ELECTRICITY MARKET CLEARING PRICE FORECASTING IN A DEREGULATED ELECTRICITY MARKET

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By

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ABASTRACT

Under deregulated electric market, electricity price is no longer set by the monopoly utility company rather it responds to the market and operating conditions. Offering the right amount of electricity at the right time with the right bidding price has become the key for utility companies pursuing maximum profits under deregulated electricity market. Therefore, electricity market clearing price (MCP) forecasting became essential for decision making, scheduling and bidding strategy planning purposes. However, forecasting electricity MCP is a very difficult problem due to uncertainties associated with input variables.

Neural network based approach promises to be an effective forecasting tool in an environment with high degree of non-linearity and uncertainty. Although there are several techniques available for short-term MCP forecasting, very little has been done to do mid-term MCP forecasting. Two new artificial neural networks have been proposed and reported in this thesis that can be utilized to forecast mid-term daily peak and mid-term hourly electricity MCP. The proposed neural networks can simulate the electricity MCP with electricity hourly demand, electricity daily peak demand, natural gas price and precipitation as input variables. Two situations have been considered; electricity MCP forecasting under real deregulated electric market and electricity MCP forecasting under deregulated electric market with perfect competition. The PJM interconnect system has been utilized for numerical results. Techniques have been developed to overcome difficulties in training the neural network and improve the training results.

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CHAPTER 1: INTRODUCTION

1.1 Electrical Systems

Electricity has become an essential commodity in a modern society. Our daily lives depend on the use of electricity in various forms. Rapid rise of industrialization in the last century has contributed to a phenomenal growth of electricity consumption and hence the tremendous increase in generation of electrical energy.

The advent of bulk generation of electrical energy required that the electrical energy be transmitted to load centres via elaborate networks of transmission lines. At the load centres, electrical energy is then distributed by a complex web of distribution networks. This basic configuration of generation, transmission and distribution is still in use all over the world.

A part of the electrical energy is lost during its transmission. This puts a physical limit as to the distances of generation centres from the load centres. That is why electrical systems have evolved mainly within their own geographical jurisdiction. Although by employing a different technique, called DC transmission, it became feasible to transport electrical energy over longer distance, electrical systems predominantly remained bound to their geographical jurisdiction.

1.2 Natural Monopoly and Regulation

Generation, transmission and distribution of electrical energy require huge capital investment for operation, maintenance and expansion. This type of investment was achieved by awarding monopoly over the entire geographical jurisdiction. In some places, crown corporations were established and given monopoly of generation, transmission and distribution of electrical energy within prespecified geographical boundaries. A single entity used to run and control all aspects of generation, transmission and distribution within a geographical jurisdiction. The single entity could set its own rate sometimes with the approval from a regulatory body. A natural monopoly guaranteed a decent return on the huge investment that a single entity or a crown corporation would typically make. However, regulation became part of the electricity industry all over the world. Its chief objective was to protect the consumer, from the inevitable consequences of a monopoly industry.

The regulated electric market is still a natural monopoly industry but carefully watched by the government. Its vertically integrated structure is shown in Figure 1.1. Back in the 1970's in North America, there was usually a limited number of huge corporations owning and operating few vertically integrated electric systems. Each corporation was an independent system. Combined, they controlled more than 90 percent of the total electric market in their country. In a vertically integrated system, local consumers have no other choice for electricity service but the local provider. In a natural monopoly (regulated) electric market, electricity price is high and services are usually limited.

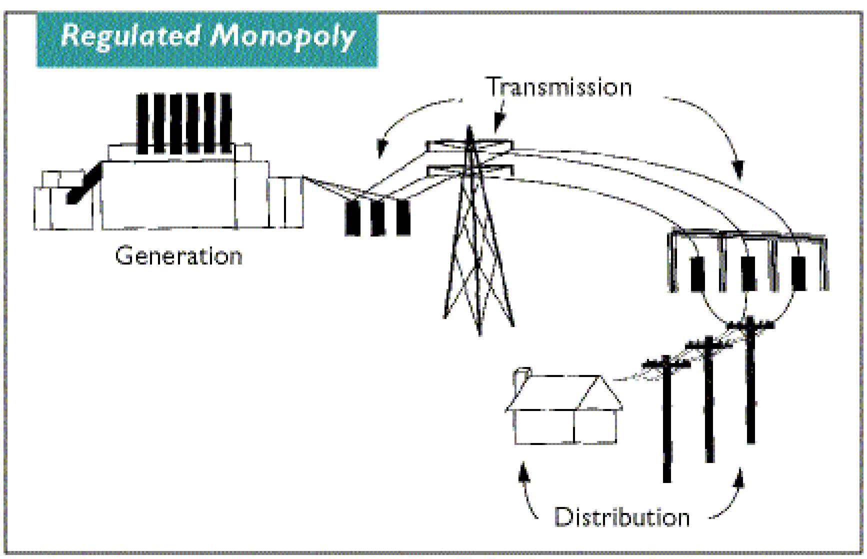


Figure 1.1: Regulated Electric Market [25]

Figure 1.2 is a typical electricity bill from BC Hydro. As BC Hydro is the only electricity provider in British Columbia, it owns and operates generation, transmission and distribution. Therefore, the bill is presented as a package based on days of usage and total amount of electricity consumed. There is no need to separate the bill on each part of generation, transmission or distribution.

BC Hydro	**Electric Charges**	
	Dec 15 to Jan 31 (Residential rate 1101)	
	Basic charge: 48 days @ $0.12110 /day	5.81*
12	Usage charge: 442 kW.h @ $0.06140 /kW.h	27.14*
	Feb 01 to Feb 14 (Residential rate 1101)	
	Basic charge: 14 days @ $0.12130 /day	1.70*
	Usage charge: 130 kW.h @ $0.06150 /kW.h	8.00*
13	Rate Rider at 2%	0.19*
	Dec 15 to Feb 14 (Residential rate 1101)	
14	Regional transit levy: 62 days @ $0.06240 /day	3.87*
	* GST	2.80
		$49.51

Figure 1.2: BC Hydro Electric Bill [46]

1.3 Deregulated Electric Market

The meaning of deregulation is the reduction or elimination of government control in a particular industry. The purpose of deregulation is to promote more competition within the same industry and same geographical jurisdiction. It is generally believed that fewer and simpler regulation will lead to a raised level of competitiveness and would overall result higher productivity, more efficiency and lower prices.

Deregulation of electrical markets calls for the restructuring of the electricity industry. The traditional vertically integrated system is to break down as three separate businesses; 1) generation company, 2) transmission company and 3) distribution company. These three businesses are to be owned and operated by three different entities. Deregulators advocate that deregulated electric market will bring cheaper electricity and meantime, more choices for the customers.

In a deregulated market, instead of only one generation provider in a local area, there are now several generation providers in the same area. The local regulatory body can no longer set the electricity price. Consumers have more choices about their local electricity providers. They can choose different electricity providers depending on their requirements and demand.

Although competition is allowed in the generation and distribution sector, the transmission sector remained regulated. The principle reason behind the continued regulation of the transmission sector is that in order for a fair competitive environment in the generation sector all competitors in that sector must have equal access to the transmission network. Same goes for the bulk energy distribution. The transmission network is operated by an independent non-profit entity called, independent system operator (ISO) or independent market operator (IMO).

A deregulated electric market bill from California is shown in Figure 1.4. Different from the bill from BC Hydro, California electricity bill is charged separately on each part of generation, transmission and distribution because these three parts are owned and operated by different companies. As a result, with the same amount of electricity usage, consumers' electricity bill would vary based on which electricity provider they choose. Transmission and distribution charge remain the same as those two parts in California are still under regulation where fixed price will be charged on every bill.

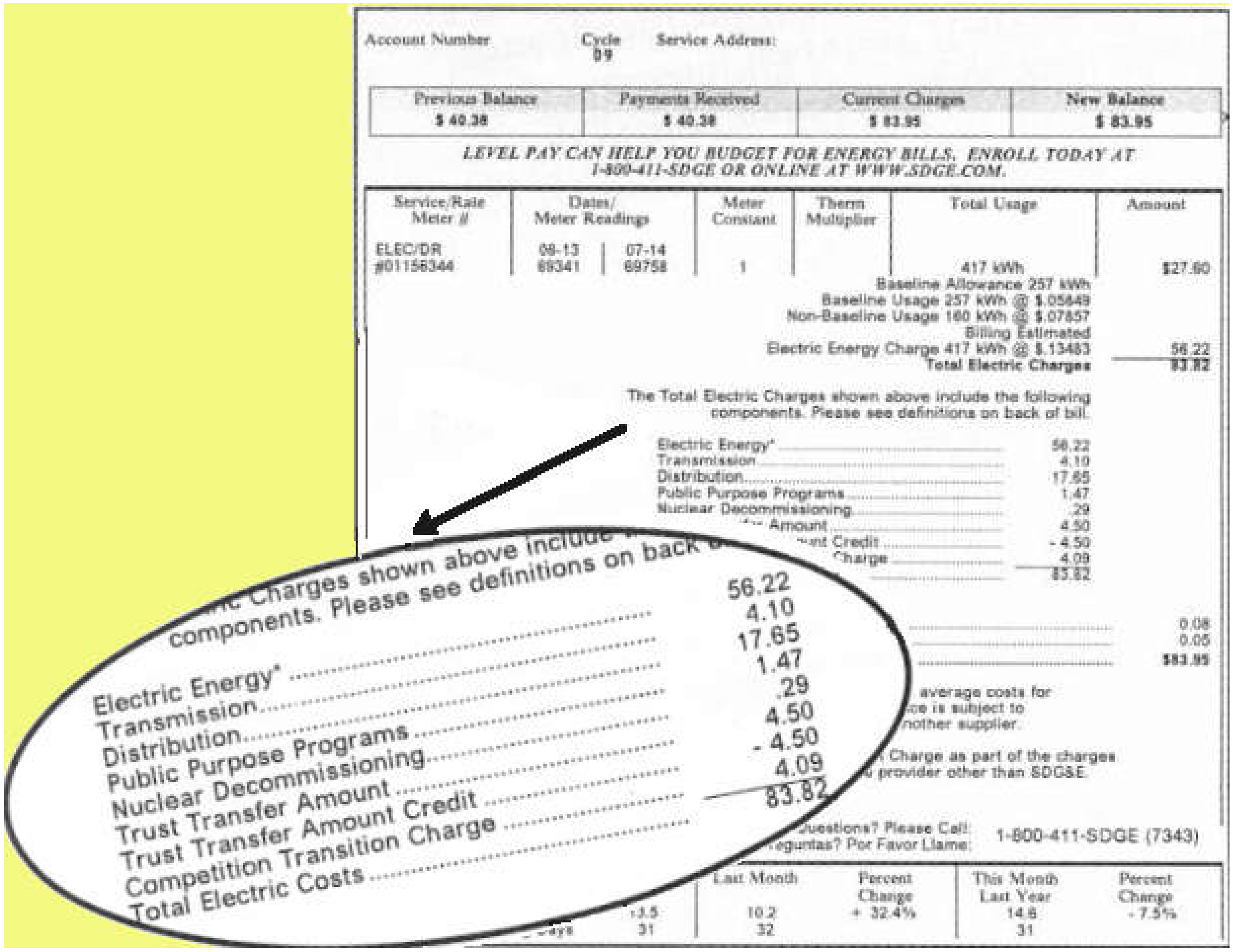


Figure 1.3: New electric bill in California [26]

Ontario electric market has the same structure as California electric market with only generation part being deregulated. Some other deregulated electric market such as Texas electric market has further deregulated the distribution part of the electric market.

1.3.1 Texas Electric Market

Texas electric market started deregulation on January 2002. Old vertically integrated operations were forced to split into several businesses; a Power Generation Company (PGC), a Transmission and Distribution Utility (TDU) and a Retail Electric Provider (REP). The REP is the entity with the primary contact with customers and purchases electricity, transmission service and distribution service on their behalf. The Texas Electric Market structure is shown in Figure

1.5. All PGCs and REPs have the equal access to the transmission and distribution grid. REPs signed contract with PGCs for purchasing electricity to serve their customers. TDU bills REPs for customers' usage of the grid.

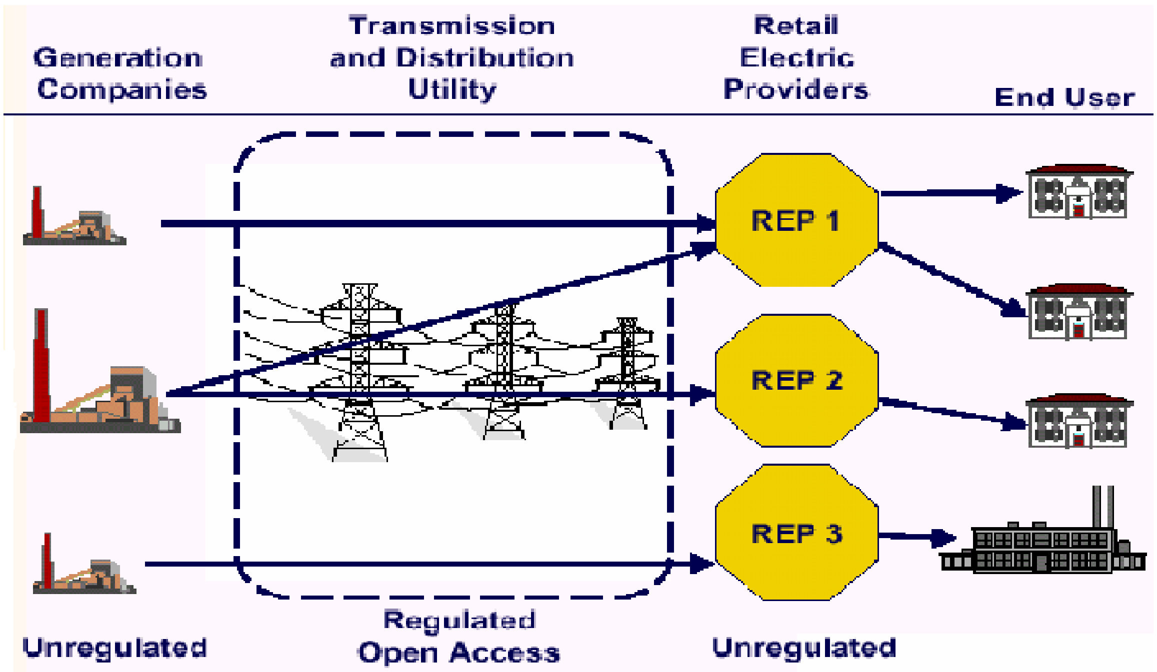


Figure 1.4: Texas Electric Market Structure [47]

Unlike Ontario electric system, in Texas, consumers can choose their electricity service from a wide variety of Retail Electrical Providers (REPs) instead of different electricity generation providers. REP offers different electricity price to their customers and compete with other retail electrical providers in the same market. The electricity wholesale price is no longer directly related to the end customers. REPs set their electricity rates based on market guide price, Price-to-Beat (PTB), and their own operating cost. For the incumbent electric utilities, the Public Utility Commission of Texas (PUCT) determines the PTB which may vary up to two times per year based on fuel cost. This is the highest rate REPs can charge for their customers. PTB is also the electric rate incumbent electric utilities will charge their customers. The reason is that new entry REPs could set price lower than PTB so that they could gain market share as a new entry company. How low their electricity rate could be depends on their operation of the company. Incumbent electric utilities will stay at the PTB rate acting like the bottom line to ensure the electricity retail price will not go skyrocket. Meanwhile, incumbent electric utilities also act as the securities in the market. If a REP went bankrupt or somehow they could not provide electricity service to their customers, these customers will automatically be transformed to the incumbent electric utilities to maintain continuous electricity service. Meanwhile, they could change to another REP at anytime they want. For these residential and small commercial customers (below 1 MW of peak demand) who do not change their electricity providers will get 6% deduction on their bill [40].

It is worth mentioning the difference between California and Texas Electric Market. The main reason that caused the California Crisis is that electricity wholesale price was higher than the retail price. This forced many retail electricity providers went bankrupt. In contrast PTB in Texas electric market can vary to cover the effect of fuel costs. REPs set their retail price based on the PTB. As incumbent utilities operate generating company and electric retail company at the same time, and PTB is their electricity price charge to their customers, PTB will efficiently reflect the electric wholesale price. This will avoid the wholesale price exceeding the retail price. The difference between PTB and the actual price REP charges their customers will be a reflection of how competitive each REP is.

1.3.2 Ontario Electric Market

The Independent Electricity System Operator (IESO) is a crown corporation responsible for operating the electricity market and directing the operation of the bulk electrical system in the province of Ontario, Canada [38]. The IESO is an independent and non-profit entity established in April 1999. A board whose directors are appointed by the Government of Ontario governs it. Ontario Energy Board sets its fees and licenses. Most importantly, it operates independently of all participants in the electricity market [38].

In Ontario, homeowner and certain designated consumers are part of the regulated price plan (RPP) set by the Ontario Energy Board (OEB). The threshold under the RPP varies by season to reflect changing consumption patterns. Some regulated prices are shown below.

Summer Regulated Price Plan Rates (May 1 to October 31)

Residential users

- 5.3 ¢/kWh for the first 600 kWh in a month
- 6.2 ¢/kWh for each additional kWh

Low-volume business users

- 5.3 ¢/kWh for the first 750 kWh in a month
- 6.2 ¢/kWh for each additional kWh

Regulated price plan applies to homeowners and designated consumers that include hospitals, universities, schools, farms and specified charitable organizations. Other consumers such as large volume users who consume more than 250,000 kWh a year pay the wholesale price of electricity. These include industrial facilities, large retail operations such as supermarkets or department stores and other medium- and large-sized businesses. These customers consume almost half of all electricity used in Ontario.

Consumers in Ontario can purchase electricity either from their local utilities or through an electricity retailer licensed by the OEB. Consumers' electricity bill includes energy use that indicates how much electricity they used in the certain time period. This is the deregulated part where price may vary depending on the providers' rates. The next part is the delivery charge where price is regulated by the OEB. This includes charge to transmit electricity though transmission and distribution systems. Other chares such as regulatory and debt retirement charges are also applied on every bill.

1.4 Electricity Market Clearing Price

Market clearing price by definition is the price that exists when a market is clear of shortage and surplus, or is in equilibrium. It is a common and non-technical term for equilibrium price. In a market graph, the market clearing price is found at the intersection of the demand curve and the supply curve [28]. Figure 1.6 shows the electricity market clearing price (MCP) in California electric market. The MCP in Figure 1.6 is $200 per MWh, and the demand at that price is 30,000 Mega Watts.

The equilibrium price or the MCP price is the final product of market bidding price. When electric market clearing price is determined, every supplier whose offering price is below or equal to the electric MCP price will then be picked up to supply electricity at that hour. They will be paid at the same price, the electricity market clearing price, but not the price they offered. The reason for that is to keep fairness of the market and to avoid market manipulation.

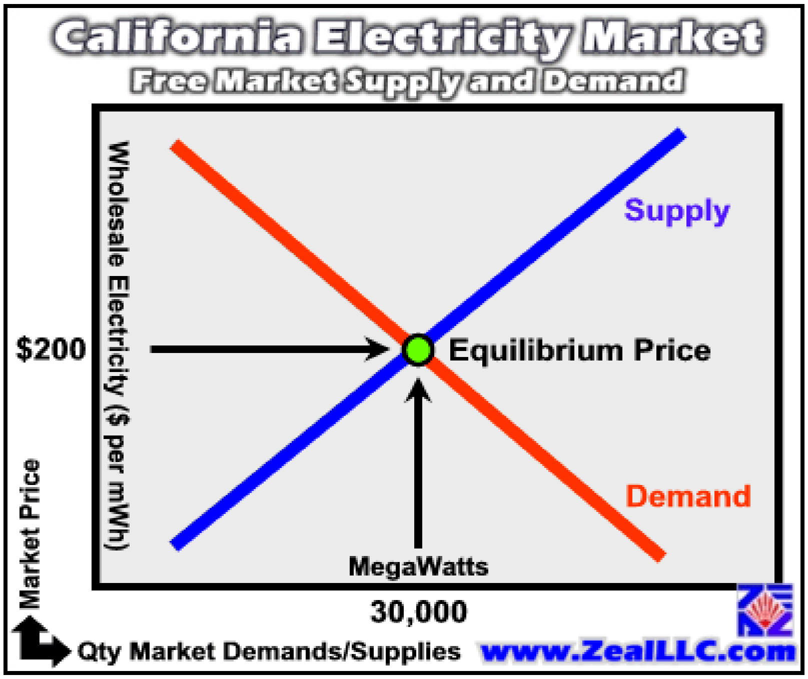


Figure 1.5: Electric Market Clearing Price [27]

In Ontario deregulated electric market, for those consumers paying wholesale price from a 24-hour operation wholesale electricity market, the wholesale price is set every 5 minutes. The process of electricity market clearing price determination starts by finding out electricity demand at the first place. Each day, the IESO issues forecasted electricity demand throughout the following day and up to the month ahead. This forecasted electricity demand also includes an energy reserve of approximately 1400 MW above what will actually be consumed. This extra 1400MW is on standby and reserved for emergency usage. The forecasted electricity demand is continually updated as new information comes in such as changes in weather. Typically, the day-ahead forecasted electricity demand from IESO are highly accurate, with less than two percents variance from the actual demand figures [37].

After the determination of electricity hourly demand, the next step is to start the electricity auction (electricity market bidding price). Generators and electricity providers review the forecasted information and decide how much electricity they will supply and what price they will charge at various hours. They will then send that information to IESO. Meanwhile, large volume consumers will send their demand information and the price they are willing to pay for the electricity. Large volume consumers have the ability to change their consumption plans. The market is structured so that the consumers can agree to cut consumption at pre-determined price levels. If these large volume consumers feel the wholesale price that offered by the electricity providers is too high to accept, they can cut their electricity usage to save money. After the actual electricity demand been finally determined, the IESO then matches the offer to supply electricity against the forecasted demand. It accepts the lowest priced offers first and then "stacks" up the higher priced offers until enough have been accepted to meet customer demands. All suppliers are paid the same price, the market clearing price. This is based on the last offer been accepted. The Market Clearing Price approach ensures the lowest possible price while maintaining reliability of the system [37].

When the market clearing price is determined, the IESO collects bids and offers until two hours before the electricity is needed. This way, new bids can still come so that the actual market clearing price can be adjusted instantly. The IESO will issue its instructions to the winning bids suppliers. Those winning bid providers or picked providers will then supply electricity into the electric system, through the transmission lines and to the end user.

1.5 Electricity Market Clearing Price Forecasting

Electricity market clearing price (MCP) forecasting is a prediction of future electricity price based on given forecast of electricity demand, temperature, sunshine, fuel coast and precipitation. Good electricity MCP forecasting can help suppliers and consumers to prepare their electricity usage and bidding strategy in order to maximize their profits. Electricity MCP forecasting is very complex task as there are too many variables with various uncertainties that affect the electricity MCP in various way. Some of these variables are straightforward and could be managed to forecast quite accurately such as temperature, sunshine, natural gas price and precipitation. Other variables, however, are very complicated and highly unpredictable such as market clearing price bidding strategy, spot market price, spinning reserve market price, business competing strategy and even unethical business behaviours.

The short-term electricity MCP forecasting is commonly known as the 24-hour day-ahead MCP forecasting. It forecasts the electricity MCP for the next 24 hours. A producer with low capability of altering MCPs (price-taker producer) needs day-ahead price forecasts to optimally self-schedule and to derive his bidding strategy in the pool [33]. Retailers and large volume consumers also need the forecasted day-ahead electricity MCP for the same reason. In most electric market, 24-hour day-ahead electricity MCPs for the next day is required around 10 a.m. in the previous day.

The mid-term electricity MCP forecasting focuses electricity price on a time frame between one month and six months. It can be utilized in decision making and mid-term planning purposes. Some examples include adjustment of mid-term schedule and allocation of resources.

The forecast of electricity MCP as mentioned before depends on variables such as fuel cost, electricity demand and supply, temperature, sunshine, congestion, transmission loss, transmission constrains and precipitation. The forecasting of electricity MCP is a highly non-linear problem. Variables such as bidding strategy, business competition strategy and unethical business behaviours impose an unrealistic burden on the forecasting process due to the fact that these variables are difficult to quantize.

1.6 Review of Current Methods

Several techniques have been proposed to forecast electricity market clearing price. The majority of these methods deal with the day-ahead energy markets and therefore forecast electricity MCPs for the next 24 hours.

Gao et al [1] developed a neural network based method for forecasting the electricity MCP and market clearing quantity (MCQ) for the California day-ahead energy markets. Their proposed network utilized a three-layer feed-forward network. Historical MCPs, MCQs, forecasted load, power import/export and weather are included as inputs and outputs when training the neural network. Weekday and weekend electricity MCP forecasting are proceeded with different models.

Contreras et al [5] proposed an approach utilizing auto regressive integrated moving average (ARIMA) models. ARIMA have been widely used to forecast commodity prices. It utilizes hypothetical probability supervised scheme to create validated models for forecasting the electricity prices.

Ferreira et al [6] proposed a neural network approach for forecasting short-term electricity MCP. Ferreira utilized a three-layer feedforward neural network trained by the Levenberg-Marquardt algorithm. The forecasted electricity price contained the hourly electricity MCP for the next week. Numerical results are obtained by forecasting the electricity markets of mainland Spain and California. Unlike other proposed works, this method used only price data to forecast the electricity MCP.

Ruibal et al [13] proposed a Monte Carlo simulation approach for forecasting the mean and the variance of electricity price. A deregulated electricity market containing 10 generating companies was designed and the unavailability of electricity generating units was model by utilizing Monte Carlo simulation technique. The mean and the variance of electricity price were calculated based on the simulation results.

Liu et al [30] proposed a short-term electricity price and load-forecasting model with the combination of non-decimated wavelet transform, neural network, and support vector machine techniques. Liu’s model had taken the weather factor into account. A set of feed-forward neural network had been utilized as one of the several modules inside the whole forecasting system to predict the load data. The proposed neural network contained only one hidden layer. The scaled conjugate gradient algorithm is used in training the neural network. Results from numerical examples indicate the capability of handling extremely chaotic market.

Nogales et al [43] proposed two short-term electricity price forecasting models using both dynamic regression and transfer function based on time series analysis. These two techniques were used to check against each other. A hypothetical probability model was set up to represent the price and demand data which are recorded in time series. The time series method is also utilized by Obradovic Z. [41] while forecasting day-ahead electricity market price and by Crespo J. [42] while forecasting electricity spot prices.

Artificial neural network (ANN) method, because of its flexibility on handling highly non-linear relationships and relatively easy implementation, is suitable for forecasting electricity MCP. Deregulated electric markets utilizing ANN method to forecast electricity MCP include PJM Interconnection, Australian electric market, England-Wales pool and New England ISO [33]. However, little work has been done to forecast electricity MCP on a mid-term basis.

1.7 Objective and Scope

The objective of this research work is to develop an artificial neural network that can be utilized to forecast the electricity market clearing price on a mid-term basis.

Electricity market clearing price under deregulated electric market varies from one moment to another depending upon the changes in various variables such as load, temperature, fuel cost, precipitation, market clearing price bidding strategy and business competing strategy. A neural network that can forecast mid-term market clearing price of electricity would be a valuable tool for planning purposes. The proposed neural network should be designed to meet the following criteria.

- Provide daily and hourly forecasted electricity market clearing price on a mid-term basis.
- Be flexible enough to accommodate changes on demand, fuel cost and precipitation.
- Be flexible enough to utilize alternative training data to avoid man-made effects such as business competing strategy and unethical business behaviours.

1.8 Thesis Outline

This thesis is organized in six chapters. Chapter 1 introduces the basic concepts of deregulated electric market, electricity market clearing price and electricity market clearing price forecasting. It also summarizes the present problems involved in electricity MCP forecasting and the methods utilized in forecasting the electricity MCP under deregulated electric market.

An introductory level of description of a typical artificial neural network (ANN) is presented in Chapter 2. The basic configuration, working principles and architecture of the artificial neural network are also described. Historical information of neural network development are also discussed in this Chapter.

In Chapter 3, an artificial neural network based electricity MCP forecasting method is described. It explains the learning process of neural network utilizing backpropagation algorithm. Testing of neural network and reviewing of previous proposed neural networks forecasting electricity MCP are also included in this Chapter.

Chapter 4 and 5 introduce the electricity market clearing price forecasting utilizing the proposed neural network. Mid-term daily market clearing price forecasting is represented in Chapter 4 and hourly based mid-term market clearing price forecasting is represented in Chapter 5. In Chapter 4, neural network models and the selection of training data for the proposed neural network are explained in detail. Proposed neural network training and creation of forecasting input data are also included. Results are obtained from two neural networks. One is trained with the entire training data set and the other one is trained with the filtered training data.

Chapter 5 is focused on hourly market clearing price forecasting rather than daily market clearing price forecasting. This Chapter is organized using the same steps as Chapter 4 including proposed neural network training, selection of training data and creation of forecasting input data. Results obtained utilizing both neural networks, one with the entire training data set and the other one with filtered training data are presented in this Chapter.

The conclusions and the scope of future work are presented in Chapter 6.

CHAPTER 2: ARTIFICIAL NEURAL NETWORKS

2.1 Introduction

Neural network simulations appear to be a recent development. However, this field was first established even before the invention of computers. The concept of neural networks started in the late 1800's as an effort to describe how the human mind performed. These ideas started being applied to computational models with Turing's B-type machines and the Perceptron [21].

In 1943, neurophysiologist Warren McCulloch and mathematician Walter Pitts wrote a paper on how neurons might work [14]. They modeled a simple neural network using electrical circuits in order to describe how neurons might work in the brain. The major development in neural network arrived in 1949 with the publication of Donald Hebb's book, "The Organization of Behaviour". The book supported and further reinforced McCulloch and Pitts's theory about neurons and how they work. A major point bought forward in the book described how neural pathways are strengthened each time they were used [15][19].

As computers became more advanced in the 1950's, Nathanial Rochester from the IBM research lab, although failed, first tried to simulate a hypothetical neural network. Frank Rosenblatt in the late 1950's and early 1960's proposed a new approach to pattern recognition problem which was then called as Perceptron. In 1960, Least Mean-Square (LMS) algorithm was introduced by Widrow and Hoff. These early stage neural networks showed promises, but they were limited in their problem solving abilities.

In the 1980's, major contributions to the theory and design of neural networks were made on several fronts.

- Grossberg, 1980: Established a new principle of self-organization
- Hopefield, 1982: Hopefield Networks
- Kohonen, 1982: Self-organizing map using one or two lattice structure
- Kirpatrick, Gallat and Vecchi, 1983: Simulated annealing
- Hinton and Sejnowski, 1985: Boltzmann learning algorithm
- Rumelhart, Hinton and Williams, 1986: Back Propagation Algorithm

Today, neural networks have established themselves as an interdisciplinary subject with deep roots in neuroscience, psychology, mathematics, physical science and engineering [20]. With the development of personal computers, new neural network techniques are invented every week. Significant progress has been made in the field to attract a great deal of attention and fund further research. Advancement beyond current commercial applications appears to be possible, and research is advancing the field on many fronts [21].

An artificial neural network (ANN), also called a simulated neural network (SNN) or commonly just neural network (NN) is an interconnected group of artificial neurons that uses a mathematical or computational model for information processing based on a connectionist approach to computation [21]. Artificial neural networks are designed for solving artificial intelligence problems without necessarily creating a model of a real biological system [21]. Because of this unique characteristic, neural network could be used to model complex relationships between input and output, such as non-linear computation, pattern recognition, voice recognition and decision making. The benefit of utilizing neural network is that we could avoid finding the real structure or any other interconnections inside a system but model the result in a more efficient way. Its practical use comes with algorithms designed to alter the synaptic weights of the connections inside the network to produce a desired signal flow [21]. Moreover, neural network could be easily expanded or redesigned by simply changing the interconnection pattern, active functions, or the number of layers and neurons. Compared to the standard mathematical simulation processing time, neural network is much more efficient. ANN are also used in the following specific paradigms: recognition of speakers in communications; diagnosis of hepatitis; recovery of telecommunications from faulty software; interpretation of multi-meaning Chinese words; undersea mine detection; texture analysis; three-dimensional object recognition; hand-written word recognition; and facial recognition [23]. In order to understand the functionality of a neural network, let us first look at how a human brain works.

2.2 Biological Neural Network

A brain is the central processing unit (CPU) of a biological neural network. The struggle to understand how a brain works, owes much to the pioneering work of Ramón Y Cajal, who first introduced the idea of neurons as structural constituents of a brain [17]. The human brain consists of 10 billions nerve cells, or neurons. The biological structure of a brain neuron is shown in Figure 2.1. Neurons are connected in a 3-dimisioncal structure. There are about 60 trillion synapses or interconnections between them [20]. Those neurons are well interconnected with each other. On average, each neuron is connecting with 10000 neurons through synapses. Therefore, the brain is indeed a massively parallel interconnected information processing system. Communication between neurons often involves an electrochemical process. The input signals are collected from the dendrites and the sum of those signals are then processed inside the nucleus. Once the sum of the input signals surpasses a certain threshold, a spike is then send through the axon to the axon terminal. The axon terminal is connected to other dendrites as input ports to other neurons.

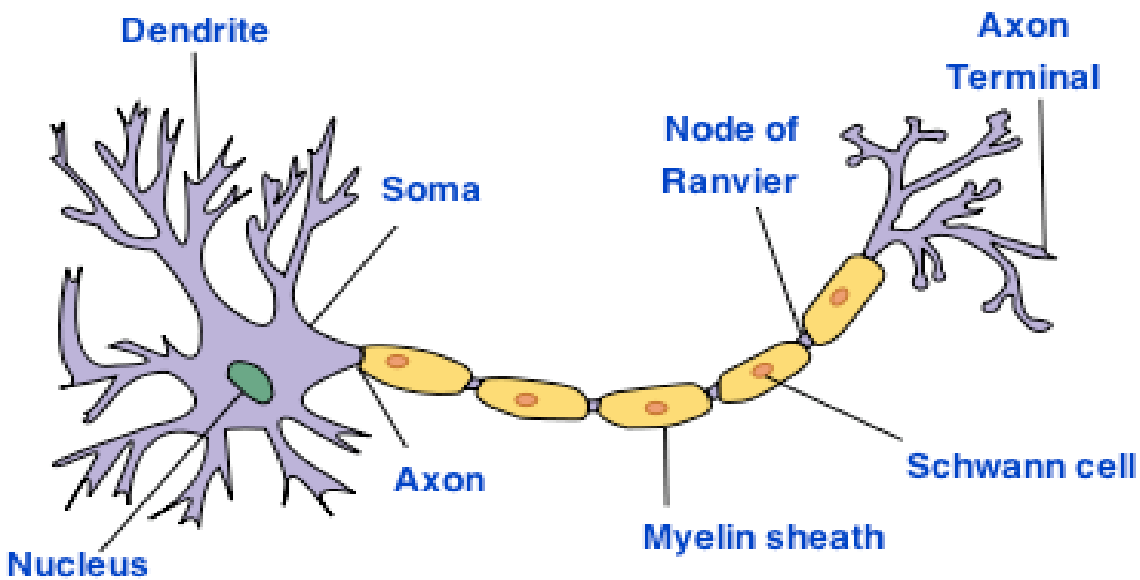


Figure 2.1: Biological Structure of a Typical Neuron [16]

2.3 Mathematical Explanation of A Neural Network

Emphasizing biologically inspired approaches to problem solving, the field of artificial neural network developed rapidly. Different from traditional computers' serial fashion architectures, artificial neural network computation occurs through parallel structured large number of simple processing units. Similarly, information is distributed across the entire network rather than being located in one specific place or address [4]. Let us first take a look at a single mathematical neuron.

2.3.1 Mathematical Model of A Neuron

A neuron with a single input vector containing R elements is shown in Figure 2.2. $P_{1,}$ $P_{2, \ldots}$ P_R are the input elements. $W_{1,1}$, $W_{1,2}$, … $W_{1,R}$, are the corresponding weights for individual input element. The dot product of input elements and corresponding weights are fed to the summing neuron. A single bias *b* is then added to the summing neuron to form *n* to feed as the input for the transfer function *f*. A mathematical explanation of *n* is shown in Eq. (2.1).

$$n = w_{1,1}p_1 + w_{1,2}p_2 + \ldots + w_{1,R}p_R + b \tag{2.1}$$

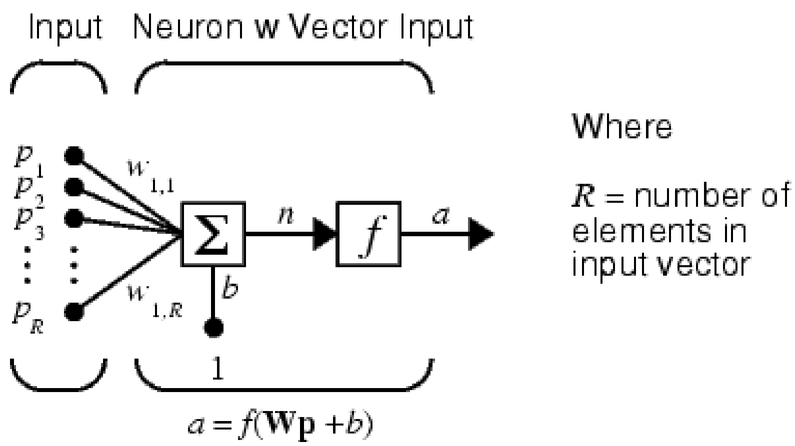


Figure 2.2: A Mathematical Neuron [8]

Finally, an output *a* is calculated through the transfer function. Some common transfer functions utilized in neural networks are shown in Figure 2.3. A transfer function acts as a squashing function, such that the output of a neural network is between certain values (usually between 0 and 1, or -1 and 1) [24]. Generally speaking, there are three major transfer functions. The first one is the Threshold Function where the output of the transfer function would be a 0 if the summed input is less than a certain threshold value. When the summed input is greater than or equal to a certain threshold value, the output of the transfer function would be a 1. Let φ be the transfer function and υ be the input. A Threshold Function is shown in Eq. (2.2).

$$\varphi(v) = \begin{cases} 1 & if \quad v \geq 0 \\ 0 & if \quad v < 0 \end{cases} \tag{2.2}$$

The second transfer function is the Piecewise-Linear Function whose values are either 0 or 1 on both ends. When the summed input is between the two end values, the output would be a linear equation with a constant slope. Eq. (2.3) shows a piecewise-linear function with a slope of 1.

$$\varphi(v)=\begin{cases}1 & v\geq\frac{1}{2}\\ v & -\frac{1}{2}>v>\frac{1}{2}\\ 0 & v\leq-\frac{1}{2}\end{cases}\tag{2.3}$$

The last transfer function is the Sigmoid Function whose range is from 0 to 1 shown in Eq. (2.4). The modified sigmoid function, also referred as the Hyperbolic Tangent Function has a range from -1 to 1 shown in Eq. (2.5).

$$\varphi(v)=\frac{1}{1+\exp(-av)}\tag{2.4}$$

where a is a slope parameter of the sigmoid function.

$$\varphi(v)=\tanh(\frac{v}{2})=\frac{1-\exp(-v)}{1+\exp(-v)}\tag{2.5}$$

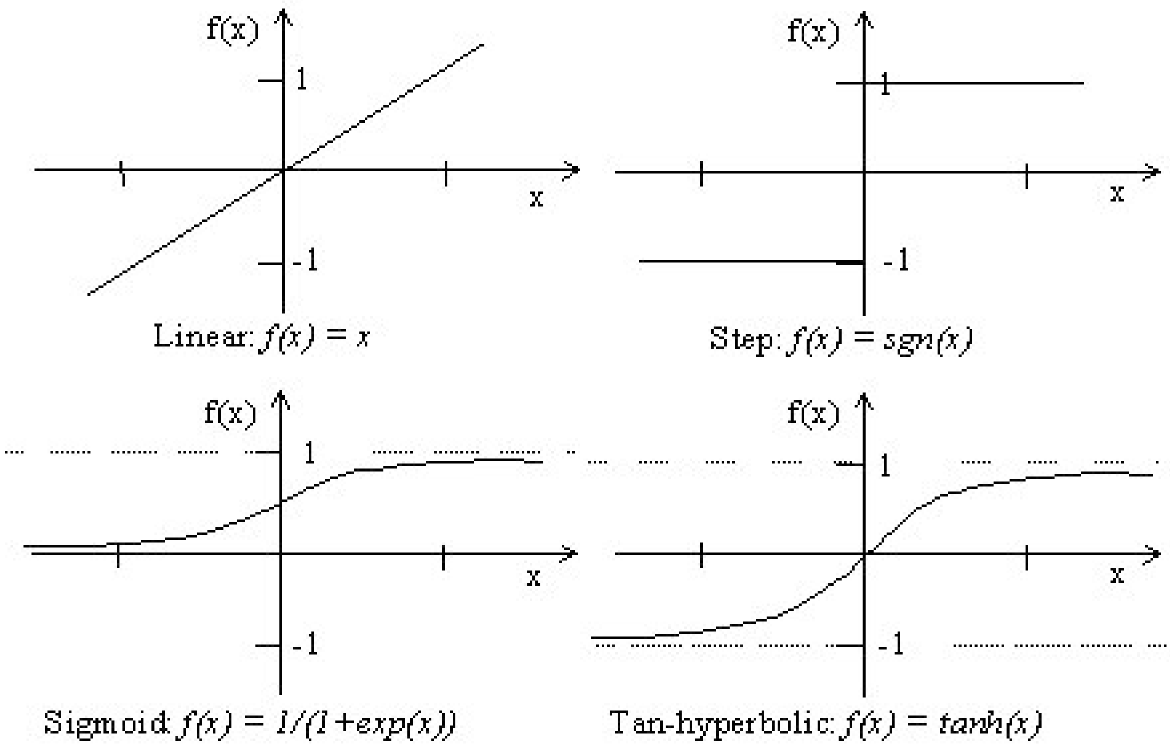


Figure 2.3: Common Non-linear Transfer Functions [24]

2.4 Working Principles of Artificial Neural Networks

The working principles of an artificial neural network are very straightforward. Let us take a three-layer feedforward neural network as shown in Figure 2.4. From left to right, starting from the input layer, each input neuron is connected to every hidden neuron in the hidden layer. Then, each hidden neuron in the hidden layer is also connected to every output neuron in the output layer. Signals are passing through the input layer and multiplied by the corresponding synaptic weights. Those multiplied signals are then summed at the hidden layer and activated by a transfer function. Let i denote the input layer, j denote the hidden layer, k denote the output layer, y_i denote an input signal, w_{ji} denote a synaptic weight between input and hidden layer, v_j denote the summed signal at a hidden neuron, and $\varphi_j(.)$ denote the transfer function at the hidden layer. We could write the summing equation at the hidden layer as

$$v_j(n) = \sum_{i=1}^{n} w_{ji}(n) y_i(n) \tag{2.6}$$

where n is the number of input signals. The activated sum through transfer function could be written as

$$y_j = \varphi_j(v_j) + b_j \tag{2.7}$$

where b_j is a threshold value at the hidden layer. The transfer function could be anyone of the step, piecewise-linear, sigmoid, or hyperbolic tangent function mentioned in Section 2.3.

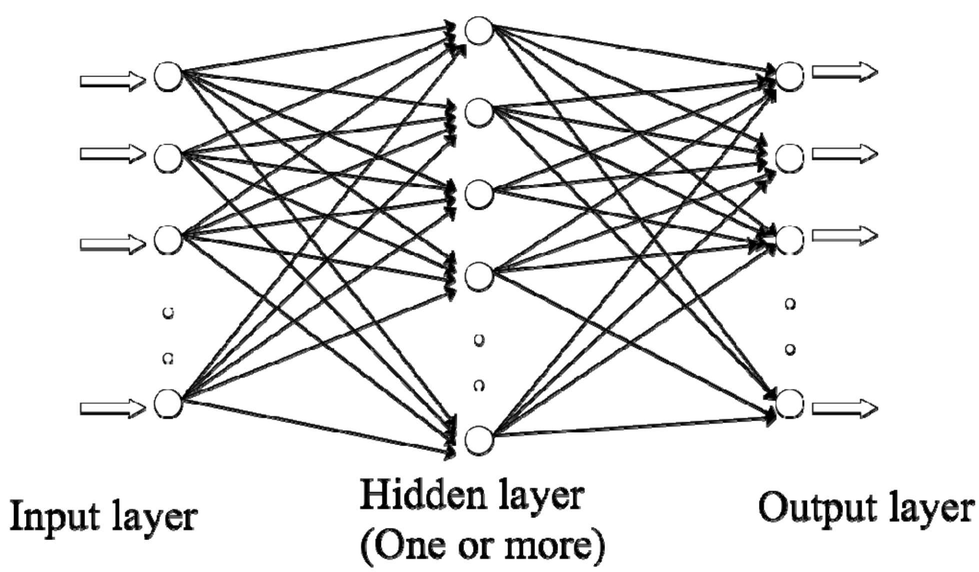


Figure 2.4: A Multi-Layer Fully Connected Feedforward Network [20]

The activated signal y_j in the hidden layer would be multiplied by the synaptic weight w_{kj} between the hidden layer and the output layer and summed at the output layer. Those summed intermediate signals would then be activated by the transfer function at the output layer. Let v_k denote the summed signal at the output layer, $\varphi_k(.)$ denote the transfer function, and y_k denote the output signal. We could write the summing equation at the output layer as

$$v_k(m) = \sum_{j=1}^{m} w_{kj}(m) y_j(m) \tag{2.8}$$

where m is the number of hidden neurons. The activated sum through transfer function could be written as

$$y_k = \varphi_k(v_k) + b_k \tag{2.9}$$

where b_k is a threshold value at the output layer. Again, the transfer function could be anyone of the step, piecewise-linear, sigmoid, or hyperbolic tangent function mentioned in Section 2.3. Usually a piecewise-linear function is utilized as a transfer function at the output layer.

2.5 Architecture of Artificial Neural Network

The architecture of artificial neural networks can be generally divided into four major classes based on different learning algorithms; the single-layer feedforward network, the multilayer feedforward network, the recurrent networks and the lattice structure. Although there are many other types of networks, these four are the most commonly utilized network architectures for artificial neural networks.

2.5.1 Single-Layer Feedforward Network

A single-layer feedforward network is the simplest type of network, contains only one layer, the output layer. Each element in the input vector is directly connected to the output layer. In a single-layer feedforward network, there is no hidden layer between input and output. Figure 2.5 shows a single-layer feedforward network.

Single-layer neural network is usually used in an application containing linear computation such as linear associative memory. The advantage of a single-layer neural network is its simple structure and therefore less synaptic weights and calculation time. The disadvantage of a single-layer neural network is that it cannot handle non-linear computation due to its structural limit.

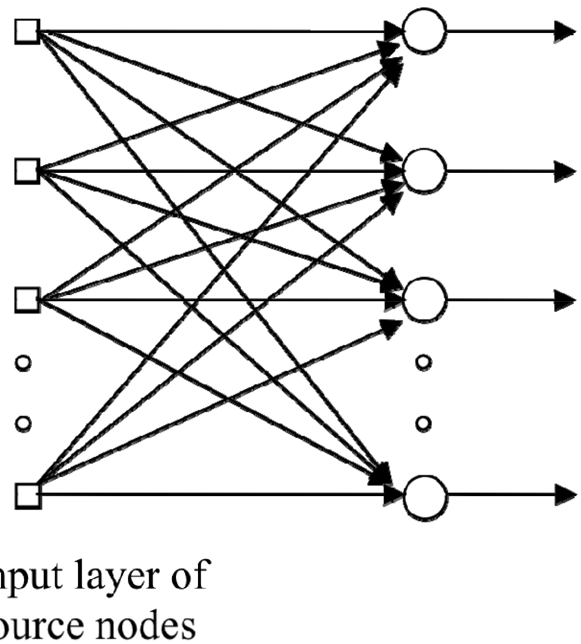


Figure 2.5: A Single Layer Feedforward Network [20]

2.5.2 Multilayer Feedforward Network

A multilayer feedforward network, often known as Multilayer Perceptron (MLP), contains at least one hidden layer. The input elements are not directly connected to the output elements. Figure 2.4 shows a simple multilayer feedforward network with one hidden layer containing more than one hidden neurons. Additional hidden layers inside a multilayer feedforward network could increase the network's capability of handling highly complex non-linear relationship between input and output.

Multilayer feedforward networks could further be divided into two broad categories: fully connected and partially connected multilayer feedforward network. Figure 2.4 is a fully connected multilayer feedforward network where every node in each layer is connected to every other node in the forward layer. Partially connected multilayer feedforward network, on the other hand, contains nodes that are not connected to every node in the forward layer. Figure 2.6 is a multilayer partially connected feedforward network. The hidden layer and the output layer are partially connected.

Multilayer feedforward neural networks are usually used in applications containing non-linear computation such as forecasting and decision making. The advantage of a multilayer feedforward neural network is its handling of non-linear computation. With additional hidden neurons and layers, a multilayer feedforward neural network could be capable of performing higher-order computation. This ability is particularly valuable when the size of the input layer is large [19]. Significant computation time, complicated interconnection structure and huge number of synaptic weights are the disadvantages of a multilayer feedforward neural network. Moreover, such a neural network also requires huge amount of training data in order to be trained properly.

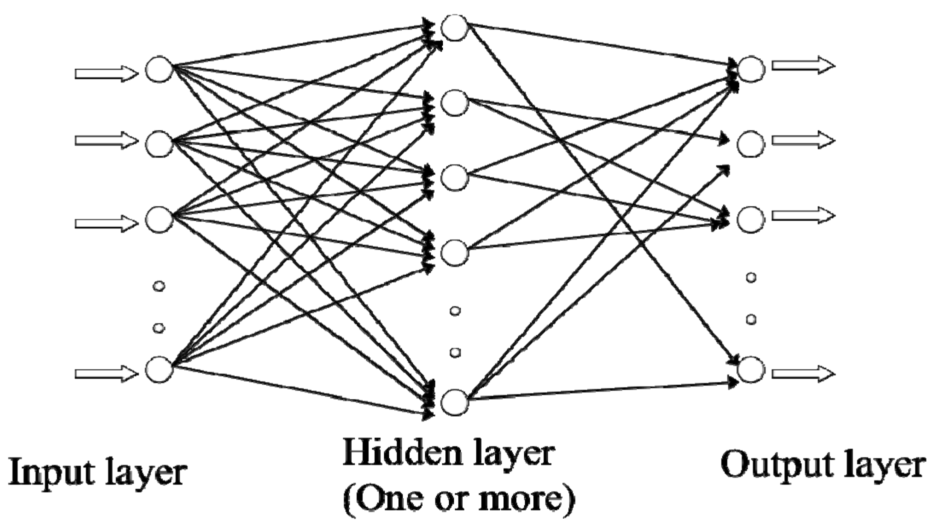


Figure 2.6: A Multi-Layer Partially Connected Feedforward Network [20]

2.5.3 Recurrent Network

A recurrent network is a looped network. A feedback loop is the major difference a recurrent network distinguishes itself from a feedforward neural network. Recurrent networks could be either with or without hidden neurons. Figure 2.7 represents a recurrent network with hidden neurons with the unit-delay element, z^{-1}.

This kind of recurrent network could be used to model nonlinear dynamical behaviour of a system [19] such as speech and online handwriting recognition. The main advantage of a recurrent network is its learning capability due to its feedback loop. Within its hidden layers, a recurrent neural network could embed theoretically infinite historic inputs which could overcome the problem of prefixed historical inputs in a feedforward neural network. The disadvantage of such a network is that they require substantially more connections and more memory for simulation than a standard back propagation network [45].

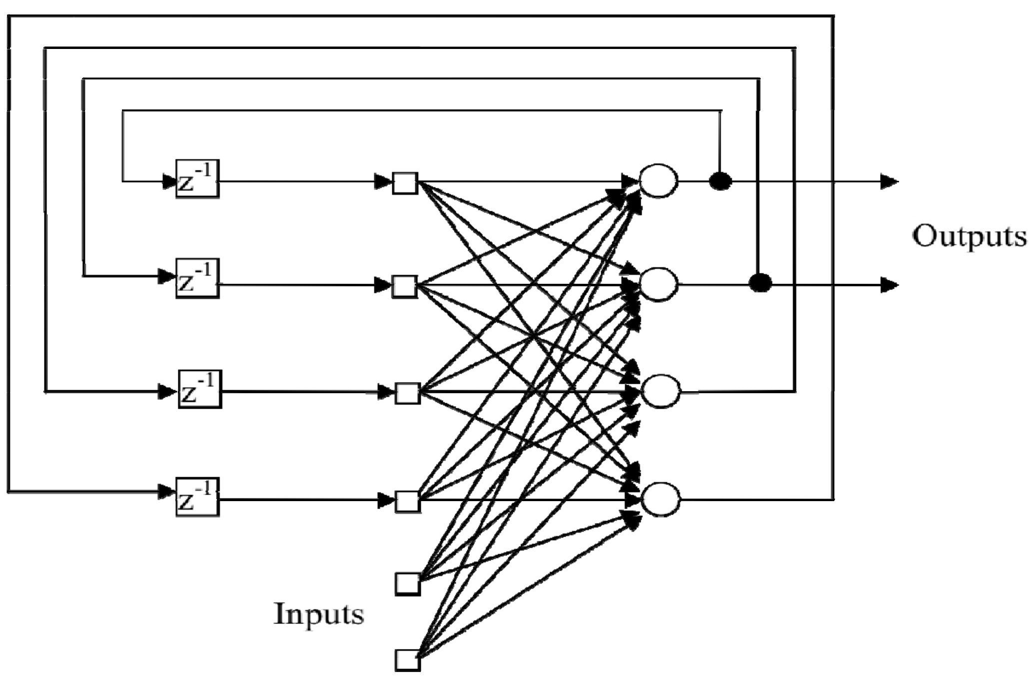


Figure 2.7: Recurrent Network with Hidden Neurons [20]

2.5.4 Lattice Structures

Lattice structures contain a set of source nodes that supply the input signals to an array. It could have one to multi-dimensional array of neurons. The dimension refers to the number of the dimensions of the space in which the graph lies. Figure 2.8 shows a two-dimension lattice structure of 3-by-3 neurons fed from a layer of three source nodes. A lattice network is really a feedforward network with the output neurons arranged in rows and columns.

Lattice structure neural networks are usually used in applications requiring the representation of one to multi dimensional space structures. The advantages and disadvantages of a lattice structure neural network are the same as that of a feedforward neural network.

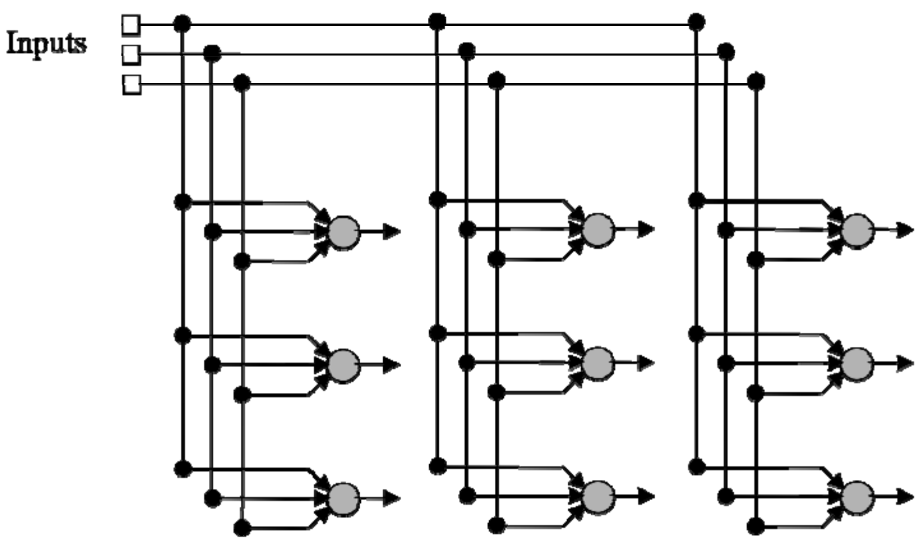


Figure 2.8: Two-Dimensional Lattice of 3-by-3 Neurons [20]

CHAPTER 3: ARTIFICIAL NEURAL NETWORK BASED MARKET CLEARING PRICE FORECASTING

3.1 Introduction

In a regulated electric market, electricity price is usually set by the utility company. A regulated electric utility performs load forecasting, solves and minimizes its operating cost in order to maximize its profit. In a deregulated electric market, the electricity price, commonly known as electricity market clearing price (MCP), varies from hour to hour depending upon the supply and demand principle. Although minimizing production cost is still important, knowing the possible electricity MCP becomes essential to maximize the potential profit. Generators and suppliers in a deregulated market employ various models and techniques to forecast MCP. Based on the forecast, a generator or a supplier can set its bidding strategy and decide which energy market it should participate to maximize its revenue. A mid-term MCP forecast is often necessary for planning and investment purposes. Utilities are paying more attention to electricity MCP forecasting. Several methods have been proposed to forecast electricity MCP. Some of these methods include ARIMA (auto-regressive integrated moving average) models [5], wavelet transform models [21, 38], Monte Carlo simulation [13], time series methods [41, 42], bid-based stochastic model [13] and dynamic regression models [43]. Artificial neural network based electricity MCP forecasting is gaining popularity in recent days. Due to its complex non-linear behaviour of MCP, artificial neural networks can be used in an effective manner to forecast MCP.

3.2 Neural Network Architecture for MCP Forecasting

Electricity MCP forecasting under deregulated electric market is a highly non-linear problem which involves parameters such as electricity demand, historical electricity price, weather information, fuel cost and business competing strategies. Therefore, the applied neural network architecture should be capable of handling highly non-linear functions with huge amount of input data while providing efficient solutions. Based on the application, advantages and disadvantages of the four basic kinds of neural networks discussed in Chapter 2, only multilayer feedforward neural network and recurrent neural network are suitable for modeling highly non-linear computations. According to previous works on electricity MCP forecasting, both neural network architectures have been utilized for electricity MCP forecasting and promising results have been achieved. Due to the inherent non-linearity associated with the forecasting of electricity MCP, a three-layer feedforward neural network is so far the most promising model for forecasting the electricity MCP in a deregulated electric market [1][6][7][8][13]. Experimental results have shown that feedforward neural networks with more than three-layers have the same level of accuracy as a three-layer feedforward neural network. Of course, the number of inputs and hidden neurons inside the hidden layer would vary from model to model. A three-layer feedforward neural network is used in this research work. An example of a three-layer feedforward neural network containing 4 inputs and 5 hidden neurons is shown in Figure 3.1.

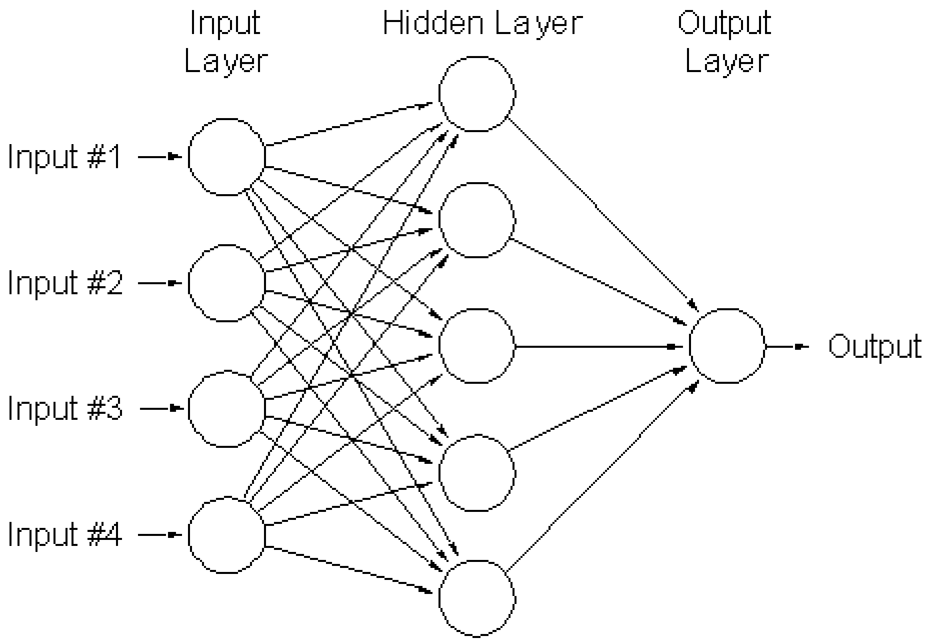


Figure 3.1: Three-Layer Feedforward Neural Network Model with Single Output [11]

The selection of training data is an important step in designing a neural network. For electricity MCP forecasting, the selected training data parameters should have direct or indirect influence on electricity MCP. Selected training data would determine the complexity of the neural network, and further more dominate the number of neurons inside the hidden layer. The selected training data should reflect and include all possible situations that affect electricity price. The number of neurons inside the hidden layer should also be carefully evaluated in order to minimize the sum of least square error and to achieve better system performance and accuracy. The selection of training input data will be explained in more details in Section 4.3. In comparison, the selection of training output data is fairly straightforward than the training input data. As the proposed neural network is used to forecast the electricity MCP, there is only one output, the electricity MCP. Historical electricity MCPs have been selected as training output data to train the proposed neural network.

3.3 Learning of Artificial Neural Network

One of the most distinguishable properties a neural network has is its ability to learn. The network could learn from its environment and improve its performance through the learning steps. By applying the adjustments on the synaptic weights and threshold though iteration, a neural network learns about its environment and becomes more knowledgeable about the environment. So far, there are three major learning paradigms: supervised learning, unsupervised learning and reinforced learning. Each of the learning paradigms is corresponding to a particular learning task. Supervised learning and reinforced learning can be used in electricity MCP forecasting. Supervised learning is applied on multilayer feedforward neural networks while reinforced learning algorithm is applied on the recurrent neural networks because of its feedback loop structure. In supervised learning, a training set $[p_1, t_1]$, $[p_2, t_2]$, … $[p_R, t_R]$ is provided. P_R is an input vector to the network, and T_R is the corresponding target vector. As the inputs are applied to the network, the calculated output using transfer functions are compared with the target vector. The learning rule is then applied to adjust the synaptic weights and thresholds of the network through each iteration in order to make the network outputs as close as possible to the targets.

In unsupervised learning, there are no target vectors. The weights and thresholds are modified in response to network inputs only. Most of these algorithms perform clustering operations. They categorize the input vectors into a finite number of classes. Unsupervised learning is especially useful in applications like vector quantization [8].

A reinforced learning system shown in Figure 3.2 consists of three elements: learning element, knowledge base and performance element. A critic is used instead of a teacher, which produces heuristic reinforce signal for the learning element. State input vector goes to critic, learning element and performance element at the same time. With the state vector and primary reinforce signal from the environment as inputs, the critic (predictor) estimates the evaluation function. By virtue of inputs received from the environment and the knowledge base, the performance element determines the input-output mapping [20]. As the proposed neural network used a three-layer feedforward neural network, the supervised learning paradigm is used to train the network.

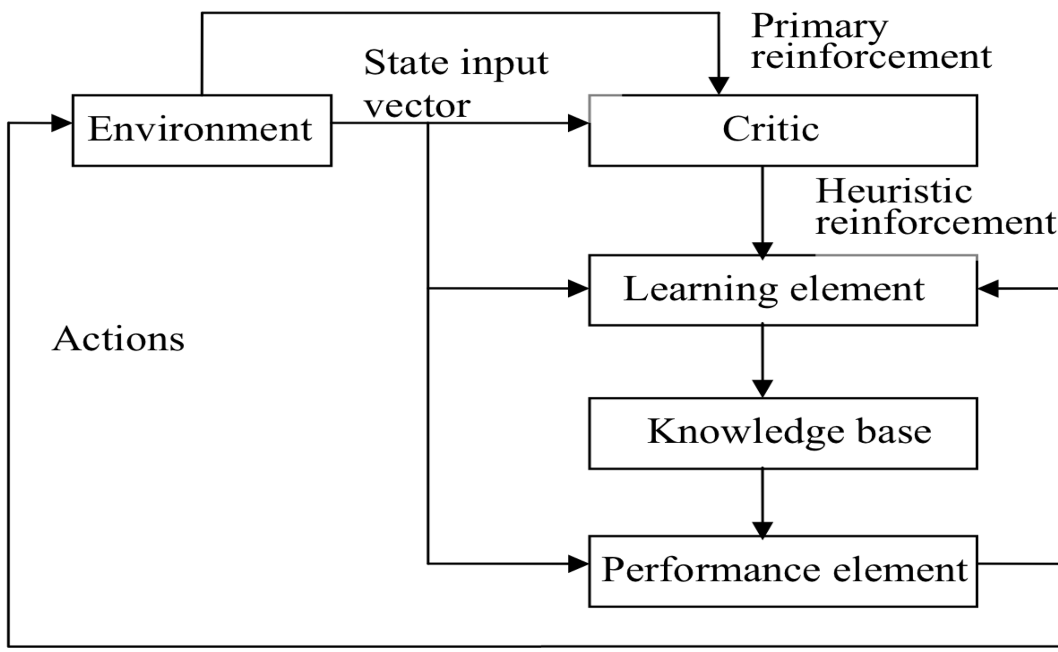


Figure 3.2: Block Diagram of Reinforced Learning System

3.4 Backpropagation Algorithm

Multilayer feedforward neural networks have been applied successfully in solving some difficult and non-linear problems by training them in a supervised paradigm with a highly popular algorithm know as the backpropagation algorithm [19]. The proposed neural network is trained using backpropagation algorithm because of its simplicity of calculation for updating synaptic weights and threshold. The rediscovery of the backpropagation algorithm was probably the main reason behind the repopularization of neural networks after the publication of "Learning Internal

Representations by Error Propagation" in 1986 (Though backpropagation itself dates from 1974). Training was done by a form of stochastic steepest gradient descent technique. The employment of the chain rule of differentiation in deriving the appropriate parameter updates results in an algorithm that seems to 'backpropagate errors', hence the name. However, it is essentially a form of gradient descent technique. Determining the optimal parameters in a model of this type is not trivial, and steepest gradient descent methods cannot be relied upon to give the solution without a good starting point.

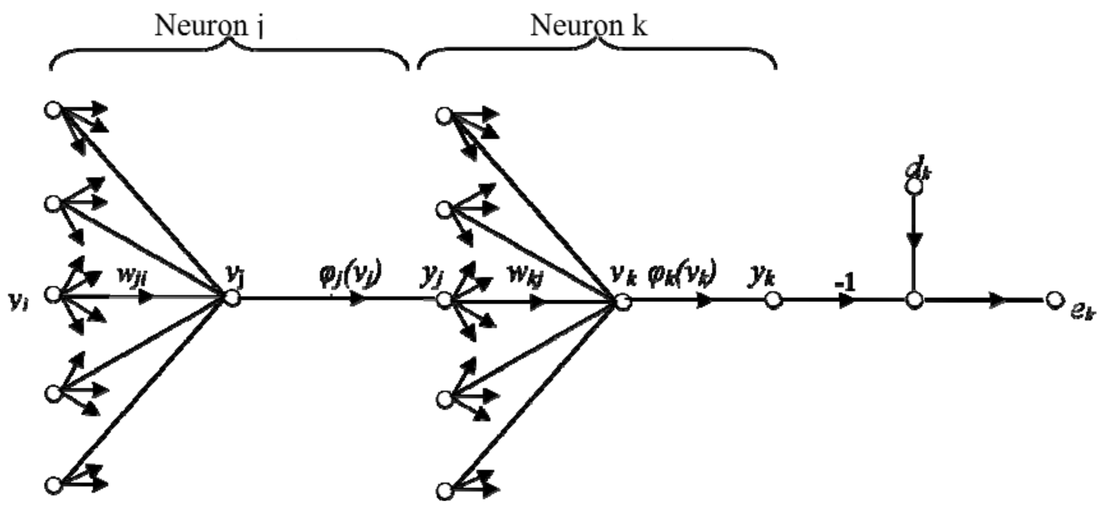


Figure 3.3: Signal Flow Diagram Inside Neural Network

Let us consider the signal flow in Figure 3.3 as an example. The error signal at the output neuron k can be defined as

$$e_k = d_k - y_k \tag{3.1}$$

The instantaneous sum of squared errors of the network can be written as

$$E = \frac{1}{2}\sum_{k=1}^{p} e_k^2 \tag{3.2}$$

where p is the total number of neurons at the output layer. As shown in Figure 3.3, the net internal activity v_k associated with neuron k is therefore

$$v_k = \sum_{j=1}^{n} w_{kj} \cdot y_j \tag{3.3}$$

where n is the total number of inputs (excluding the threshold) applied to neuron *k*. Hence, the output of neuron *k* is.

$$y_k = \varphi_k(v_k) \tag{3.4}$$

where $\varphi_k(.)$ is the activation function for neuron *k*. The activation function could be a threshold function, a piecewise-linear function, or a sigmoid function depending on the mathematical algorithm needed from each layer. The back propagation algorithm is utilized to apply a correction, Δw_{kj} to the synaptic weight w_{kj}, which is proportional to the instantaneous gradient $\partial E / \partial w_{kj}$. Applying chain rule, this gradient can be written as

$$\frac{\partial E}{\partial w_{kj}} = \frac{\partial E}{\partial e_k} \frac{\partial e_k}{\partial y_k} \frac{\partial y_k}{\partial v_k} \frac{\partial v_k}{\partial w_{kj}} \tag{3.5}$$

Differentiating Eq. (3.2) with respect to e_k, we get

$$\frac{\partial E}{\partial e_k} = e_k \tag{3.6}$$

Differentiating both sides of Eq. (3.1) with respect to y_k, we get

$$\frac{\partial e_k}{\partial y_k} = -1 \tag{3.7}$$

Differentiating Eq. (3.4) with respect to v_k, we get

$$\frac{\partial y_k}{\partial v_k} = \varphi_k'(v_k) \tag{3.8}$$

Differentiating Eq. (3.3) with respect to w_{kj}, we get

$$\frac{\partial v_k}{\partial w_{kj}} = y_j \tag{3.9}$$

Hence, using equations (3.6) to (3.9), Eq. (3.5) can be rewritten as

$$\frac{\partial E}{\partial w_{kj}} = -e_k \cdot \varphi_k'(v_k) \cdot y_j \tag{3.10}$$

The correction Δw_{kj} applied to w_{kj} using delta rule could be defined as

$$\Delta w_{kj} = -\eta \frac{\partial E}{\partial w_{kj}} \tag{3.11}$$

where η is a constant which defines the rate of learning. It is also called the learning parameter of the back-propagation algorithm. The minus sign in Eq. (3.11) accounts for gradient descent in weight space. Rewrite Eq. (3.11) as

$$\Delta w_{kj} = \eta \cdot \delta_k \cdot y_j \tag{3.12}$$

where δ_k is the local gradient defined as

$$\begin{aligned} \delta_k &= -\frac{\partial E}{\partial e_k}\frac{\partial e_k}{\partial y_k}\frac{\partial y_k}{\partial v_k} \\ &= e_k \cdot \varphi_k'(v_k) \end{aligned} \tag{3.13}$$

A linear function was used as an activation function for layer k. Therefore, the output at layer *k* is defined by

$$y_k = a_k \cdot v_k + b_k \tag{3.14}$$

where a_k and b_k are both constants. Differentiating Eq. (3.14) and utilizing Eq. (3.13), the local gradient δ_k can be rewritten as

$$\delta_k = a \cdot e_k \tag{3.15}$$

A summarized expression of back-propagation algorithm could be defined as

Weight correction Δw_{kj}={Learning rate parameter η}.{local gradient δ_k}.{input signal of neuron k y_j}

The next step is to calculate the weight update for layer j. According to Eq. (3.13), the local gradient for hidden neuron j could be redefined as

$$\begin{aligned} \delta_j &= \frac{\partial E}{\partial v_j} \\ &= -\frac{\partial E}{\partial y_j}\frac{\partial y_j}{\partial v_j} \end{aligned} \tag{3.16}$$

The output of neuron *j* is defined as

$$y_j = \varphi_j(v_j) \tag{3.17}$$

Differentiating Eq. (3.17), we get

$$\frac{\partial y_j}{\partial v_j} = \varphi_j'(v_j) \tag{3.18}$$

From Eq. (3.16) and (3.18), we get

$$\delta_j = -\frac{\partial E}{\partial y_j}\varphi_j'(v_j) \tag{3.19}$$

Differentiating Eq. (3.2) with respect to y_j, we get

$$\begin{aligned}\frac{\partial E}{\partial y_j} &= \sum_k \frac{\partial E}{\partial e_k}\frac{\partial e_k}{\partial y_j} \\ &= \sum_k e_k \frac{\partial e_k}{\partial y_j} \\ &= \sum_k e_k \frac{\partial e_k}{\partial v_k}\frac{\partial v_k}{\partial y_j}\end{aligned} \tag{3.20}$$

From Eq. (3.1) we know that

$$\begin{aligned}e_k &= d_k - y_k \\ &= d_k - \varphi_k(v_k)\end{aligned} \tag{3.21}$$

Differentiating Eq. (3.21), we get

$$\frac{\partial e_k}{\partial v_k} = -\varphi_k'(v_k) \tag{3.22}$$

Also, differentiating Eq. (3.3) with respect to y_j, we get

$$\frac{\partial v_k}{\partial y_j} = w_{kj} \tag{3.23}$$

Therefore, rewrite Eq. (3.20) using Eq. (3.22) and (3.23), we get

$$\frac{\partial E}{\partial y_j} = -\sum e_k \cdot \varphi_k'(v_k) \cdot w_{kj} \tag{3.24}$$

From Eq. (3.24) and Eq. (3.19), we could define the local gradient δ_j as

$$\delta_j = \varphi_j'(v_j)\sum_k e_k \cdot \varphi_k'(v_k) \cdot w_{kj} \tag{3.25}$$

Using Eq. (3.13), we could rewrite Eq. (3.25) as

$$\delta_j = \varphi_j'(v_j)\sum_k \delta_k \cdot w_{kj} \tag{3.26}$$

A hyperbolic tangent function was used as an activation function in the hidden neuron *j*.

$$\varphi_j = a_j \cdot \tanh(b_j \cdot v_j) \tag{3.27}$$

Differentiating with respect to v_j, we get

$$\varphi_j'(v_j) = a_j \cdot b_j \sec h^2(b_j \cdot v_j) \tag{3.28}$$

Therefore, the local gradient for hidden layer *j* is:

$$\delta_j = a_j \cdot b_j \sec h^2(b_j \cdot v_j) \cdot \sum_k \delta_k \cdot w_{kj} \tag{3.29}$$

Weight correction for w_{ji} is:

$$\begin{aligned} \Delta w_{ji} &= -\eta \frac{\partial E}{\partial w_{ji}} \\ &= -\eta \frac{\partial E}{\partial v_j} \frac{\partial v_j}{\partial w_{ji}} \end{aligned} \tag{3.30}$$

Same as Eq. (3.3), v_j is:

$$v_j = \sum_{i=1}^{n} w_{ji} \cdot y_i \tag{3.31}$$

Differentiating with respect to w_{ji}, we get

$$\frac{\partial v_j}{\partial w_{ji}} = y_i \tag{3.32}$$

Using Eq. (3.32) and (3.16), Eq. (3.30) can be rewritten as:

$$\Delta w_{ji} = \eta \cdot \delta_j \cdot y_j \tag{3.33}$$

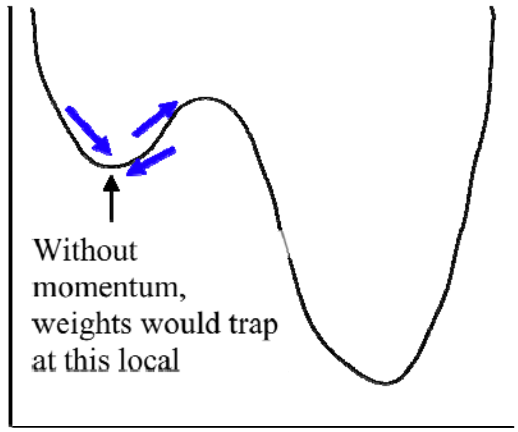
A summarized expression of back-propagation algorithm could be defined as:

Weight correction Δw_{ji}={Learning rate parameter η}.{local gradient δ_j}.{input signal of neuron j y_i}

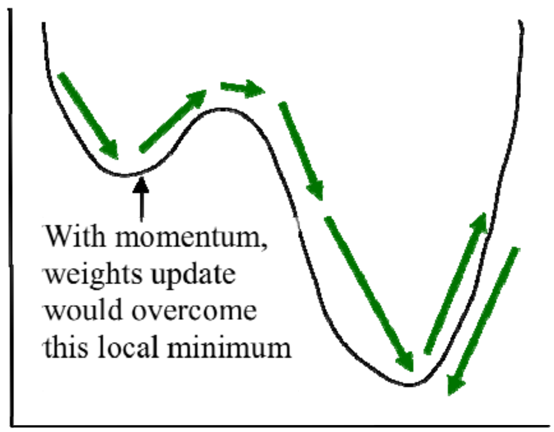
Although backpropagation algorithm is very efficient on calculating the synaptic weight correction, there is no guarantee that it will not be trapped at a local minimum. By introducing an additional momentum factor (a factor multiplied by previous change in weight), the algorithm can overcome a local minimum. Figures 3.4 show the effect of adding a momentum factor. The new weight update formula with a momentum is then defined by

$$\Delta w_{ji}(n) = \eta \cdot \delta_j(n) \cdot y_i(n) + \alpha \Delta w_{ji}(n-1) \tag{3.34}$$

where α is the momentum factor and n represents iteration number.



a.



b.

Figure 3.4: a) Weight update without momentum; b) Weight update with momentum

3.5 Testing Neural Networks

After design and training of a neural network, the network would then be tested in order to check the system performance. To do so, a test pattern is generated usually using 20% of the input and output data whose values have never been used to train the network. The network output, using the corresponding testing pattern input vector, is then compared with the target vector. For a properly designed and trained neural network, the difference between network outputs and targets should be within a pre-determined tolerance. The smaller the difference, the better the performance of the neural network. If the difference between the network outputs and targets are bigger than a pre-determined tolerance, additional inputs and outputs will be considered as training pattern in order to provide enough data to train the system. System configuration (number of hidden layers and hidden neurons) would also be adjusted in order improve the system performance.

CHAPTER 4: MID-TERM ELCTRICITY MARKET CLEARING PRICE FORECASTING

4.1 Introduction

Unlike the day-ahead or long-term electricity market clearing price (MCP) forecasting discussed in the Chapter 1.6, the mid-term forecasting has a time frame usually between that of day-ahead and long-term electricity MCP forecasting. Generally speaking, mid-term electricity MCP forecasting deals with the electricity price one month to six months from now. Mid-term MCP forecasting can be utilized in decision making and mid-term planning purposes, such as adjustment of mid-term schedule and allocation of resources. A mid-term MCP forecasting can be utilized to forecast two types of MCP in future; a daily peak MCP for a given duration and an hourly MCP for a 24-hour period. Mid-term forecasting of daily MCP will be discussed in this Chapter. The data utilized for mid-term forecasting include electricity hourly demand and supply, daily price of natural gas, monthly precipitation and historical hourly electricity MCPs. A feedforward artificial neural network (ANN) is proposed that can be utilized to forecast mid-term daily peak MCP. The daily peak MCP for a month can be forecasted utilizing available historical data mentioned before.

4.2 Proposed Artificial Neural Network Model

A neural network model has been designed to forecast mid-term electricity MCP. The proposed neural network is trained with the help of historical data. The training data contains two parts: training input data and training output data (target data). The neural network contains three layers as shown in Figure 4.1. The first layer is the input layer which receives four historical data (training data, input #1-input #4). The four historical data are: 1) electricity hourly demand data,

2) electricity daily peak demand data, 3) daily price of natural gas and 4) monthly precipitation data. The precipitation data is only available on a monthly basis. The reason why these four types of data are selected as training input data and the significance of each type of data will be explained in details in Section 4.3. The next layer is the hidden layer and the last layer is the output layer. This type of three-layer configuration has been proven to be a universal mapper, provided that the hidden layer has enough hidden neurons [7]. In the hidden layer, there are 25 hidden neurons connecting the input layer and the output layer. This hidden neuron number is determined from the convergence evaluation of various number of neurons from as few as 2 to as many as 100. Referring to the convergence evaluations, 25 hidden neurons have the best convergence for the proposed neural network. Therefore, according to this three-layer 25 hidden neuron neural network configuration, there are 100 synaptic weights between the first and the second layer and 25 synaptic weights between the second and the third layer. This level of interconnection was found to be adequate to best represent the nonlinear characteristics of the electricity MCP in deregulated electric market. The output layer contains only one output, the hourly electricity MCP.

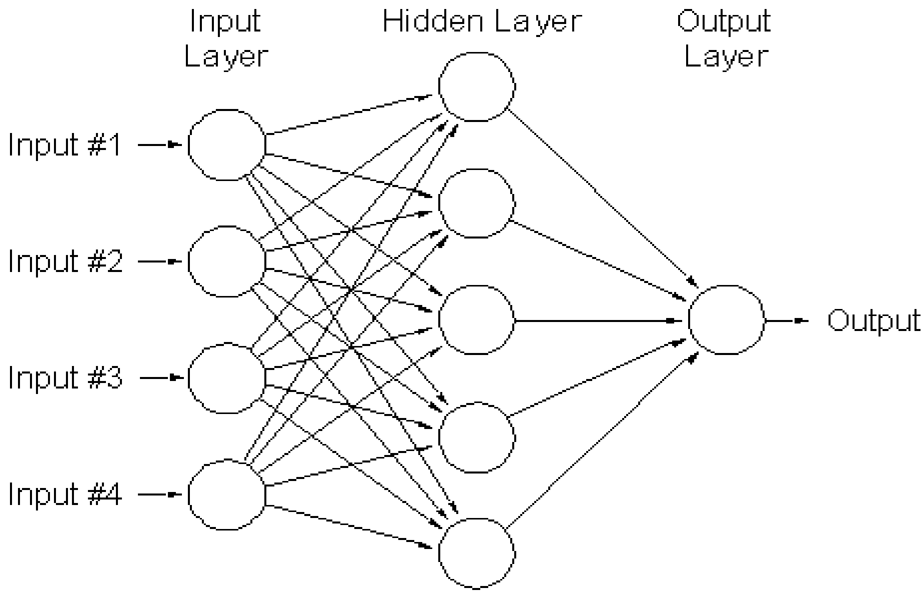


Figure 4.1: Example of a Three-Layered Feedforward Neural Network Model with a Single Output Unit [11]

Once the training is completed, the neural network would use all the corresponding synaptic weights and biases from the training period for the purpose of forecasting electricity MCP. For a forecast to be useful, we need to generate simulated forecasting input data that can represent a wide variety of input conditions. During the forecasting input data generation, each element of the input data is adjusted in turn while the other input elements are held constant. By doing so, the proposed neural network will encounter a wide range of input situations and forecast a total of approximate 1413 MCPs for a day. 1413 simulated input arrays are used for each day to forecast 1413 MCPs for that day. The generation of input data and forecasting repeat one day at a time for the entire duration. Final results are derived using statistical techniques. The results contained three components: the maximum value, the minimum value and the mean value of electricity MCPs for a given duration.

4.3 Selection of Training Data

MCP of electricity can be forecasted by evaluating variety of elements [1] such as electricity demand, supply, natural gas price, coal price, hydro capacity, weather and temperature. An ideal forecasting system for electricity MCP should include all possible elements which affect the final electricity price. However, in reality, it is impossible and unnecessary to include all those elements when forecasting electricity MCP. Since weather conditions including daily temperature are already considered in load forecasting, they don't have to be included in MCP forecasting process. Other elements such as coal price is fairly stable within three to six month period (the price varies within 3 cents), and therefore, does not influence the MCP forecasting. Moreover, there are some elements such as business strategy and unethical competition behaviours that cannot be easily represented mathematically. Finally, elements like generator status, representing the current failure or operating mode of a generator, in many deregulated electric market is confidential information.

Based on the factors mentioned above and the findings of the previous published works [1] [6] [7] [9], the final input elements that have been taken into account for the proposed neural network are limited to electricity hourly demand, electricity daily peak demand, daily price of natural gas, monthly precipitation and historical electricity hourly MCP. Electricity hourly demand directly influences the electricity price, and therefore should be a part of the training input data. As electricity hourly demand increases, electricity price will also increase. When electricity hourly demand decreases, electricity price will also decrease. Electricity daily peak demand is also an important factor that influences the electricity price in a significant manner. When electricity daily peak demand is high, expensive units are run to meet the demand which in turn boosts the electricity price. During peak load, most generating units would be running under high and even full capacity, usually away from their most economic operating point. Unlike coal price, natural gas price fluctuates every hour just like electricity MCP. Thermal generating plants that use natural gas are widely used for peak shaving and load following due to their relatively short starting time. As electricity cannot be stored and has to be used as produced, a sudden increase in electricity demand is met by these type of fast starting generating units and usually cost 10 to 100 times more than the regular electricity MCP. Therefore, the daily price of natural gas also influences the electricity MCP and should be included as a part of the training input data.

It is assumed that the electricity hourly demand data already included the related influence of temperature, sunshine and special events. Special events may include events such as Super Bowl, Grey Cup and New Year's Eve. That is why these factors are not included explicitly as inputs. The electricity hourly demand data, electricity daily peak demand data and hourly price of electricity of PJM system are utilized for the illustration of numerical examples in this thesis. PJM interconnection is a regional transmission organization (RTO) that coordinates the movement of wholesale electricity in all or parts of Delaware, Illinois, Indiana, Kentucky, Maryland, Michigan, New Jersey, North Carolina, Ohio, Pennsylvania, Tennessee, Virginia, West Virginia and the District of Columbia [3]. The past 12-month data from August 1, 2007 to July 31, 2008 have been selected for numerical examples. The daily natural gas price data is obtained from the Energy Information Administration (EIA) [2].

Compared to thermal generating units, hydroelectric units have the lowest operating cost as the cost of operating a hydroelectric plant is nearly immune to increases in the cost of fossil fuels such as oil, natural gas or coal [4]. The availability of hydroelectric generation has the potential to significantly affect the electricity MCP in a deregulated market. The precipitation data reflecting the potential for hydroelectric power is, therefore, utilized as input in the numerical examples.

PJM interconnected electric market is the largest interconnected electricity market in the world. It contains up to 13 states. In order to monitor the precipitation data more efficiently and logically, only the states containing hydroelectric power plants have been considered for precipitation data collection. There are total three hydroelectric power plants inside the region of PJM interconnected electric market. All of them are located in the Pennsylvania state on the Susquehanna River. Those three hydroelectric power plants are: Haltwood Dam, Safe Harbor Dam and York Haven Dam. Figure 4.2 is a map from Google Earth showing the location of the three hydroelectric power plants (Haltwood Dam is on the east side of Safe Harbor Dam and York Haven Dam is on the opposite side). As all of the hydroelectric power plants are located inside Pennsylvania State, we are only interested in the precipitation information of Pennsylvania State. All the precipitation data are from Northeast Regional Climate Center (NRCC) [29]. Table 4.1 shows the precipitation data of Pennsylvania State from August, 2007 to July, 2008. The precipitation datum of August, 2007 (6.09 in) has been used as a reference. All precipitation data have been converted into percentages with respect to the reference.

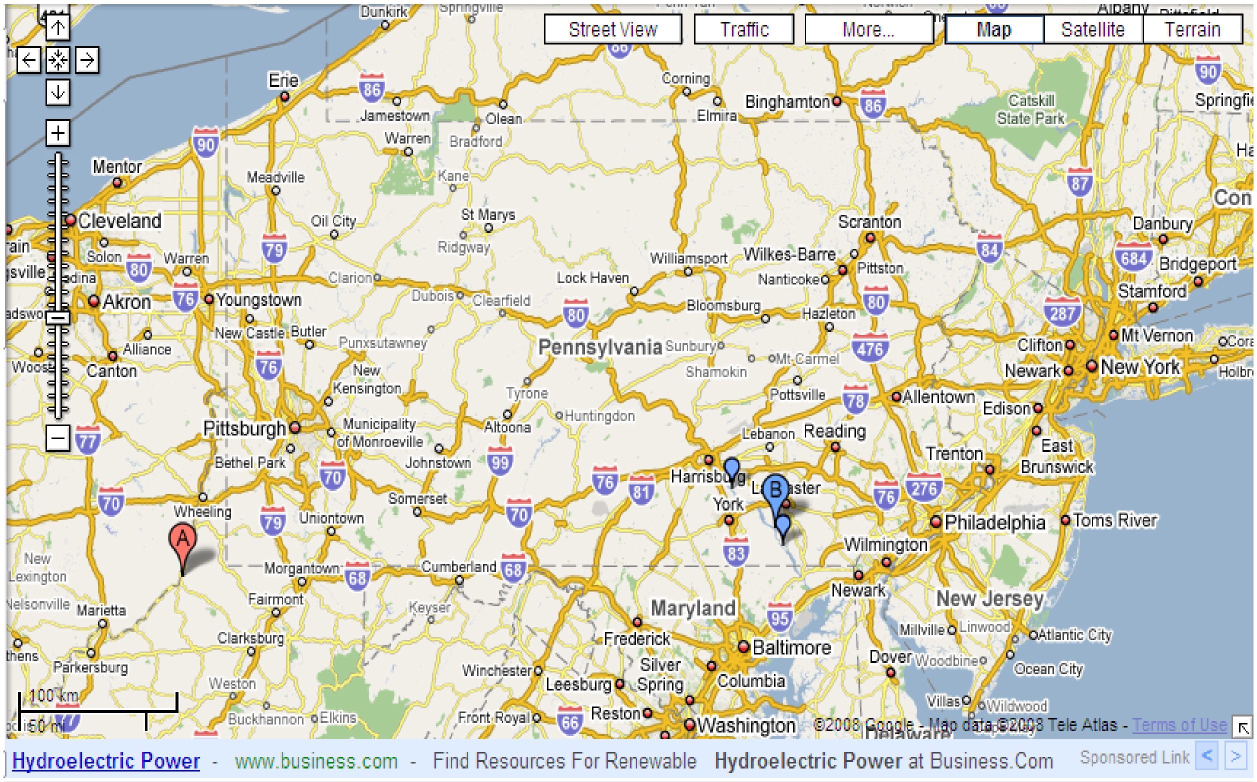


Figure 4.2: Safe Harbor Dam (B) (Hydroelectric Power Plants)

Table 4.1: Precipitation Data from August, 2007 to July, 2009

Month	Precipitation (in)	Precipitation (%)
Aug-07	6.09	100.00%
Sep-07	1.99	32.68%
Oct-07	3.98	65.35%
Nov-07	4.07	66.83%
Dec-07	5.00	82.10%
Jan-08	2.34	38.42%
Feb-08	5.09	83.58%
Mar-08	5.41	88.83%
Apr-08	2.68	44.01%
May-08	4.51	74.06%
Jun-08	4.07	66.83%
Jul-08	4.38	71.92%

MATLAB Artificial Neural Network Toolbox is utilized to model the proposed neural network. When working with it, one has to consider not only the physical limitations, such as data size and processing time of the elements, but also the suitability, such as convergence for the forecasting model. According to the characteristics of any artificial neural network, the selection of input data is the single most important factor for the accuracy of desired output. In order to avoid under or over training and to expect a reasonable output, input data for training should be carefully selected. The selected training input data should fully reflect all of the factors that influence electricity MCP in a deregulated electric market and cover all possible scenarios of price change. The output should respond to a corresponding change in input, and reflect the fluctuation between demand and supply, between precipitation and price, and between peak demand and price.

4.4 Training

In this section, the training of the proposed neural network model is explained. The selection of training data is a crucial factor in the successful operation of a neural network. The selection process of the input data and its size is also discussed in this section. The algorithm utilized for the trainings of the proposed neural network is discussed in detail. Two different ways to handle the training results are discussed at the end of this section.

4.4.1 The Size of the Training Data

In order to successfully train a neural network, both under and over training of a neural network should be avoided [6]. When under training occurs, a neural network could not cover all possible scenarios. On the other hand, over training would result long processing time and may require bigger size memory.

The training data for the proposed neural network are comprised of historical data that include electricity hourly demand data, electricity hourly MCP data, electricity daily peak demand data, daily price of natural gas and monthly precipitation data. The historical data, only for the past four years, from January 1, 2004 to July 31, 2008 are available at the PJM website. The selection of the right size of the training data is essential for the training of the proposed neural network. Therefore, three different time frames have been selected and compared: six-month, one year, and two-year. The six-month time frame is from February 1, 2008 to July 31, 2008. The one year time frame is from August 1, 2007 to July 31, 2008. The two-year time frame is from August 1, 2006 to July 31, 2008. The performance of a trained network can be measured by utilizing regression analysis between the network response and the corresponding targets [8]. Therefore, the convergence of the proposed neural network with training data of three different lengths of time frame is examined utilizing regression analysis in order to find out which length of time frame should be selected to train the proposed neural network.

Figures 4.3, 4.4 and 4.5 show the outputs of the regression analyses of the three different time frames. The regression analysis is a common tool utilized to visualize the relationship between the calculated data points and the corresponding targets. Three parameters are calculated from a regression analysis: slope of the best linear fitting line, y-intercept of the best linear fitting line and correlation coefficient (R-value) between the neural network calculated outputs and the training output data (targets). The x-axis is the target axis and the y-axis is the neural network calculated outputs. The ideal case should result a regression analysis where all calculated output data points lie right on the best linear fitting line. Under ideal case, the slope and R-value equal to 1 and y-intercept equal to zero. In reality, the data points are expected to locate as close as possible to the best linear fitting line, the closer the better. In other words, the closer the R-value to 1, the better the correlation between the neural network calculated outputs and the training outputs. The R-value for Figures 4.3, 4.4 and 4.5 are: 0.75339, 0.68546 and 0.61682 respectively. Therefore, mathematically, six-month time frame resulted the best correlation between the neural network calculated outputs and the training outputs. However, electricity daily demand pattern is different from month to month. In January, there are two demand peaks, one at 10 a.m. and the other at 6 p.m. Electricity hourly demands between these two hours are quite low compared to the two peak loads. As time goes on, the electricity hourly demand between these two hours increase month by month and finally almost equal to the load value at one of the peak hour in August. After August, the electricity hourly demand between these two hours start decrease and eventually back to the shape as January. Therefore, logically, one year time frame is better because it could include every month of a year.

Based on the results of regression analyses and including the consideration of electricity demand and MCP characteristics from each month, one year historical data were selected for the training of the proposed neural network. One year historical data from August 1, 2007 to July 31, 2008 that include electricity hourly demand data, electricity daily peak demand data, daily price of natural gas and monthly precipitation were selected as the training input data, and electricity hourly MCP data were selected as the training output data (target data). The training input data could be viewed as a matrix with 8784 (24×366) rows and 4 columns. The 8784 rows are the number of hours from hour 1 (1:00 a.m.) on August 1, 2007 to hour 24 (12:00 a.m.) on July 31, 2008. The 4 columns are the four different historical training input data: 1) electricity hourly demand data, 2) electricity daily peak demand data, 3) daily price of natural gas and 4) monthly precipitation data. The training output data (target data) also form a matrix with 8784 rows and 1 column. The training output data are the historical electricity hourly MCP from hour 1 (1:00

a.m.) on August 1, 2007 to hour 24 (12:00 a.m.) on July 31, 2008. After determining the size of the training data, the next step is to decide which backpropagation algorithm should be used.

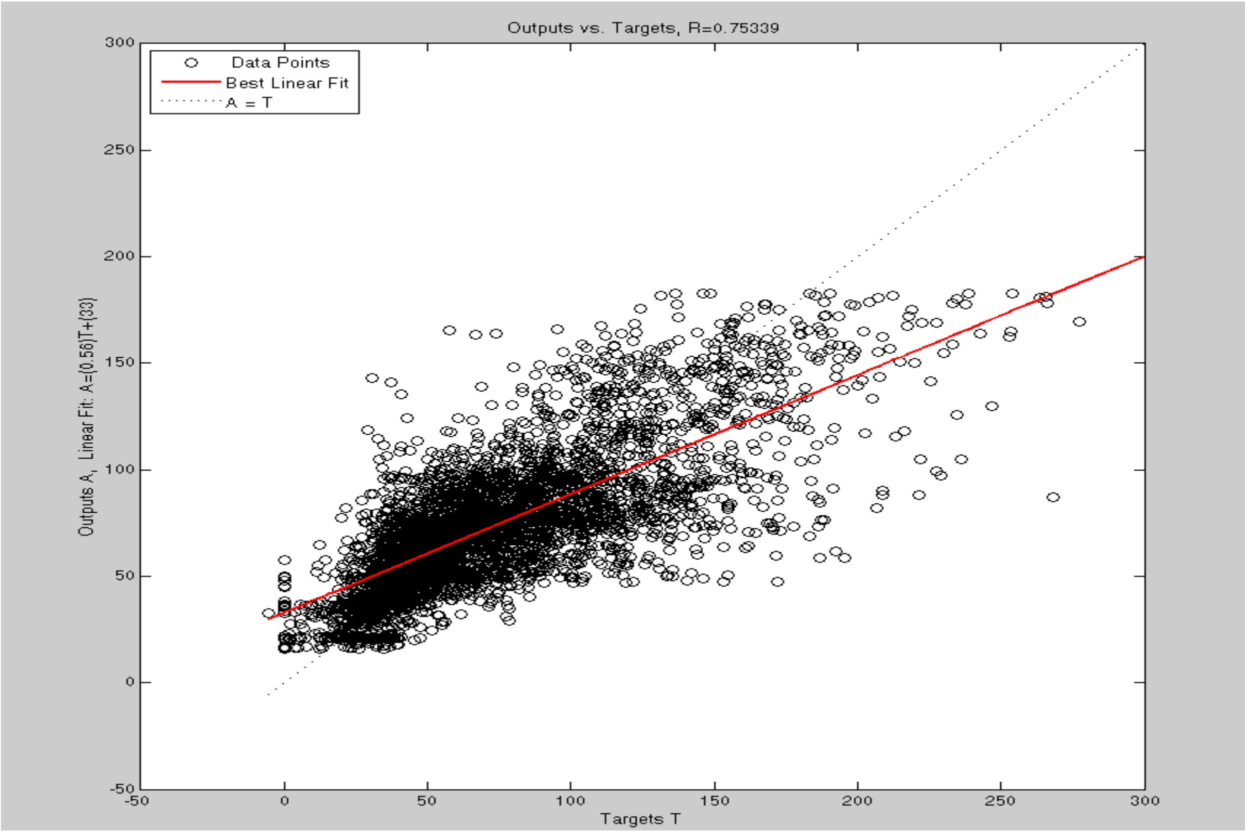


Figure 4.3: Regression Analysis of Six-Month Data Points

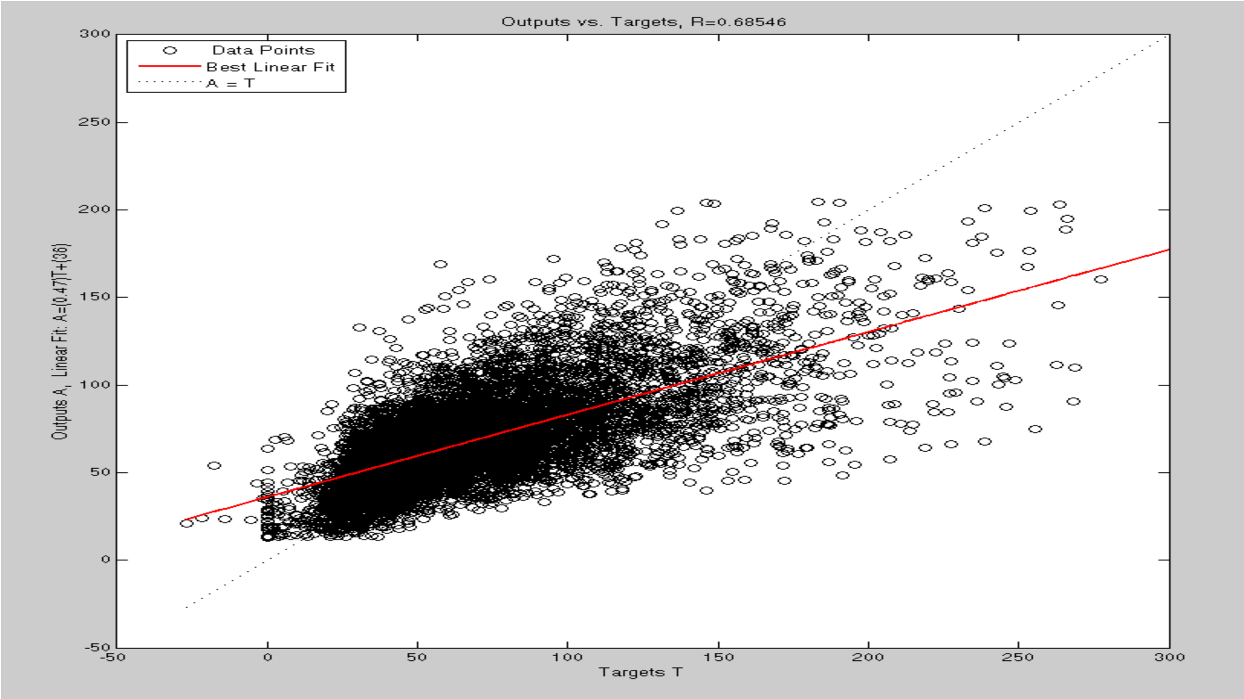


Figure 4.4: Regression Analysis of One Year Data Points

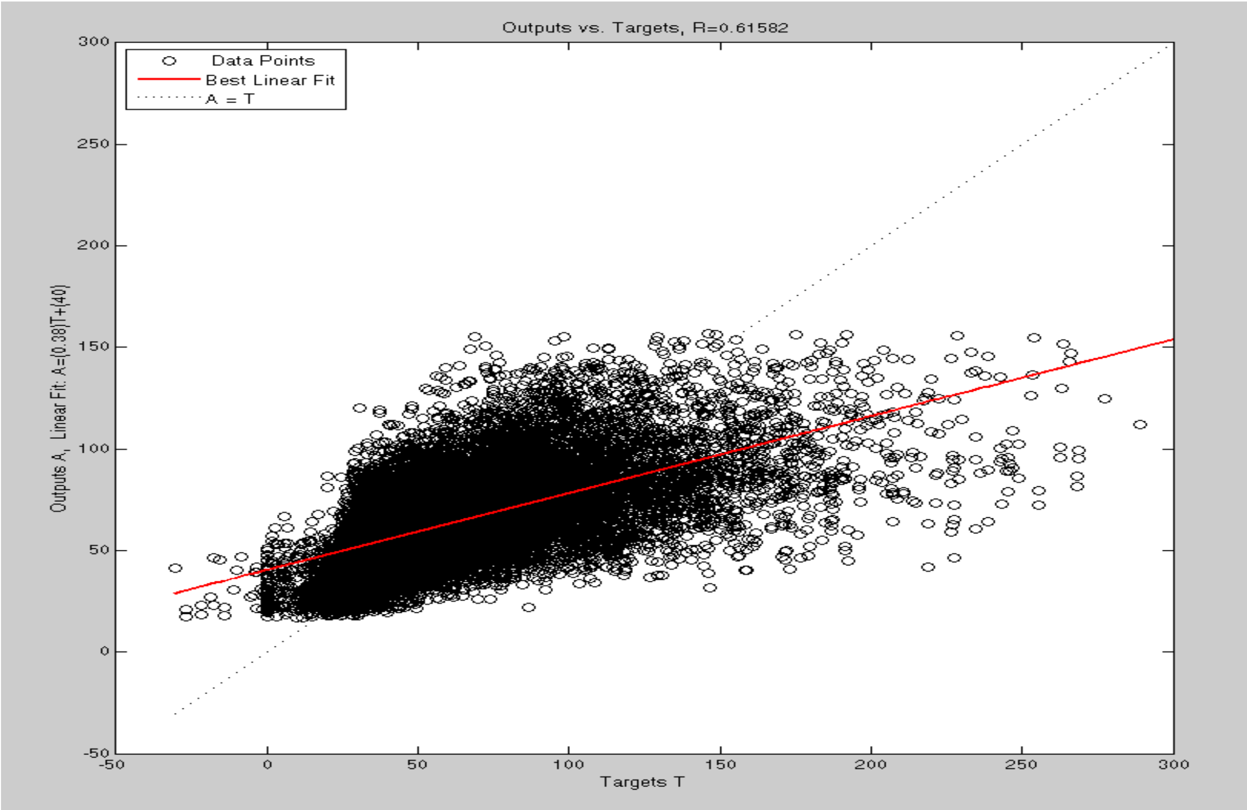


Figure 4.5: Regression Analysis of Two-Year Data Points

4.4.2 Levenberg-Marquardt Algorithm

The goal of training a neural network is to minimize the sum of squared errors. For simplification purposes, the sum of squared errors was replaced by the sum of the absolute error. The steepest descent algorithm is the most common algorithm that is used to train a neural network. Other training algorithms include conjugate gradient algorithm, Quasi-Newton algorithm and Levenberg-Marquardt algorithm. All four algorithms were tested under a three-layer feedforward neural network with 25 hidden neurons in order to find the most suitable training algorithm for the proposed neural network. The most suitable training algorithm should result the shortest convergence time, lowest sum of absolute errors and despondence to the market and operating conditions. According to the test results, steepest descent algorithm, conjugate gradient algorithm and Quasi-Newton algorithm were failed to respond to the market and operating conditions. They were immune from changes in electricity demand, natural gas price or precipitation. The sum of the absolute errors (267530) from these three training algorithms was also higher than the sum of the absolute errors (179230) from Levenberg-Marquardt training algorithm. As a result, a three-layer feedforward neural network with 25 hidden neurons utilizing Levenberg-Marquardt algorithm was selected to train the proposed neural network.

The Levenberg-Marquardt algorithm is a variation of Newton's method [8]. Let us first recall Taylor's Series Expansion approximation of a function $f(x)$ where all terms above the second order are ignored:

$$f(x) = f(x_k) + f'(x_k)\Delta x + \frac{1}{2} f''(x_k)\Delta x^2 \tag{4.1}$$

Taking the derivative on both sides and ignore the 3rd order terms and set the function equal to zero will yield an approximation finding the minimum or maximum of the function where:

$$f'(x) = f'(x_k) + f''(x_k)\Delta x = 0 \tag{4.2}$$

Therefore, Δx could be rewritten as:

$$\Delta x = -\frac{f'(x_k)}{f''(x_k)} \tag{4.3}$$

This will introduce the final Newton's Method Optimization Algorithm as:

$$x_{k+1} = x_k - \frac{f'(x_k)}{f''(x_k)} \tag{4.4}$$

Newton's method could also be used to solve nonlinear equations. From the multi dimension $R^n \to R$ at point k we could rewrite Eq. 4.4 as:

$$X_{k+1} = X_k - \frac{F'(X_k)}{F''(X_k)} \tag{4.5}$$

where X_k represents a vector at point k and X_{k+1} denotes another point very close to k. Under multi dimensions, $R^n \to R$, gradients replace first derivatives. Therefore, the derivative of function F with respect to vector X_k is denoted by:

$$\begin{aligned} F'(X_k) &= \nabla F(X_k) \\ F''(X_k) &= \nabla^2 F(X_k) \end{aligned} \tag{4.6}$$

Using Eq. (4.6), Eq. (4.5) could be rewritten as:

$$X_{k+1} = X_k - [\nabla^2 F(X_k)]^{-1} \nabla F(X_k) \tag{4.7}$$

Eq. (4.7) could be rewritten as:

$$X_{k+1} = X_k - \left[H(X_k)\right]^{-1} \nabla F(X_k) \tag{4.8}$$

where $H(X_k)$ is the Hessian matrix and could be rewritten as

$$H(X_k) = J^T(X_k) J(X_k) \tag{4.9}$$

where $J(X_k)$ is the Jacobian matrix given by:

$$J(X) = \begin{bmatrix} \frac{\partial f_1}{\partial x_1} & \frac{\partial f_1}{\partial x_2} & \dots & \frac{\partial f_1}{\partial x_n} \\ \frac{\partial f_2}{\partial x_1} & \frac{\partial f_2}{\partial x_2} & \dots & \frac{\partial f_2}{\partial x_n} \\ \dots & \dots & \dots & \dots \\ \frac{\partial f_n}{\partial x_1} & \frac{\partial f_n}{\partial x_2} & \dots & \frac{\partial f_n}{\partial x_n} \end{bmatrix} \tag{4.10}$$

and $\nabla F(X_k)$ is the gradient and could be rewrite as:

$$\nabla F(X_k) = J^T(X_k) E(X_k) \tag{4.11}$$

where E is a vector of network errors. The Jacobian matrix can be computed through a standard backpropagation technique that is much less complex than computing the Hessian matrix [8]. Using Eq. (4.6) to Eq. (4.11), Newton's method under multi dimensions (Eq. (4.5)) could be rewritten as:

$$X_{k+1} = X_k - \left[J^T(X_k) J(X_k)\right]^{-1} J^T(X_k) E(X_k) \tag{4.12}$$

The Levenberg-Marquardt algorithm is given by:

$$X_{k+1} = X_k - \left[J^T(X_k)J(X_k) + \mu I\right]^{-1} J^T(X_k)E(X_k) \tag{4.13}$$

where μ is just a scalar which could be modified after each iteration. When μ is zero, Levenberg-Marquardt algorithm becomes Newton's algorithm which will result faster convergence. On the other hand, while for higher values of μ, when the value of μI is much higher than the value of $J^T(X_k)J(X_k)$, the algorithm becomes steepest descent. Hence, the Levenberg-Marquardt provides a nice compromise between the speed of Newton and the guaranteed convergence of steepest descent [10]. Numerical results indicate that by using Levenberg-Marquardt algorithm, function converge in less than 30 iterations.

A three-layered feedforward Neural Network utilizing Levenberg-Marquardt algorithm is proposed in this work for forecasting the electricity MCP six months from now. The MATLAB Neural Network Toolbox was selected due to its simplicity and flexibility [8]. The transfer function used in the hidden layer is the MATLAB nonlinear function: 'tansig', shown in Figure 4.7. 'Tansig' is a hyperbolic tangent sigmoid transfer function with output range from -1 to +1. The transfer function used in the output layer is the MATLAB linear function: 'purelin', which is a pure linear transfer function as shown in Figure 4.7.

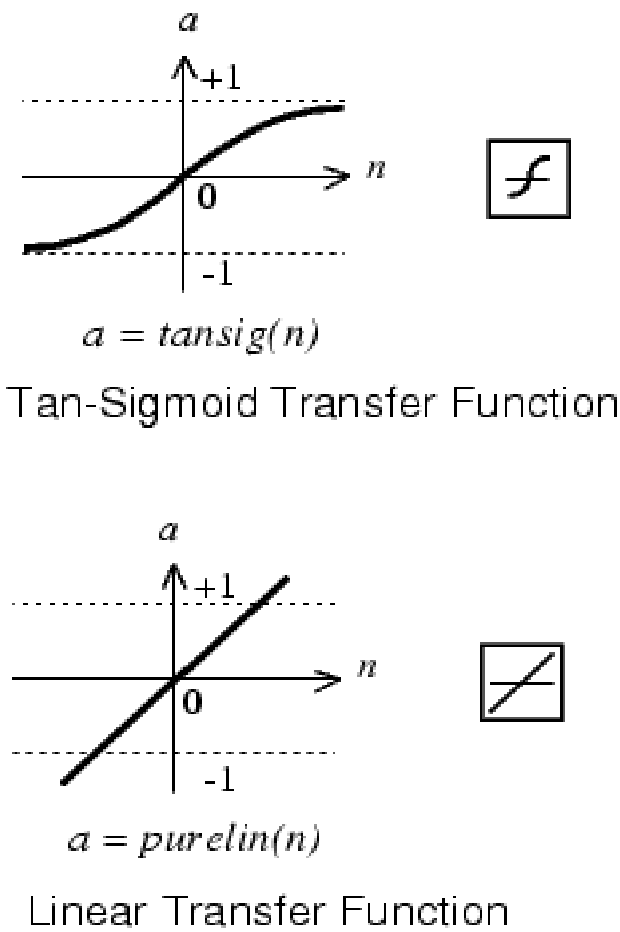


Figure 4.6: MATLAB Transfer Functions: Tan-Sigmoid & Linear

4.4.3 Training with the Entire Training Data

The proposed neural network was trained utilizing one year historical data from hour 1 (1:00 a.m.) on August 1, 2007 to hour 24 (12:00 a.m.) on July 31, 2008. The data include electricity hourly demand data, electricity hourly MCP data, electricity daily peak demand data, daily price of natural gas and monthly precipitation data as the training data. The input training data is an 8784 (366*24)-by-4 matrix and the output training data is an 8784-by-1 row matrix.

When training the proposed neural network, MATLAB Neural Network Toolbox randomly divides the training input data and training output data into three sets. 60% of the data are used to train the network, 20% of the data are used to validate the performance of the network. The final

20% of data will provide an independent test of the network generalization to data that the network has never seen [8]. By doing so, different results are expected every time the proposed neural network is trained. Utilizing the Levenberg-Marquardt algorithm and the entire one year historical data, the proposed neural network was set to train for 500 times and the one with the lowest sum of squared errors was selected. The corresponding synaptic weights and biases from the selected neural network were used to forecast the future electricity MCP. Even though the Levenberg-Marquardt algorithm is the best one among the other neural network training algorithms, the actual convergence due to variety of reasons, are still not satisfied. In other words, sum of the square errors are still high. The regression analysis result shown in Figure 4.4 shows that a fairly large range of variance occurred when training the proposed neural network. For a properly trained neural network, the accuracy of the neural network simulating new data is expected to be close to the accuracy during training period [8]. Therefore, as the trained neural network still had a fairly large range of variance (Figure 4.4), high level of accuracy when forecasting the future electricity MCP could not be expected.

The advantage of using the entire training data is that the proposed neural network could actually be modeling all possible scenarios in a deregulated electric market such as application of various business competition strategies, sudden surplus or supply shortage of electricity and even unethical behaviours.

4.4.4 Training with Filtered Training Data

Unexpected market behaviours and unethical competitions are part of a deregulated market. These phenomenons influence the market clearing price. A historical data set, therefore, contains many data points that cannot be explained with usual market principles. Although a complex behavioral model could include the abnormal market behaviour, it is beyond the scope of this work. Due to a variety of unexpected market scenarios and possible unethical competition, regression analysis utilizing all training data from hour 1 (1:00 a.m.) on August 1, 2007 to hour 24 (12:00 a.m.) on July 31, 2008 exhibited a poor correlation. In order to reduce the sum of the absolute errors of the proposed neural network, a filtering technique to reduce the unexpected data points had been implemented during the training. Modified training data set containing less data points were used to train the proposed neural network.

The filtering began with training simulation utilizing all training data. This resulted the same regression analysis shown in Figure 4.4. After that, the absolute error between the trained output and the desired output for every hour was computed (Figure 4.7). It is obvious from Figure 4.7 that some errors are too big. The largest difference between the trained output and the desired output is about $600. The electricity MCP from August 1, 2007 to July 31, 2008 is between about $20 and $200. The training data that produce these huge errors would obviously reduce the accuracy of the proposed neural network. Therefore, in order to obtain an improved neural network, those points (hours) containing huge errors were eliminated from the historical training data. The undesirable points could only be reduced but cannot be eliminated completely. In order to reduce the number of undesirable data points, the training data that generated absolute error beyond the 90% confidence interval were discarded. For the given training input data set, this resulted the elimination of data points that resulted absolute error greater than or equal to $49.06. Training input data points that resulted absolute error less than $49.06 were utilized for training. A regression analysis was performed (results shown in Figure 4.8) and the correlation coefficient was found to be 0.78851. The sum of the absolute errors of the neural network utilizing filtered training data was found to be 134030 instead of 179230. All of these indicate a great improvement on the selection of training data. After applying the filtering approach, the number of training data rows dropped from 8784 to 8100. MATLAB Neural Network Toolbox training program was utilized with the filtered training data.

Since the filtered training input data are relatively highly correlated, we can expect a better correlation of the resulting simulated MCP. Figure 4.8 shows the results of regression analysis performed in this forecast.

However, the disadvantage is that a real deregulated electric market containing unethical competition behaviours could not be modeled. The forecasted future electricity MCP obtained using this filtered neural network can only be applied to situations where market principles are adhered to by all participants.

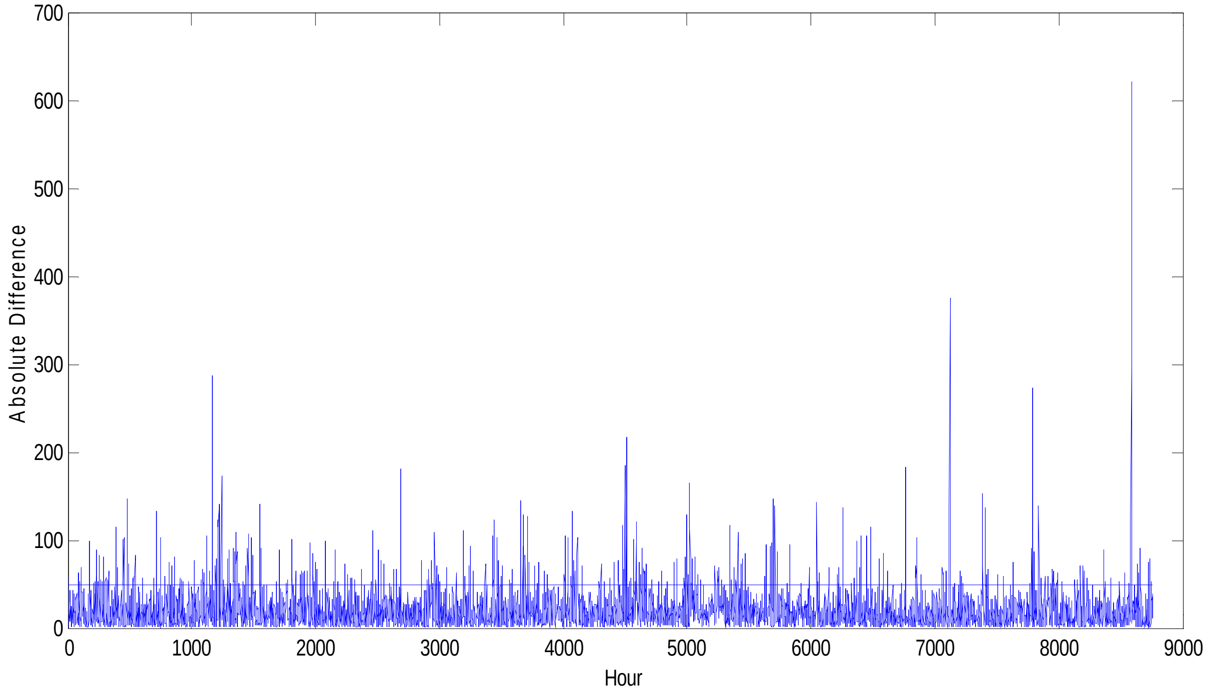


Figure 4.7: Difference Between Neural Network Output and Input Target

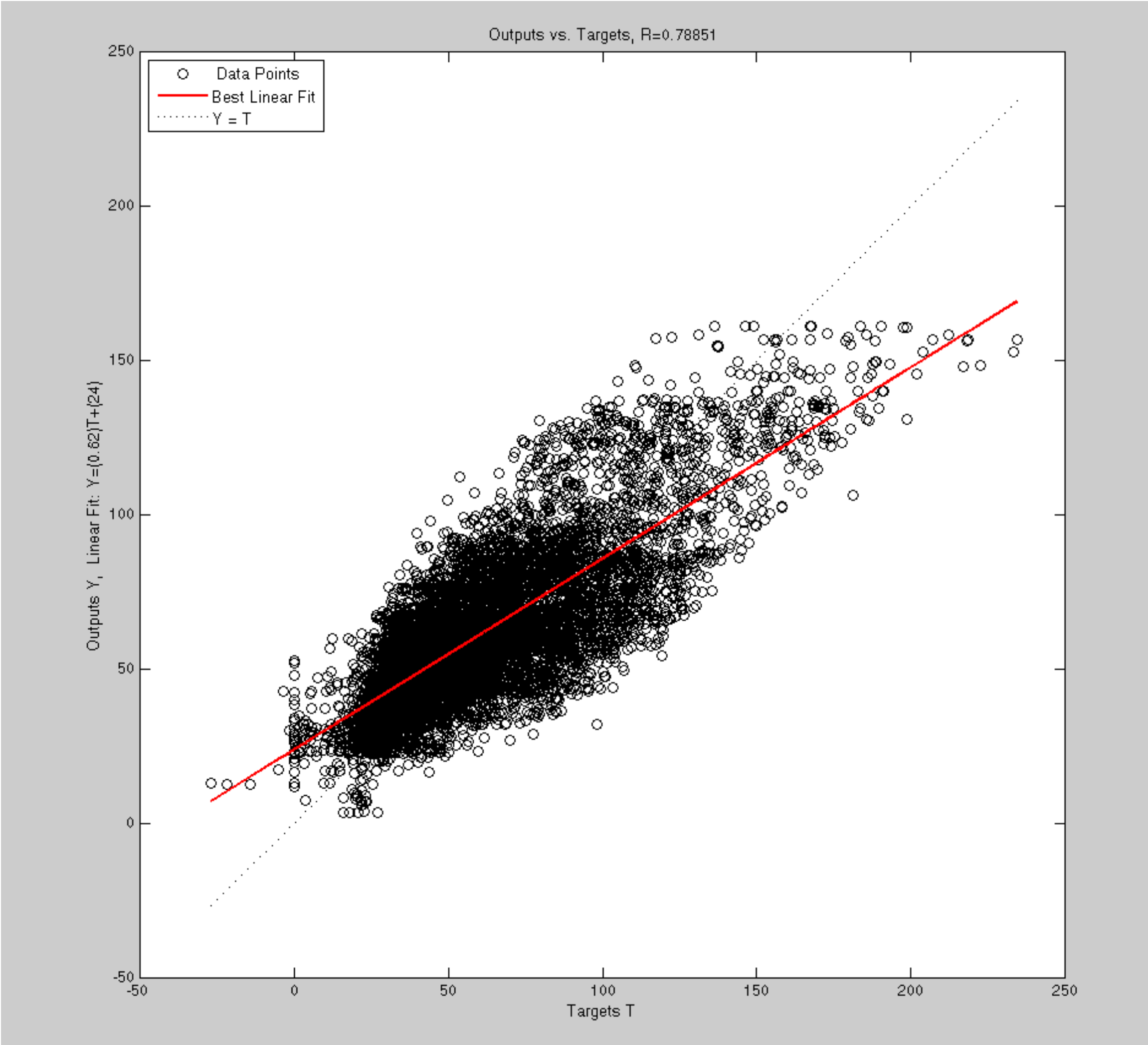


Figure 4.8: Regression Analysis of Output Utilizing Filtered Training Data

4.5 Forecasting Input Data Generation

To forecast electricity MCP, forecasting input data should be created first. One of the main components of the forecasting input data is the future electricity demand. The future electricity hourly demand is influenced among other things by forecast of weather, sunshine and special events. According to the Energy Information Administration (EIA) [2], the annual electricity peak demand is increasing with a rate of 8.1%. Therefore, the mean value of the future electricity hourly demand and daily peak demand from hour 1 (1:00 a.m.) on February 1, 2009 to hour 24

(12:00 a.m.) on February 28, 2009 were created by increasing the historical electricity hourly demand and daily peak demand from hour 1 (1:00 a.m.) on February 1, 2008 to hour 24 (12:00 a.m.) on February 28, 2008 by 8.1%. At this point, there are 24 electricity hourly demand data containing 1 electricity daily peak demand data for each day of total 28 days. These data would then be further modified in order to create the forecasting input data matrix.

EIA has full detail on forecasting the future price of natural gas. The natural gas price data were used directly from EIA website. However, the forecasted natural gas price was only available as monthly basis. The forecasted value of monthly natural gas price in February 2009 is $7.33. The natural gas price varied from as low as $0.69 to as high as $4.85 within a month from August 2007 to July 2008. In order to have a relatively wide range of natural gas price, a $4 range for natural gas price was set with an increment of $0.01 for each step. Finally, the forecasted monthly precipitation data from NRCC [29] were used to indicate the potential hydroelectric power. The forecasted monthly precipitation data were converted into percentage with respect to the reference precipitation datum of August, 2007 (6.09 inch). The forecasted monthly precipitation data from NRCC contains three values: the minimum value (53.03%), the maximum value (69.14%), and the mean value (60.65%).

Table 4.1 is an example of the summarized forecasting input data for forecasting the future electricity MCP for February 1, 2009. The range of the electricity daily peak demand is determined by the minimum and the maximum forecasted electricity daily peak demand value from February 1, 2009 to February 28, 2009. While forecasting electricity MCP for each day, the electricity daily peak demand would then vary within this predetermined range. The range of the electricity hourly demand for each day is determined by the minimum and the maximum forecasted electricity hourly demand for each day. For example, examining the 24 forecasted electricity hourly demand in February 1, 2009, the minimum and the maximum electricity hourly demand values are 64984 MW and 120774 MW respectively as shown in Table 4.1. Therefore, when forecasting the electricity MCP for February 1, 2009, the forecasting input data of electricity hourly demand would vary from 64984 MW to 120774 MW. The range of electricity hourly demand data is different everyday based on the range of historical hourly demand data from hour 1 (1:00 a.m.) on February 1, 2008 to hour 24 (12:00 a.m.) on February 28, 2008. According to Table 4.1, the range of each element in the table are: electricity hourly demand, from 64984 MW to 120774 MW, electricity daily peak demand, from 111724 MW to 138324 MW, monthly price of natural gas, from $5.33 to $9.33, and monthly precipitation data, from 50.03% to 69.14%. The fourth row of Table 4.1 indicates the adjustment value for each trial for forecasting the electricity MCP. The first trial would start with a corresponding set of values of [64984 120774 7.33 60.65%] as the very first input data. The second input data would retain all the values of daily peak demand, monthly price of natural gas and monthly precipitation data except the electricity hourly demand which will be increased by 100 MW. The second input vector, therefore, would be [65084 120774 7.33 60.65%]. The same method would apply until the electricity hourly demand value reached its maximum value [120774 120774 7.33 60.65%]. By doing so, all possible electricity hourly demand would be covered. Next, the electricity daily peak demand would be varied while the other three data remain fixed. The forecasting input data with modified electricity daily peak demand data are from [91570 111724 7.33 60.65%] to all the way to [91570 138324 7.33 60.65%]. Applying the same method, the forecasting input data would vary from [91570 120774 5.33 60.65%] to [91570 120774 9.33 60.65%] with an increment of $0.01 to account for the variation in monthly natural gas price. Finally, the forecasting input data would be adjusted from [91570 120774 7.33 50.03%] to [91570 120774

7.33 69.14%] with an increment of 0.1% to account for the variation in precipitation. The forecasting input data set for February 1, 2009 is a 1413-by-4 matrix. In other words, there were 1413 possible combinations of electricity hourly demand, electricity daily peak demand, monthly natural gas price and monthly precipitation data. By forecasting future electricity MCP for February 2009, 1413×28 outputs were expected. Those data would be the forecasted electricity MCPs for the 28 days of February 2009.

Table 4.2: Summarized Forecasting Input Data for February 1, 2009

	Hourly Demand (MW)	Daily Peak Demand (MW)	Price of Natural Gas ($)	Hourly Water Level (%)
Minimum	64984	111724	5.33	53.03
Maximum	120774	138324	9.33	69.14
Mean	91570	120774	7.33	60.65
Step Value Increment	100	50	0.01	0.1

4.6 Results

Using both training data, the entire training data and the filtered training data, electricity MCP have been obtained for 28 days. The forecasting input data can be viewed as a matrix of approximately 1413×4×28 (number 1413 would vary due to the different range of electricity hourly demand for each day). Therefore, for a total of 28 days, 1413×28 output were obtained, 1413 for each day. These 1413 outputs represent all possible electricity MCPs for a day for corresponding input forecasting data within the designed range. To make the output data more meaningful, the daily minimum, the daily maximum and the daily mean values of the electricity MCPs were calculated for each of the 28 days. In addition, the most likely electricity MCP for each of the forecasting days in the month of February 2009 was also calculated. The most likely electricity MCP was obtained by utilizing a histogram analysis of the calculated 1413 results. These 1413 results were distributed by histogram algorithm into 10 price groups which were separated by ($Max-$Min)/10 apart from each other. The probabilities were then calculated by counting the times of each of the 1413 results fall into different price group. Finally, the price group with the highest probability within the 10 price groups would be selected as the most likely electricity MCP group.

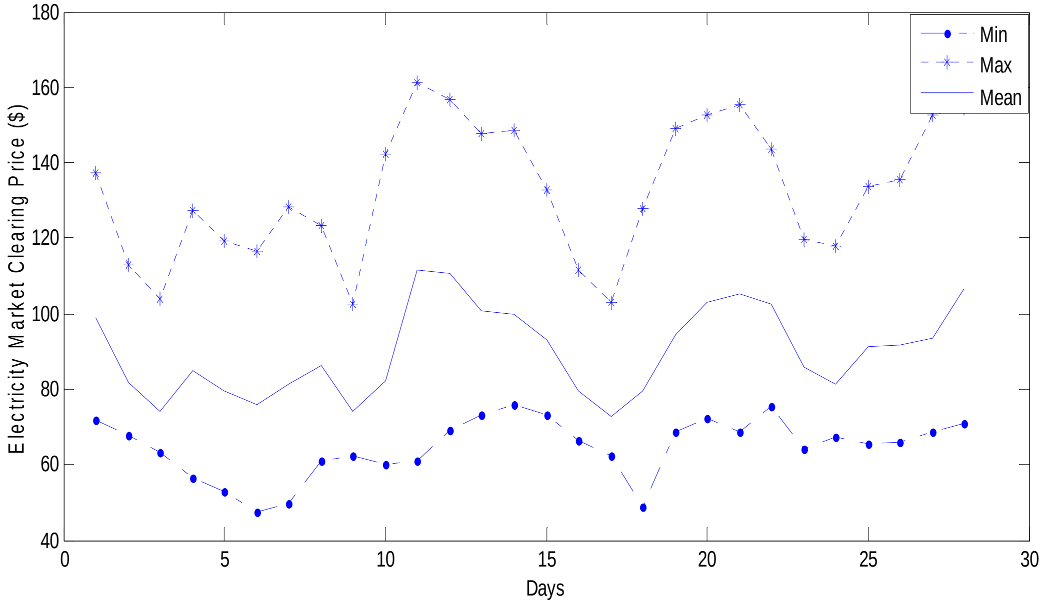


Figure 4.9: Forecasted Electricity MCP for 28 Days Using the Entire Training Data

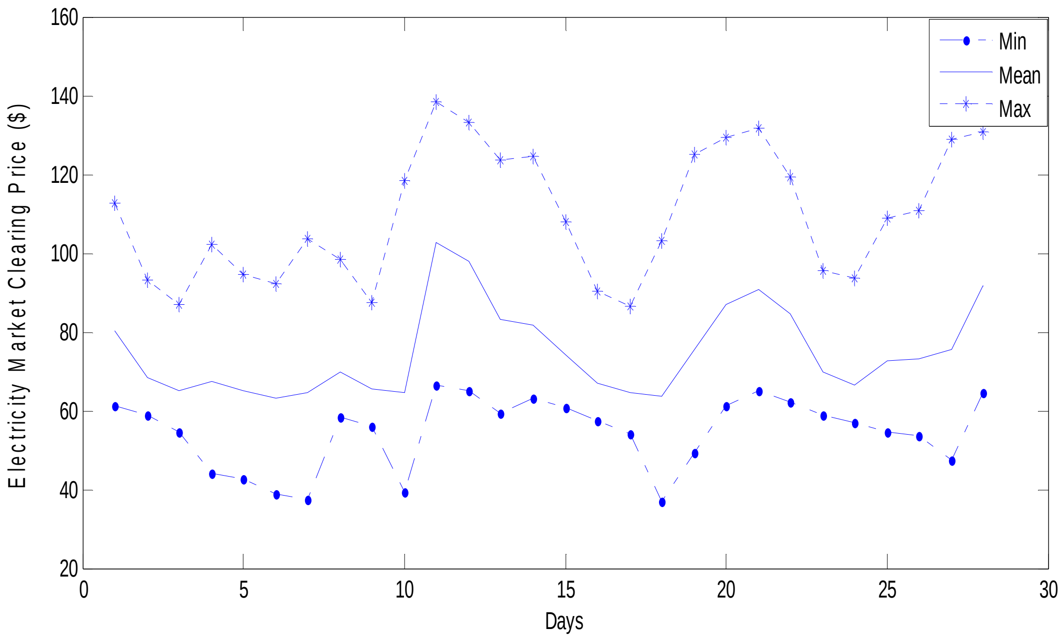


Figure 4.10: Forecasted Electricity MCP for 28 Days with Filtered Training Data

Figures 4.9 and 4.10 show the daily minimum, the daily maximum and the daily mean values of forecasted electricity MCPs for all 28 days of February 2009. As shown in Figure 4.9, the forecasted electricity MCP varies between $45 to $160 dollars for February 2009. In Figure 4.10, the forecasted electricity MCP varies between $40 to $140 dollars.

Both neural networks indicated a similar range of forecasted electricity MCP. The neural network using filtered training data resulted a lower electricity MCP than the neural network using the entire training data. The difference was due to the reduction of unexpected high prices utilizing filtering technique. Due to the fact that the forecasted monthly precipitation in February 2009 is only half compared to February 2008, the forecasted average electricity MCP for February 2009 from both neural networks are higher than the average electricity MCP in February 2008. As mentioned earlier, precipitation level is directly related to the potential for hydroelectric power which in turn influences the electricity price.

Knowing the daily minimum, the daily maximum and the daily mean values of forecasted electricity MCPs, the most likely forecasted electricity MCP for each day in February 2009 was also calculated. The histogram technique was used to find out the probabilities of different electricity MCP ranges. By collecting the probabilities of forecasted electricity MCP from approximately 1413 possible results for each day, the forecasted electricity MCP range with the highest probability was obtained. This result represents the most expected daily forecasted electricity MCP for a day in February 2009. Figure 4.11 shows the most likely forecasted electricity MCP for each day in February 2009.

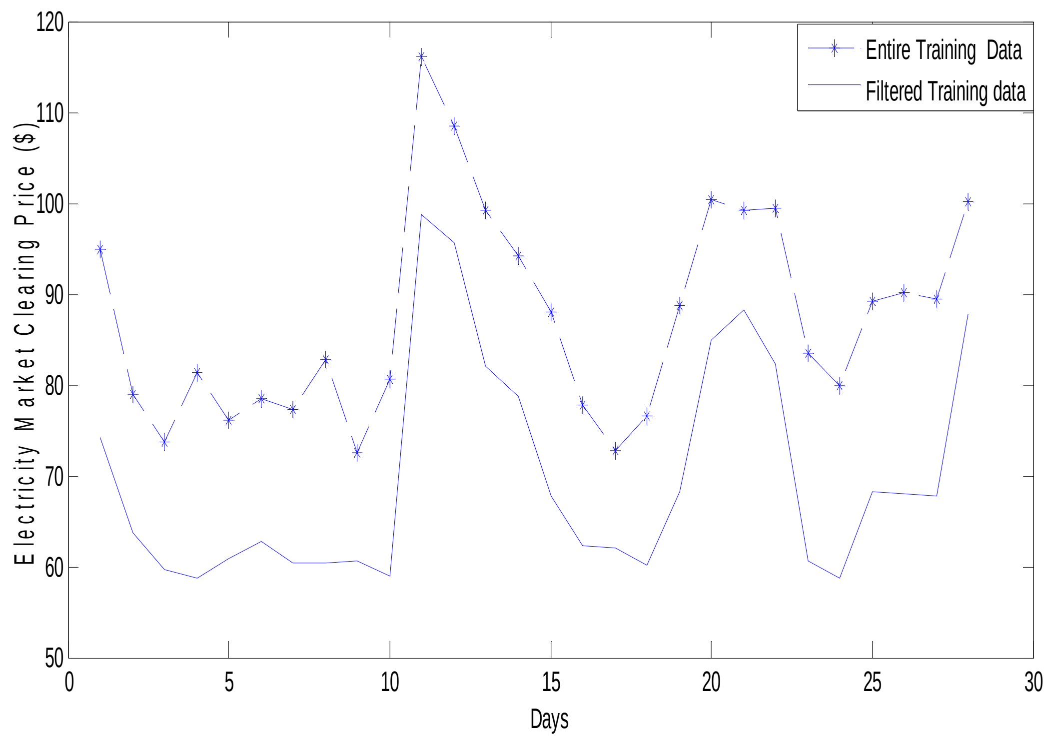


Figure 4.11: Most likely Electricity MCP for February 2009 Using the Entire Training Data and Filtered Training Data

4.7 Summary

Two artificial neural networks were discussed for forecasting the future daily electricity MCP. One was based on the utilization of the entire training data set and the other one was based on the utilization of filtered training data. The training input data is an 8784-by-4 matrix and the training output data is an 8784-by-1 matrix which is based on 29 days in February 2008. The results obtained by the two neural networks exhibit similarities in terms of the most likely electricity price. The results from the forecasting modules shown in Figure 4.11 indicate that the most likely MCP for each of the 28 days has a probability greater than 50 percent. The neural network utilizing the entire training data set could simulate the characteristics of electricity MCP under a real deregulated electric market. Meanwhile, the neural network utilizing the filtered training data could simulate the characteristics of electricity MCP under deregulated electric market with perfect competition.

CHAPTER 5: 24-HOUR BASED MID-TERM ELETRICITY MARKET CLEARING PRICE FORECASTING

5.1 Introduction

In this Chapter, instead of forecasting a daily electricity MCP, an hourly electricity MCP forecasting for a 24-hour period will be discussed. In PJM and most other energy markets, electricity is traded on an hourly basis. This would require the forecasted electricity MCP not only available on a daily basis but also available on an hourly basis. The purpose behind the 24-hour mid-term electricity MCP forecasting is the desire for sensitivity analysis performed on the fuel cost, anticipated peak demand, hydroelectric power supply, and price elasticity of demand. The proposed 24-hour mid-term electricity MCP forecasting was designed to capture the dependency of the electricity MCP on demand, peak demand, fuel cost and hydroelectric power supply. The training data utilized for 24-hour mid-term electricity MCP forecasting include electricity hourly demand and supply, daily price of natural gas, monthly precipitation and hourly electricity MCPs. Same artificial neural networks (ANN) proposed in the previous Chapter are used to forecast 24-hour mid-term electricity MCP. For the purpose of illustration, a 24-hour period in February 2009 is considered in this Chapter. The maximum, the minimum, and the mean values for each of the 24-hour electricity MCPs have been determined and presented in this Chapter. Moreover, the most likely hourly forecasted electricity MCPs for the 24-hour period is presented.

5.2 Proposed Artificial Neural Network Model

Same neural networks proposed and reported in the previous Chapter have been utilized for the 24-hour based mid-term electricity MCP forecasting. Historical data from August 1, 2007 to July 31, 2008 are used to train the proposed neural network. 100 synaptic weights will be generated between the input and the hidden layer through training. At the same time, 25 synaptic weights will also be generated between the hidden and the output layer.

The difference between the daily and hourly electricity MCP forecasting lies in the creation of the forecasting input data. Instead of creating daily forecasting input data for 28 days, hourly forecasting input data from hour 1 (1:00 a.m.) on February 1, 2009 to hour 24 (12:00 a.m.) on February 28, 2009 are created. The forecasting input data contain electricity hourly demand data, electricity daily peak demand data, monthly natural gas price and monthly precipitation data. During the forecasting simulation, each element of the input data was adjusted in turn while the other input elements were held constant. Depending on the range of historical electricity hourly demand data and the range of historical electricity daily peak demand data, the proposed neural network simulated all possible situations and forecasted from as less as 950 MCPs (low demand hour) to as many as 1300 MCPs (peak hour) an hour. Then, the proposed neural network simulated other 950 to 1300 forecasting input data and forecasted another total of 950 to 1300 MCPs for the next hour. The simulation and forecasting started at hour 1 (1:00 a.m.) on February 1, 2009 and repeated till hour 24 (12:00 a.m.) on February 28, 2009. A detailed explanation of forecasting input data creation will be presented in Section 5.5.

5.3 Selection of Training Data

In the short-term, a producer needs to forecast electricity prices to set the bidding strategy and to optimally schedule its electric energy resources [12]. During a mid-term electricity MCP forecasting, the effects of spinning reserve and spot energy can be ignored. Their effects are only considered in a day-ahead market. Moreover, factors related to transmission congestion, transmission outages and unit commitment are not considered either [13]. These factors usually affect the electricity MCP in the short-term. The training data used for the hourly based mid-term electricity MCP forecasting are the same training data used in the previous Chapter. The training input data include four historical data: 1) electricity hourly demand, 2) electricity daily peak demand, 3) daily natural gas price and 4) monthly precipitation. The training output data (target data) is the historical electricity MCP. Historical training data are selected from hour 1 (1:00 a.m.) on August 1, 2007 to hour 24 (12:00 a.m.) on July 31, 2008. The electricity hourly demand data, electricity hourly price and electricity daily peak demand data are all from PJM [3] interconnected electric system. The daily natural gas price is from the Energy Information Administration (EIA) [2]. The monthly precipitation data shown in Table 5.1 are from the Northeast Regional Climate Center (NRCC) [29]. Again, the precipitation datum of August 2007 (6.09) has been used as a reference. All precipitation data have been converted into percentages with respect to the reference.

Table 5.1: 12 Month Precipitation Data

Month	Precipitation (in)	Precipitation (%)
Aus-07	6.09	100.00%
Sep-07	1.99	32.68%
Oct-07	3.98	65.35%
Nov-07	4.07	66.83%
Dec-07	5.00	82.10%
Jan-08	2.34	38.42%
Feb-08	5.09	83.58%
Mar-08	5.41	88.83%
Apr-08	2.68	44.01%
May-08	4.51	74.06%
Jun-08	4.07	66.83%
Jul-08	4.38	71.92%

5.4 Training

The training for hourly mid-term electricity MCP forecasting is same as the training for daily mid-term electricity MCP forecasting. Again, the two proposed neural networks have been utilized. The first one used the entire training data set. The second neural network used only the filtered training data. The MATLAB Artificial Neural Network Toolbox with backpropagation was chosen to train the two neural networks. Levenberg-Marquardt algorithm was utilized for faster training and better performance.

5.5 Forecasting Input Data Generation

The proposed hourly mid-term electricity MCP forecasting was designed to capture the dependence of the electricity MCP on demand, peak demand, fuel cost and hydroelectric power supply. During hourly mid-term electricity MCP forecasting, the effects of spinning reserve and spot energy have been ignored. Because spinning reserve and spot energy requirement affect the short-term forecasting rather than the mid-term forecasting. Moreover, factors related to transmission congestion, transmission outages and unit commitment are not considered either [13] due to the same reason. Therefore, the forecasting input data are limited to electricity hourly demand, electricity daily peak demand, monthly natural gas price, and monthly precipitation of February 2009.

The forecasting input data are generated by combining electricity hourly demand, electricity daily peak demand, monthly natural gas price and monthly precipitation varied between their respective minimum to maximum levels. When forecasting the daily electricity MCP, the forecasting input data were created on a daily basis. On the other hand, when forecasting the 24-hour period electricity MCP, the forecasting input data are created on an hourly basis.

In order to forecast hourly electricity MCP, a forecasting input data matrix was created for each hour of February 2009. A total of 24×28 input data matrix were created to forecast the hourly electricity MCP from hour 1 on February 1, 2009 to hour 24 on February 28, 2009. The future electricity hourly demand for February 2009 was estimated by escalating the historical demand in February 2008. An example of a forecasted 24-hour electricity hourly demand data for February 5, 2009 is shown in Table 5.2. There are total 24 columns of data representing each of the 24 hours. Inside each column, there are minimum, maximum and mean values of electricity hourly demand. Each mean value of electricity hourly demand was calculated by finding the corresponding demand data from the same day and same hour on February 2008 and elevating them by 108.1%. 8.1% is the annual rate of increase in electricity demand from EIA [2]. Electricity demand data at 7:00 a.m. on February 5, 2009 is taken as an example to explain the generation of the forecasted electricity hourly demand data. In order to find all three values (minimum, maximum and mean) for 7:00 a.m., the mean value of electricity hourly demand at 7:00 a.m. on February 5, 2008 needed to be found first. This was done by accessing electricity hourly demand data at 7:00 a.m. on February 5, 2008 from PJM [3]. After the historical electricity hourly demand was found, this value would then be multiplied by 108.1% in order to get the forecasted electricity hourly demand at 7:00 a.m. on February 5, 2009. The minimum and the maximum electricity hourly demand were calculated by adding ± 14.1% on top of the forecasted mean value of electricity hourly demand. The adjustment value 14.1% was determined by analyzing the electricity hourly demand variations of all the demand values at the same hour during the 28 days of February 2008. For example, taking all 28 days electricity hourly demand value at 7 a.m. on February 2008, the maximum and the minimum was found to be within ± 14.1% of the mean of 28 electricity hourly demand values. The forecasted hourly minimum, maximum and mean values of electricity demand data for 7 a.m. on February 5, 2009 are 75453 MW, 100223 MW and 87838 MW respectively. The electricity daily peak demand data is the highest electricity hourly demand data in the same day. Therefore, the forecasted minimum, maximum, and mean values of electricity daily peak demand data for each of the 28 days in February 2009 are generated by collecting the highest electricity hourly demand data from each of the 28 days in February. Other forecasted input data of monthly natural gas price and monthly precipitation were obtained from the EIA [2] and NRCC [29]. The minimum, the maximum and the mean values of the input data for 7 a.m. on February 5, 2009 are shown in Table 5.3. The complete forecasting input data matrix is then generated by incrementally changing the demand or other input factors from their minimum levels to their maximum levels in a sequential manner.

Table 5.2: A Summarized 24-Hour Forecasted Hourly Electricity Demand Data for February 5, 2009

Columns: 1-6						
Hour	1	2	3	4	5	6
Minimum (MW)	64853	62758	61660	61525	63117	67818
Maximum (MW)	86144	83361	81902	81723	83837	90082
Mean (MW)	75498	73059	71781	71624	73477	78950
Columns: 7-12						
Hour	7	8	9	10	11	12
Minimum (MW)	75453	79816	80118	79988	79869	79334
Maximum (MW)	100223	106018	106419	106248	106090	105378
Mean (MW)	87838	92917	93268	93118	92980	92356
Columns: 13-18						
Hour	13	14	15	16	17	18
Minimum (MW)	78490	78049	77546	77156	78252	81294
Maximum (MW)	104257	103672	103004	102486	103941	107982
Mean (MW)	91373	90860	90275	89821	91097	94638
Columns: 19-24						
Hour	19	20	21	22	23	24
Minimum (MW)	83817	83243	81276	77564	72447	66945
Maximum (MW)	111333	110571	107958	103028	96231	88922
Mean (MW)	97575	96907	94617	90296	84339	77934

Table 5.3: Summarized Forecasted Input Vectors Modifier

	Hourly Demand 7:00 a.m. on February 5, 2009 (MW)	Daily Peak Demand (MW)	Daily Price of Natural Gas ($)	Monthly Precipitation Data (%)
Minimum	75453	83817	5.33	50.03
Maximum	100223	111333	9.33	69.14
Mean	87838	97575	7.33	60.65
Step Increment Value	100	50	0.01	0.10

Using 7:00 a.m. on February 5, 2009 as a quick example, the electricity hourly demand data will vary from its minimum of 75453 MW all the way to its maximum of 100223 MW with an increment of 100 MW for each step. Next, keeping the hourly demand datum fixed at its mean value of 87838 MW, the electricity daily peak demand was varied from its minimum of 83817

MW to its maximum of 111333 MW with a step increment of 50 MW. The reason for keeping the step increment value of electricity daily peak demand small is that the electricity daily peak demand is more sensitive in capturing price elasticity compared to the electricity hourly demand. The forecasted electricity hourly demand could never be higher than the forecasted electricity daily peak demand. For special situations where the electricity hourly demand data is higher than the electricity daily peak demand, the electricity daily peak demand will be set equal to the same value as the electricity hourly demand. For example, at hour 19 from Table 5.2, when varying the electricity daily peak demand from its minimum to its maximum, the electricity daily peak demand could not start from its minimum value of 83817 MW because hour 19's electricity hourly mean demand of 97575 MW was greater than the minimum daily peak demand. Therefore, the electricity daily peak demand for hour 19 would start from 97575 MW (hour 19's electricity hourly mean demand) instead of 83817 MW. The same thing occurred when the electricity hourly maximum demand at hour 19 was greater than the electricity daily mean peak demand. Under this situation, the electricity daily peak demand would be set equal to the hourly demand as soon as the hourly demand exceeds 97575 MW (daily mean peak demand).

Table 5.4: Brief Forecasted Input Data Matrix for 7:00 a.m. on February 5, 2009

Hourly Demand Hour 7 (MW)	Daily Peak Demand (MW)	Price of Natural Gas ($)	Hourly Water Level (%)	
75453	97575	7.33	60.65	Start
75553	97575	7.33	60.65	Hourly Demand +100 MW
… … …	… … …	… … …	… … …	
97575	97575	7.33	60.65	Daily Peak Demand Equal to Hourly Demand
97675	97675	7.33	60.65	Hourly Demand +100 MW
100223	100223	7.33	60.65	Hourly Demand Variance Done
87838	87838	7.33	60.65	Daily Peak Demand Variance Start/ Equal to Hourly Demand
87838	87888	7.33	60.65	Daily Peak Demand +50 MW
… … …	… … …	… … …	… … …	
87838	111333	7.33	60.65	Daily Peak Demand Variance Done
87838	97575	5.33	60.65	Daily Natural Gas Price Variance Start
87838	97575	5.34	60.65	Daily Natural Gas Price +$0.01
… … …	… … …	… … …	… … …	
87838	97575	9.33	60.65	Daily Natural Gas Price Variance Done
87838	97575	7.33	50.03	Precipitation Variance Start
87838	97575	7.33	50.13	Precipitation +0.1%
… … …	… … …	… … …	… … …	
87838	97575	7.33	69.14	Hour 7’s Forecasting Input Vector Finished

The price of natural gas would vary from $5.33 to $9.33 per m^3 with a step increment value of $0.01. The precipitation was varied from 50.03% to 69.14% with a step increment value of 0.1%. A brief forecasted input data matrix for hour 7 on February 5, 2009 is shown in Table 5.4. There were total 672 (24×28) forecasting input data matrix generated to forecast the hourly electricity MCP from hour 1 on February 1, 2009 to hour 24 on February 28, 2009.

5.6 Results

Hourly electricity MCP forecasts have been obtained utilizing two neural networks. One was trained with the entire training data set and the other was trained with filtered training data. Each neural network has been utilized 672 (24 × 28) times to forecast the electricity MCP from hour 1 on February 1, 2009 to hour 24 on February 28, 2009. The forecasting input data for each hour is an N-by-4 matrix, where N is the difference between the maximum and the minimum hourly load. N varied from 950 to 1300. N dictated the size of each input and consequently the size of the out. A smaller N implies that the electricity MCP for that hour will stay within a narrow range. On the other hand, a larger N implies that the electricity MCP for that hour may vary within a wide range.

The output of forecasted electricity MCP for each hour is an N-by-1 matrix where N is a number from 950 to 1300 depending on the forecasting input data. For each hour, the minimum, the maximum and the mean values of forecasted electricity MCP were calculated utilizing the same approach discussed in the previous Chapter.

Next, the most likely electricity MCP for each hour is determined from the output electricity price range. A histogram analysis is applied to represent the probabilities of each forecast output within the output price range. The most likely electricity MCP for an hour is determined from the histogram.

Figures 5.1 and 5.2 show the results for the forecasting modules with the entire training data set and filtered training data in a respective manner. The minimum, the maximum and the mean values for each hour are shown in each graph. The graphs include the electricity MCP forecast from 1:00 a.m. on February 1, 2009 to 12:00 a.m. on February 28, 2009.

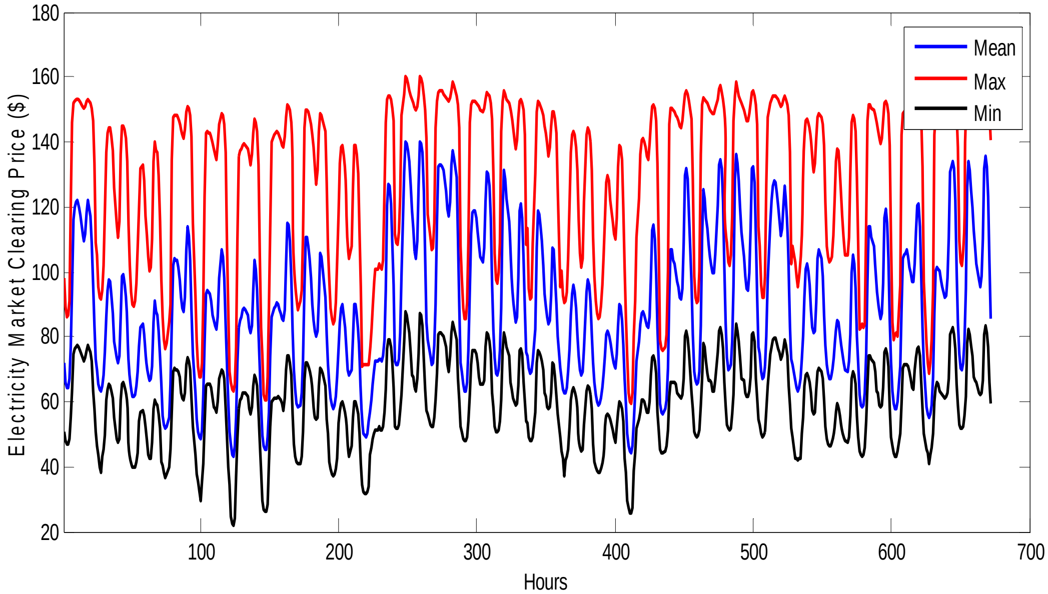


Figure 5.1: Hourly Forecasted Electricity MCP for February 2009 Using the Entire Training Data Set

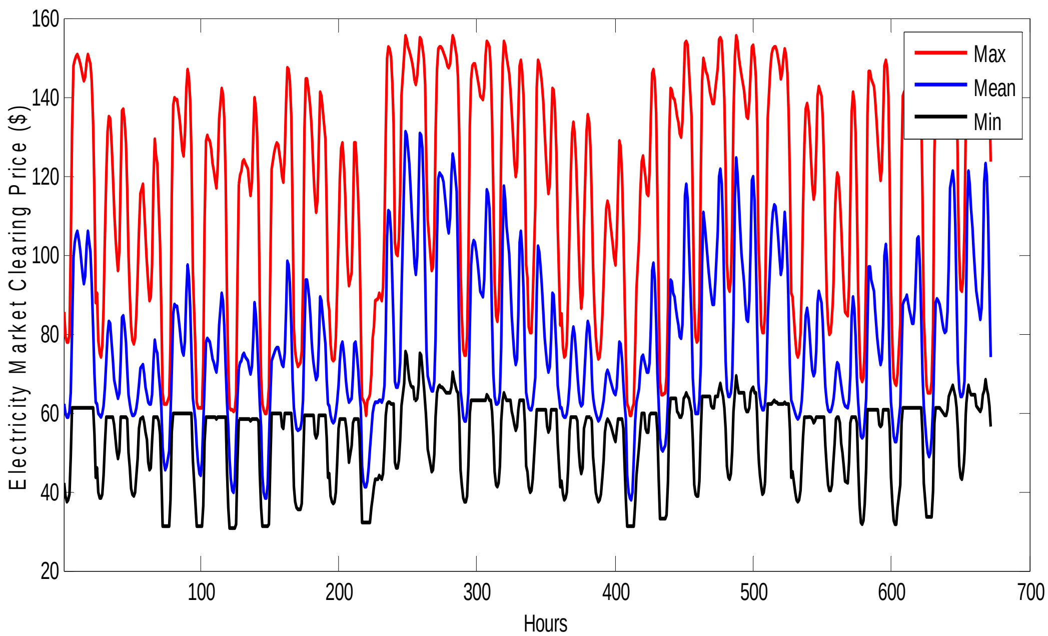


Figure 5.2: Hourly Forecasted Electricity MCP for February 2009 Using the Filtered Training Data

Figures 5.1 and 5.2 represented the electricity MCP for every hour in February 2009. A 24-hour period electricity MCP forecast for any day in the month of February 2009 could be easily obtained by zooming on to the two graphs. Figures 5.3 and 5.4 show the 24-hour period electricity MCP forecast for February 1, 2009 utilizing the entire training data set and the filtered training data in a respective manner.

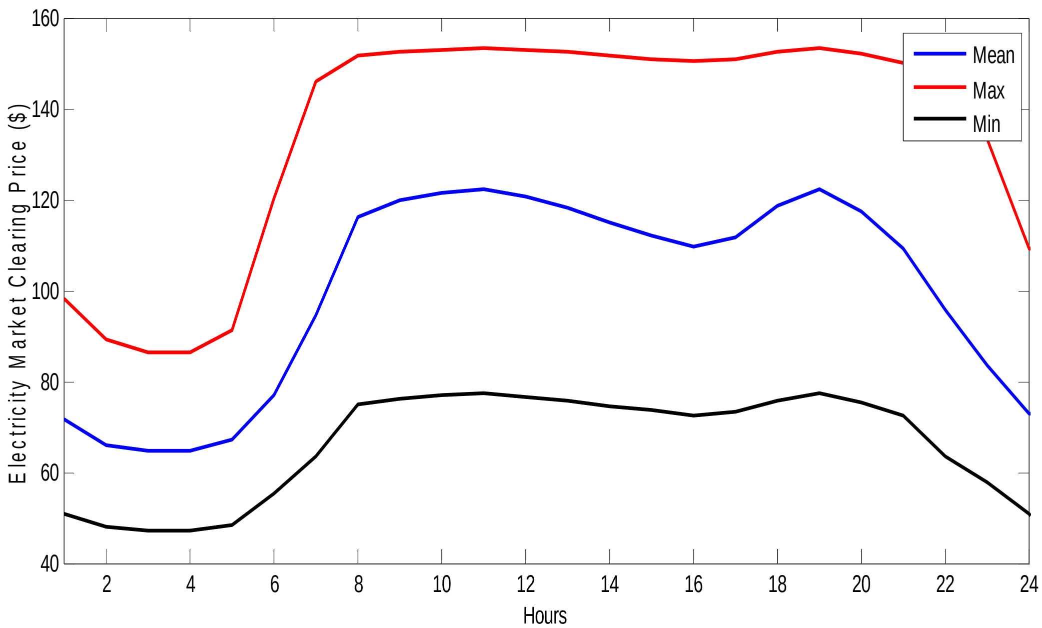


Figure 5.3: 24-Hour Electricity MCP Forecast for February 1, 2009 Utilizing the Entire Training Data Set

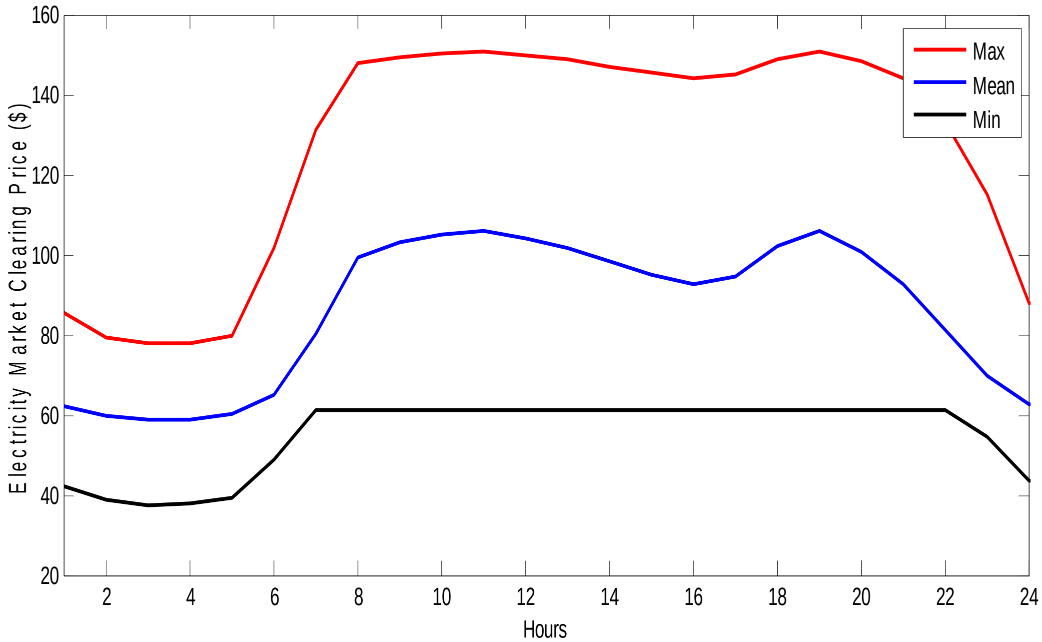


Figure 5.4: 24-Hour Electricity MCP Forecast for February 1, 2009 Utilizing the Filtered Training Data

Following the statistical analysis, a histogram analysis is applied to the forecasted electricity MCPs on February 1, 2009. The forecasted and real time electricity MCPs with the highest probabilities for each hour on February 1, 2009 are shown in Figure 5.5.

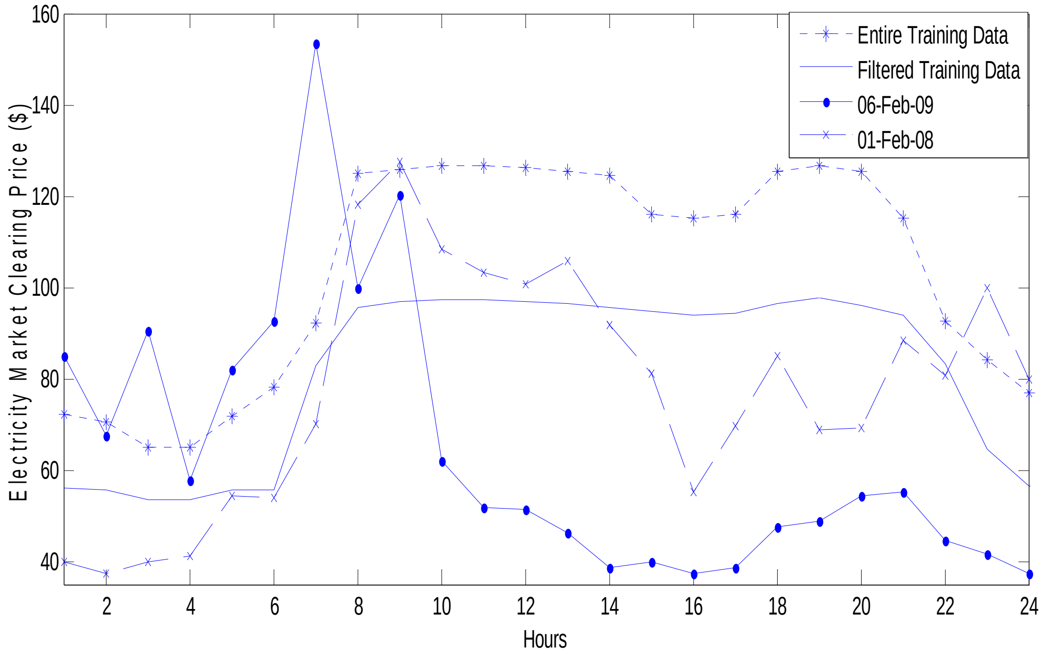


Figure 5.5: Most Likely 24-Hour Forecasted Electricity MCP on February 1, 2009 Utilizing the Entire Training Data Set and the Filtered Training Data

It can be seen from Figure 5.5 that both forecasted 24-hour electricity MCP for February 1, 2009 exhibit similar characteristics. However, the neural network trained with the entire training data set forecasted a higher price than that forecasted by the neural network trained with the filtered training data. The maximum and the minimum hourly mid-term forecasted electricity MCPs with the 24 hour period agree with the daily maximum and minimum forecasted electricity MCP reported in the previous Chapter. The hourly forecasted MCPs for the 24 hour period in February 2009 are generally higher than the hourly electricity prices in February 1, 2008 (Friday). This is attributed to the fact that the forecasted precipitation in February 2009 is lower than that of February 2008. The hourly real time electricity MCPs on February 6, 2009 (Friday) are also shown in Figure 5.5. Both February 1, 2008 and February 6, 2009 are the first Friday in the month of February.

5.7 Summary

Two artificial neural networks were proposed for forecasting hourly mid-term electricity MCP for a 24 hour period. One was based on the utilization of the entire training data set and the other one was based on the utilization of the filtered training data. The results obtained by the two neural networks exhibit similarities in terms of the most likely electricity price. The results from the forecasting modules shown in Figure 5.5 indicate the future hourly electricity MCP with more than 50 percent probability for February 1, 2009. It was observed that both neural networks could simulate the characteristics of electricity MCP under deregulated electric market. The neural network utilizing the entire training data set could simulate the characteristics of electricity MCP under a real deregulated electric market. Meanwhile, the neural network utilizing the filtered training data could simulate the characteristics of electricity MCP under deregulated electric market with perfect competition.

CHAPTER 6: CONCLUSIONS

6.1 Conclusions

Four Artificial Neural Networks have been developed for forecasting the daily and the hourly electricity mid-term MCPs six months from now. For each of the daily and hourly forecasting, there was one neural network based on the utilization of the entire training data set and there was another one based on the utilization of filtered training data. The forecasting duration of the proposed neural networks is for an entire month. Historical data including electricity hourly demand, electricity daily peak demand from PJM [3], daily natural gas price from the Energy Information Administration (EIA) [2] and monthly precipitation data from the Northeast Regional Climate Center (NRCC) [29] were used as the training input data. Historical electricity hourly MCPs from PJM [3] were used as the training output data (target data). The MATLAB Artificial Neural Network Toolbox with backpropagation was chosen to train the two neural networks. Levenberg-Marquardt algorithm was utilized for faster training and better performance. During the electricity daily MCP forecasting, neural networks utilizing the entire training input data result a much wider price range while neural networks utilizing filtered training data result a fairly smaller price range. The same methodology was applied when forecasting the 24-hour based mid-term electricity MCP.

When forecasting the daily electricity MCP, the training input data is an 8784-by-4 matrix and the training output data is an 8784-by-1 matrix which was based on 28 days hourly electricity MCPs in February 2008. The results obtained by the two neural networks exhibit similarities in terms of the most likely electricity price. The results from the forecasting modules utilizing histogram method indicate the future electricity MCP with more than 50 percent probability for each of the 28 days. It was observed that both neural networks could simulate the characteristics of electricity MCP under deregulated electric market.

During the forecasting of hourly electricity MCP, the forecasting input data was based on the modification of historical electricity hourly demand from every hour of February 2008 with the statistical calculated annual rate of increase in electricity hourly demand from EIA [2]. The results obtained by the two neural networks exhibit similarities in terms of the most likely electricity price. Same as the mid-term daily electricity MCP forecasting, it was observed that both neural networks could simulate the characteristics of electricity hourly MCP under deregulated electric market. For low demand period, the price elastic to demand seems quite stable. Therefore, the forecasted electricity MCP resulted in a small range. When forecasting the electricity MCP at a higher demand and peak demand period, the price elastic to demand was violated and resulted a much wider price range. This also explained the fact that according to the historical data, the electricity MCP didn’t vary much during low demand period. During high and peak demand period, electricity MCP varied by hundreds of dollars due to the unexpected sudden surplus or short supply. Spinning reserve and spot energy were also the two huge driving forces affecting the electricity MCP. With 10 to 100 times higher electricity price, generating companies and all other participants inside the energy market are trying their best to take advantages from the two energy markets. Unethical competition is hardly avoided as they are chasing for the pure profits. Through a long run, the energy market is still predictable which agree with the proposed neural networks for the mid-term electricity MCP forecasting. However, focusing on the short-term, price varies dramatically.

6.2 Scope of Future Work

Performance of an artificial neural network is reliant relying on the training data and the actual training process is self oriented through the MATLAB Artificial Neural Network Toolbox utilizing backpropagation algorithm. Therefore, selection of training data, number of input data, number of hidden layer and number of hidden neurons were the only things that could be controlled and modified. There was no supervision that could be applied to the neural network during the simulation. Therefore, the future work on this project would be to design a neural network that would be supervised during the simulation. The objective of supervision would be to control training not just be selecting training data and number of neurons but also be controlled from the inside of the simulation simultaneously. Fuzzy logic could be a possible solution and a hybrid forecasting model including both neural network and fuzzy logic will be expected in the further research.

During this project, only historical data including electricity hourly demand, electricity daily peak demand, daily natural gas price and monthly precipitation data were used as the training input data. Historical electricity hourly MCPs were used as the training output data (target data). MCP bidding strategy was not included in the forecasting process. Future work could involve designing a Monte Carlo simulation technique that would include MCP bidding strategy.

REFERENCE

[1] Feng Gao, Xiaohong Guan, Xi-Ren Cao, Papalexopoulos, A., "Forecasting power market clearing price and quantity using neural network method", Power Engineering Society Summer Meeting, 2000. IEEE Vol. 4, 16-20 July 2000 Page(s): 2183-2188

[2] URL: http://www.eia.doe.gov

[3] URL: http://www.pjm.com

[4] URL: http://www.itee.uq.edu.au/~cogs2010/cmc/chapters/Introduction/

[5] Contreras, J., Espínola, R., Nogales, F.G., Conejo, A.J., "ARIMA models to predict next day electricity prices", IEEE Trans. Power Systems 18 (2003) 1014-1020

[6] Catalao J. P. S. (1), Mariano S. J. P. S. (1), Mendes V. M. F. (2), Ferreira L. A. F. M. (3), "Short-term electricity prices forecasting in a competitive market: A neural network approach", Electric Power Systems Research 77 (2007) 1297–1304

[7] J.C. Principe, N.R. Euliano, W.C. Lefebvre, "Neural and Adaptive Systems: Fundamentals Through Simulations", Wiley, New York, 2000.

[8] URL: http://www.mathworks.com

[9] L.M. Saini, M.K. Soni, "Artificial neural network based peak load forecasting using Levenberg-Marquardt and quasi-Newton methods", IEE Proc. Gener. Transm. Distrib. 149 (5) (2002) 578-584

[10] URL: http://smig.usgs.gov/SMIG/features_0902/tualatin_ann.html

[11] A. Angelus, "Electricity price forecasting in deregulated markets", Electricity J. 14 (3) (2001) 32-41

[12] A.J. Conejo, J. Contreras, R. Esp´ınola, M.A. Plazas, “Forecasting electricity prices for a day-ahead pool-based electric energy market”, Int. J. Forecast. 21 (3) (2005) 435–462.

[13] Claudio M. Ruibal, Mainak Mazumdar, “Forecasting the Mean and the Variance of Electricity Price in Deregulated Markets”, IEEE Transactions on Power System, vol. 23, No. 1, February, 2008

[14] URL: http://csc.stanford.edu/class/sophomorecollege/projects00/euralnetworks/History/history1.html

[15] URL: http://www.dacs.dtic.mil

[16] URL: http://derfred.com/wp-content/uploads/2007/06/picture-1.png

[17] Santiago Ramón Y Cajal, “The structure and Connexions of Neurons’, Nobel Lecture, December 12, 1906 (URL: http://nobelprize.org/medicine/laureates/1906/cajal-lecture.html)

[18] URL: http://www.willamette.edu/~gorr/classes/cs449/intro.html

[19] Simon Haykin, “Neural Networks A Comprehensive Foundation”, 2nd Edition, IEEE Press, 1999

[20] Rezaul Haque, “Transmission Loss Allocation Using Artificial Neural Networks”, A M.Sc. thesis, Department of Electrical Engineering, University of Saskatchewan, 2006

[21] Yao, S.J., Song, Y.H., “Prediction of system marginal prices by wavelet transform and neural network”. Elect. Mach. Power Syst. 28 (2000) 983-993

[22] URL: http://www.doc.ic.ac.uk/~nd/surprise_96/journal/vol4/cs11/report.html

[23] URL: http://www.doc.ic.ac.uk/~nd/surprise_96/journal/vol4/cs11/report.html#Neural%20netwoks%20in%20medicine

[24] URL: http://www.stowa-nn.ihe.nl/pictures/transfer.jpg

[25] URL: http://www.nu.com/energy/restruct/default.asp

[26] URL: http://www.eng.nus.edu.sg/EResnews/0602/rd/rd8.htm

[27] URL: http://www.gold-eagle.com/gold_digest_01/hamilton060501.html

[28] URL: http://www.amosweb.com/cgi-bin/awb_nav.pl?s=wpd&c=dsp&k=market-clearing+price

[29] URL: http://www.nrcc.cornell.edu/index.html

[30] Xu, Z., Dong, Z. Y. and Liu, W (2005), "Neural Network Models for Electricity Market Forecasting", In D. Wang and N.K. Lee (Ed.), Neural Networks Applications in Information Technology and Web Engineering 1 ed. (pp. 233-245) Sarawak, Malaysia: Borneo Publishing Co.

[31] URL: http://www.answers.com/deregulated&r=67

[32] URL: http://www.answers.com/topic/deregulation

[33] Pavlos S. Georgilakis, "Market clearing price forecasting in deregulated electricity markets using adaptively trained neural networks", Hellenic Conference on Artificial Intelligence N°4, Heraklion, GRECE (2006), vol. 3955, pp. 56-66

[34] URL: http://www.swtec.com/deregula.htm

[35] URL: http://www.amosweb.com/cgibin/awb_nav.pl?s=wpd&c=dsp&k=marketclearing+price

[36] URL: http://www.gold-eagle.com/gold_digest_01/hamilton060501.html

[37] URL: http://www.ieso.ca/imoweb/siteShared/regulated_prices.asp?sid=ic

[38] Kim, C.-I., Yu, I.-K., Song, Y.H., "Prediction of system marginal price of electricity using wavelet transform analysis", Energy Convers. Manag. 43 (2002) 1839-1851

[39] URL: http://www.texasenergyservice.com/texas_deregulation.html

[40] "New Market Structures: THE TEXAS ALTERNATIVE", Robert W. Gee President. THE GEE STRATEGIES GROUP

[41] Obradovic, Z., Tomsovic, K., "Time series methods for forecasting electricity market pricing", IEEE Power Eng. Soc. Summer Meeting, 1999

[42] Crespo, J., Hlouskova J., Kossmeier, S., Obersteiner, M., "Forecasting electricity spot prices using linear univariate time series models", App. Energy **77** (2002) 87-106

[43] Nogales, F.G., Contreras, J., Conejo, A.J., Espínola, R., "Forecasting next-day electricity prices by time series models", IEEE Trans. Power Systems 17 (2002) 342-348

[44] Huaien Gao, Hans-Peter Kriegel, "Spiral Recurrent Neural Network for Online Learning", 15th European Symposium On Artifical Neural Networks Advances in Computational Intelligence and Learning (ESANN) 2007

[45] Paolo Tenti "Forecasting Foreign Exchange Rates Using Recurrent Neural Networks", International Conference on Artificial Intelligence Application on Wall Street No. 3, New York City, NY, ETATS-UNIS (06/1995)

[46] URL: http://www.bchydro.com

[47] URL: http://www.weatherfordtx.gov/index.aspx