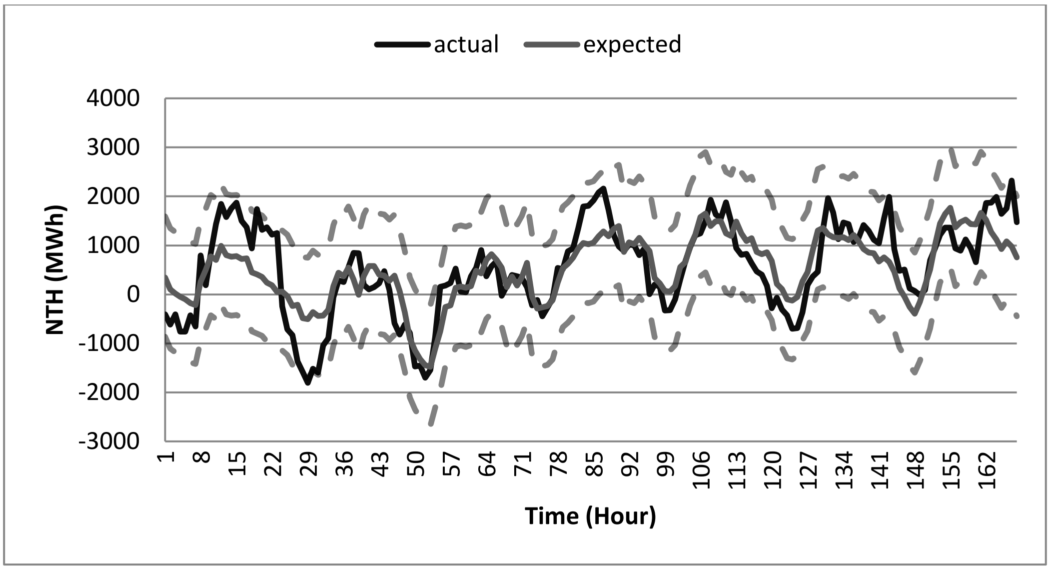

Figure 59 Expected and real NTH values together with the lower and upper bound for the winter week (from 07/01/2012 to 13/01/2012)

The same approach can be used for spring week, from 11/05/2012 to 17/05/2012 and summer week, from 11/06/2012 to 17/06/2012. The last two weeks volatilities for the spring and summer weeks are 650.3 and 465.33 respectively. According to 80% probability, the n values are found as 1454 MWh for the spring week and 1040 MWh for the summer week. Therefore, the Bienayme-Chebycheff inequality for the spring week is:

$$\Pr\left(NTH_{k,\exp} - 1521 < NTH_k < NTH_{k,\exp} + 1387\right) \geq 1 - \frac{650.3^2}{1454^2} = 0.8$$

The Bienayme-Chebycheff inequality for the summer week is:

$$\Pr\left(NTH_{k,\exp} - 1092 < NTH_k < NTH_{k,\exp} + 989\right) \geq 1 - \frac{465.33^2}{1040.5^2} = 0.8$$

The expected and real NTH values for the spring and summer week were given in Figure 51-52 and when we use this information together with the above NTH interval, we can obtain the following results shown in Figure 60-61. These figures show the forecasted NTH values as red line, actual NTH values as blue line together with the interval as dashed lines. As seen from Figure 60-61, nearly all the real NTH values are again within the found interval.

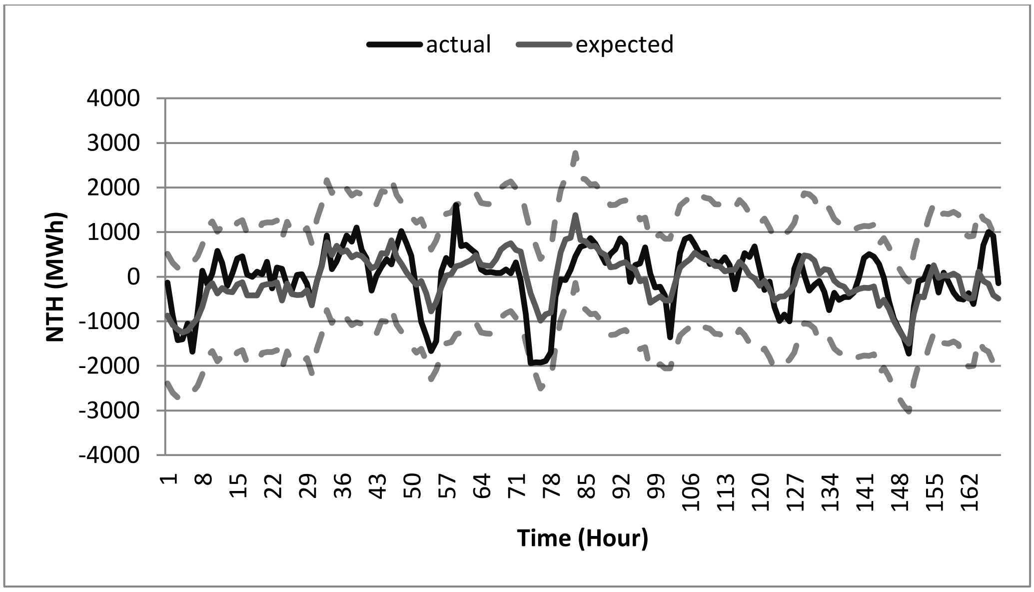

Figure 60 Expected and real NTH values together with the lower and upper bound for the spring week (from 11/05/2012 to 17/05/2012)

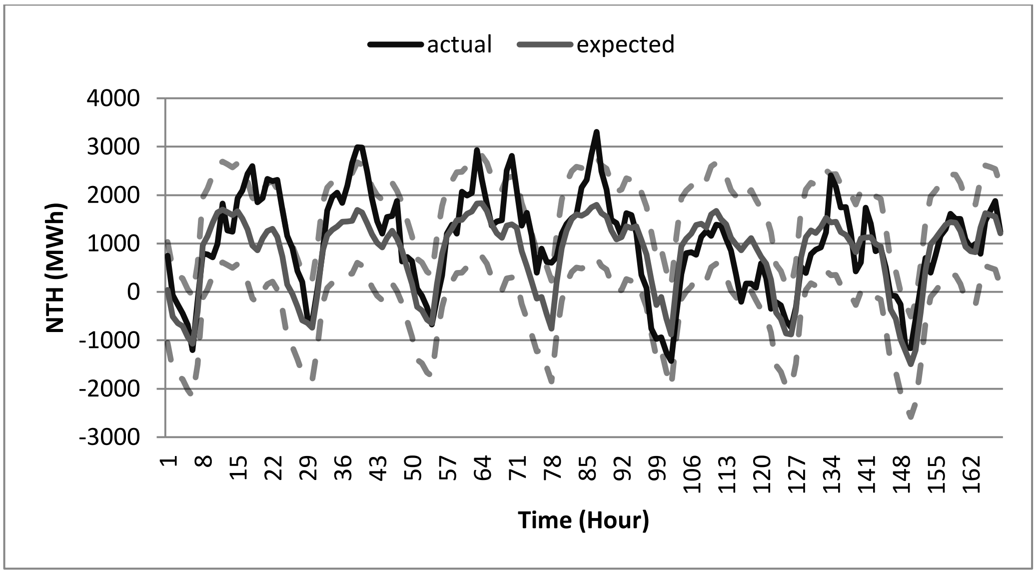

Figure 61 Expected and real NTH values together with the lower and upper bound for the summer week (from 11/06/2012 to 17/06/2012)

4.3.4 SMF Forecasting with Upper and Lower Boundaries

After finding the NTH forecasting values together with the lower and upper boundaries, we can use this information as input to the Model 4 given in Table 10 for week ahead SMF forecasting together with lower and upper SMF boundary forecasts. We can forecast week ahead SMF values by using NTH forecast values as input to the Model 4. Moreover, if we use lower and upper NTH boundary values as input to the Model 4 separately, we can obtain lower and upper SMF boundary forecasts respectively. By this method, we can forecast week ahead SMF values together with lower and upper boundaries. The results of this method are shown in Figure 62 for the winter week, from 07/01/2012 to 13/01/2012, Figure 63 for the spring week, from 11/05/2012 to 17/05/2012 and Figure 64 for the summer week, from 11/06/2012 to 17/06/2012. As seen from the Figures 62-64, nearly all SMF values are fall within the lower and upper boundaries.

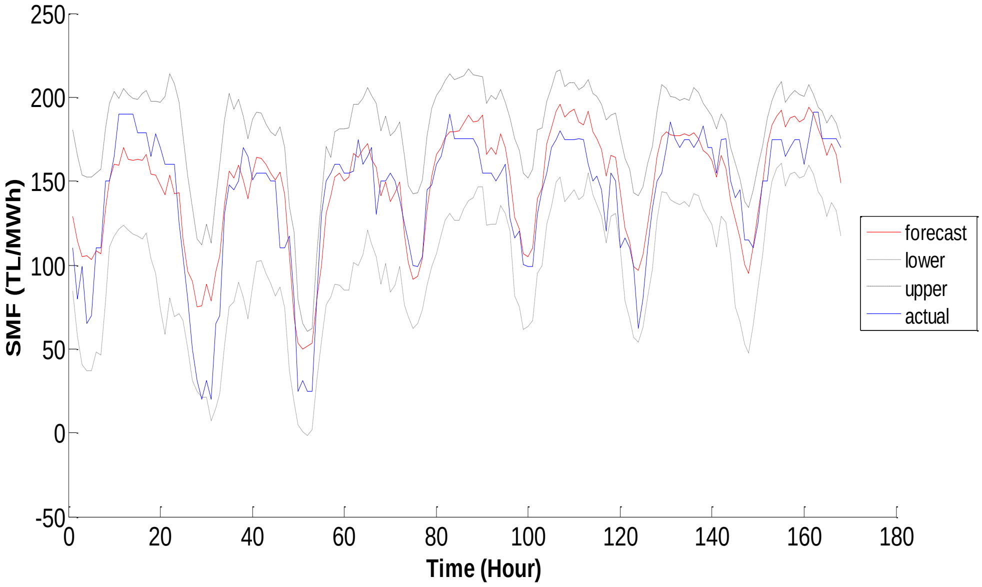

Figure 62 Forecasted and actual SMF values together with the lower and upper boundaries for the winter week (from 07/01/2012 to 13/01/2012)

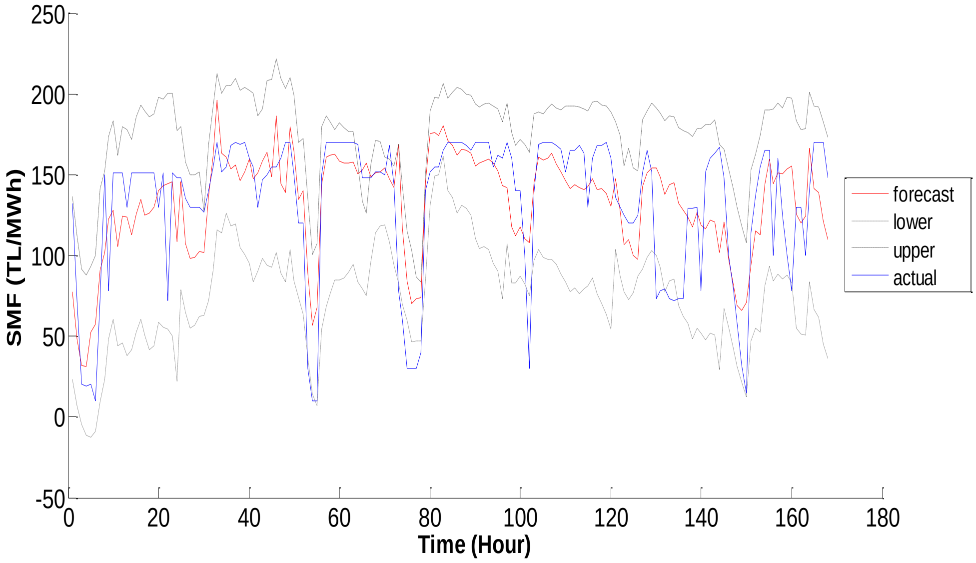

Figure 63 Forecasted and actual SMF values together with the lower and upper boundaries for the spring week (from 11/05/2012 to 17/05/2012)

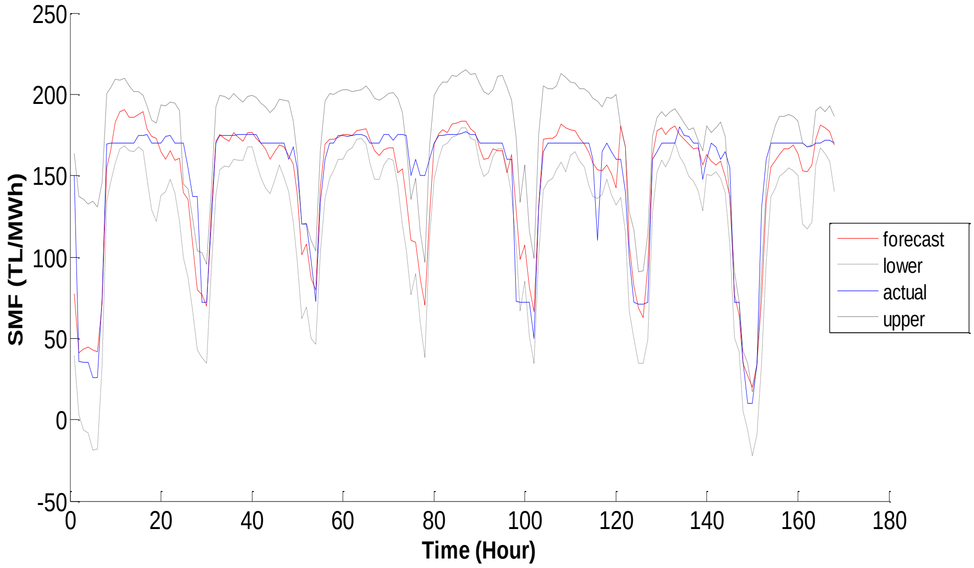

Figure 64 Forecasted and actual SMF values together with the lower and upper boundaries for the summer week (from 11/06/2012 to 17/06/2012)

CHAPTER 5

CONCLUSIONS AND FUTURE WORK

Due to increasing competition in the electricity market, an accurate electricity price forecasts have become a very vital need for all market participants. Accurate forecasting of electricity prices can help suppliers to derive their bidding strategy and optimally design their bilateral agreements in order to maximize their profits and hedge against risks. In other words, if suppliers forecast the electricity price more accurately, they can manage the risks of over/underestimating the income earned from supplying energy to the system. Also electricity price is a good indicator for making decision on investing new generation facilities for the suppliers. Consumers need accurate price forecasts for deriving their electricity usage and bidding strategy for minimizing their utilization costs.

In this thesis study, an artificial neural network approach is proposed in order to forecast system day ahead prices (SGOF) at the day ahead market and system marginal prices (SMF) at the balancing power market in Turkish electricity market. The methodology used for determination of system day ahead price (SGOF) and system marginal price (SMF) is studied and the parameters used in determination of day ahead and real time system prices and which of them play main roles and are important than others are investigated in this study. Also general review to the time series techniques are given and especially artificial neural networks and multiple linear regression methodology are explained in detail with error minimization process.

According to the results found in this thesis study, proposed model developed for SGOF forecasting generated reasonably good SGOF forecast results for seasons of 2011 and 2012, especially for weeks where the price and load did not show too much fluctuation between each hour and days. For the year 2011, the summer SGOF forecasting performance is the best among the four seasons forecasting with the MAPE of 4.77% because the fluctuation of the price is very small and the price and load trends are very periodical. The worst one is the spring SGOF forecasting with the MAPE of 12.77% and the reason behind this is that the fluctuation of the price is considerably higher compared with the other seasons. For the year 2012, the SGOF forecasting performances are also reasonably good with MAPE's of 6.13% for the winter week, 5.96% for the spring week and 7.97% for the summer week. It can be concluded from the SGOF forecasting results that all of the forecasting MAPE's except for the spring week of 2011 are below 10% and therefore the proposed model can be considered as capable of producing reasonable accuracy for SGOF forecasting.

The proposed model for SGOF forecasting is not suitable for SMF forecasting because the weekly MAPE values are quite higher compared with those of SGOF forecasting. Essentially, the proposed neural network model was revised according to SMF forecasting and new input parameters were added to the proposed model in order to improve the forecasting performances. According to SMF forecasting results of different models composed of different input parameters, it can be seen that the best forecasting performances were obtained when additional forecasted day NTH information was considered as input to the ANN model developed for SMF forecasting. This result is very reasonable since SMF highly depends on the amount of NTH and using the forecasted day NTH information significantly improves the SMF forecasting performance. However, this information is not available and future NTH values are hard to predict very accurately because NTH is related to real time system imbalances and it depends on some random events such as energy deficit, energy surplus, congestion or generation outages in the real time balancing system. Since the point forecast of NTH is very difficult and the forecasting results are not at the desired level, we can use the volatility analysis and Bienayme-Chebycheff inequality that we can estimate the probability of the future NTH values falling within a predefined range, taking into account previous 2 weeks volatility values. After finding the future probable NTH range, we use these range as input to the proposed ANN model developed for SMF forecasting in order to forecast future probable SMF range instead of single SMF value forecasting, which is actually more reasonable for forecasting and risk analysis applications. As the SMF forecasting results together with upper and lower bounds shows that nearly all of the SMF values are within the lower and upper boundaries which means that the model has been a success for SMF forecasting.

For future work, hybrid price forecasting techniques such as fuzzy logic and ANN combination can be developed for Turkish electricity market in order to improve the forecasting performances. The results found in this thesis can be used for price based unit commitment applications and also probability of price spikes forecasting can be studied in detail.

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