SHORT-TERM ELECTRICITY PRICE FORECASTING USING ARTIFICIAL NEURAL NETWORK

SITI SYAKIRAH BINTI MOHD SIDIN

This report is partial fulfillment of requirements for the Bachelor Degree Electrical Engineering

Faculty of Electrical Engineering

Universiti Teknikal Malaysia Melaka

2017/18

ENDORSEMENT

"I hereby declare that I have read through this report entitled "Short-Term Electricity Price Forecasting Using Artificial Neural Network" and found that it complies the partial fulfillment awarding the degree of Bachelor of Electrical Engineering"

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Signature :

Supervisor's Name : Dr Intan Azmira Binti Wan Abdul Razak

Date :

DECLARATION

I declare that this report entitled "Short-Term Electricity Price Forecasting Using Artificial Neural Network" is the result of my own research except as cited in references. The report has not been accepted for any degree and is not concurrently submitted in candidature of any other degree.

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ACKNOWLEDGEMENT

I want to thank to all the peoples that help me a lot during this project was conducted. I want to say thank you especially to my supervisor, Dr Intan Azmira Binti Wan Abdul Razak. She really helps me a lot in finishing my final year project. Thank you for all the patience and her time for willing to help me in this project.

I also want to appreciate to all my family and friends for giving me strength and motivation in finishing this project.

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ABSTRACT

Electricity price forecasting has become a crucial job in energy market around the world. Hence, price forecasting also has become a major area of research in the electrical engineering field in recent years. However, predicting electricity price forecasting is a challenging task as the prices show complex volatility patterns. Price forecasting plays an important role in power system planning and operation as these are helpful for dispatch and short terms or spot trading. There are many methods in electricity price forecasting. One of the methods is artificial neural network. Artificial neural network is a computational system that inspired by the structure, ability to learn and method to learn by the human brain. Neural network is a good tool to forecast electricity price in deregulation energy market. Hence, neural network model for short term electricity price forecasting is developed in this project. The sensitivity analysis of neural network is performed to get better accuracy in price forecasting by varying learning rate, momentum rate and number of hidden neurons. Correlation analysis was performed to observe the strength of the relationship between input features and targeted output. The neural network model is examined on the Ontario energy market. The use of neural network to forecast electricity price is proven to produce better result compared to the other existing methods.

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ABSTRAK

Peramalan harga elektrik telah menjadi perkara penting dalam pasaran tenaga di seluruh dunia. Oleh itu, ramalan harga juga telah menjadi bidang penyelidikan utama dalam bidang kejuruteraan elektrik dalam beberapa tahun kebelakangan ini. Walau bagaimanapun, meramalkan harga elektrik adalah satu tugas yang mencabar kerana harga menunjukkan pola turun naik yang kompleks. Peramalan harga memainkan peranan penting dalam perancangan dan operasi sistem kuasa kerana ini berguna untuk penghantaran atau perdagangan spot. Terdapat banyak kaedah dalam ramalan harga elektrik. Salah satu kaedah yang boleh digunakan adalah dengan menggunakan rangkaian neural buatan. Rangkaian neural tiruan dikenali sebagai sistem pengiraan yang diilhamkan oleh struktur, keupayaan untuk belajar dan kaedah untuk belajar oleh otak manusia. Rangkaian saraf adalah alat yang baik untuk meramalkan harga elektrik dalam pasaran tenaga deregulasi. Rangkaian neural menunjukkan ramalan yang tepat walaupun dalam keadaan tidak menentu. Analisis kepekaan dalam rangkaian saraf perlu dilakukan untuk mendapatkan ketepatan yang lebih baik dalam ramalan harga yang termasuk kadar pembelajaran, kadar momentum dan bilangan neuron tersembunyi. Analisis korelasi dilakukan untuk mengkaji kekuatan hubungan antara kedua pembolehubah tersebut. Permintaan menunjukkan pekali korelasi yang tinggi. Oleh itu, input pilihan untuk rangkaian saraf adalah permintaan. Ramalan harga elektrik jangka pendek bermaksud tempoh dari beberapa minit hingga satu minggu dan seterusnya. Untuk projek akhir tahun ini, rangkaian neural tiruan telah digunakan sebagai kaedah dalam ramalan harga elektrik jangka pendek. Model rangkaian saraf akan digunakan untuk ramalan harga elektrik jangka pendek di pasaran tenaga Ontario. Penggunaan rangkaian saraf untuk meramalkan ramalan harga elektrik telah menghasilkan hasil yang lebih baik berbanding dengan kaedah lain.

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INTRODUCTION

1.1 Introduction

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Electricity price forecasting has become one of the most important mechanisms in the electricity markets. In the deregulated power markets, the price is fluctuated because of rivalry among the power suppliers. Benefit expansion has turned into a noteworthy inspiration in the electricity market. The imbalance amongst free market activity brings about unpredictable power costs [1]. There are many entities in the energy market that are involved in the price forecasting such as generators, developers, investors, and customers.

The main issues that connected with electricity prices in planning and operation of competitive market is to perform an accurate forecasting of electricity prices. This is because in nature the price is highly volatile. The volatility of electricity price give more uncertainties and complexities to power system operation and consequently affecting the behavior of generation, transmission and demand in electricity market. Therefore, it is important to forecast the electricity price accurately as it can help to develop well-functioning of power system operation and markets. Thus, it can give advantage to the market operator to compute various indices and measurements for market monitoring.

Forecasting is a planning tool that helps management in its attempts to cope with the uncertainty of the future, relying mainly on data from the past and present and analysis of trends. Furthermore, the forecasting starts with certain assumptions based on management's experience, knowledge and judgment. These estimates are projected into the coming months or years using one or more techniques such as neural network, ARIMA and fuzzy.

Short-term electricity price forecasting considers as the duration from a few minute to one week onwards. These are helpful for dispatch and short terms or spot trading. Here and now exchanging is intended to benefit the transient varieties in a stack and genuine costs are just known in the wake of coordinating of offers and offers by the market administrators [2]. Therefore, price forecasting is complex tasks because of the agitated price.

In the bidding process, producers submit selling bids to the market operator with their minimum selling prices and in the same time, the consumers submit buying bids to the market operator. Then, the market operator clears the market using a proper market clearing procedure that results in hourly energy prices and accepted selling and buying bids.

Because of the specialized, physical and financial factors, the fluctuation is very common for electricity price. There are many factors that affect the prediction of the electricity price. The factors are weather, demand, supply, and fuel market.

There are many artificial intelligence techniques used in electricity price forecasting such as neural network, ARIMA and fuzzy inferences. Among the different techniques of forecasting, application of neural network for forecasting in power system has received much attention recent years. The main reason of neural network becoming so popular because its ability to learn complex and nonlinearity relationship that are difficult to model with conventional techniques.

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1.2 Motivation

Nowadays, there are several changes in the electricity market around the world since the smart meter, real-time pricing and deregulation are introduced. Before deregulation was introduced, the energy market was controlled by the utility companies and the government. The customers can only accept the energy and electricity from the utility companies and need to pay the price that has been specified by the utility companies. After deregulation was introduced, the customers might choose their electricity suppliers. Thus, this situation creates rivalry among the electricity suppliers, provide extensive price flexibility and low electricity price. But, the utility companies still can set their market prices but need to buy the electricity during the stage of the generation before selling to the customers. The company that involved in energy market aggravate far-reaching utilization value prediction strategies whichever on bid alternately should support against instability [3]. That is why developers and electricity traders need to know the future electricity price for their profit.

Other than that, there are two mechanisms for trading which are the pool and bilateral contract. In the pool trading, the energy producers and the consumers submit their prices for bidding and selling respectively. In this condition, there are market operators that in charged to clears the market gives out clearing price on the next day. Developers and electricity traders need to know the future electricity price for their profit. Hence, the electricity price forecasting has become more important. Besides, the companies also want to hedge against the risk of daily price volatility using bilateral contracts. These two mechanisms exist at the same time.

In the deregulated energy market, there is market clearing price (MCP) where the independent system operator (ISO) will be using the market clearing algorithm by referring to the single round disposals to clear the biddings [4]. A good market clearing price (MCP) forecast and its certainty interim estimation can enable utilities independent system operator (ISO) to submit viable offers with low risks [3]. Hence, this forecasting gives benefit for the dispatch and spot trading where spot trading means to service short-term variation in loads and the actual price only known after matching the bids and offers by market operator.

1.2 Problem Statement

Price forecasting plays an important role in power system planning and operation. Price forecasting is a difficult task. It is very challenging to predict the accuracy of electricity price because the price is highly volatile and non-linear. Based on the previous researchers, correlation analysis can show good relationship between input and output. Researches that have been conducted show the result of forecasting are still need to be improved.

In order to get a better forecast price, the sensitivity analysis needs to be determined. The sensitivity analysis includes learning rate, momentum rate and the number of hidden neurons. The network is able to extract higher statistics by using one or more hidden layer [8]. Furthermore, some researchers did not consider the number of hidden neurons, momentum rate and learning rate in price forecasting by using the neural network, which may lead to inaccurate forecasting.

There are many forecasting methods that have been applied to the short-term price forecasting (STPF). The method that has been applied to price forecasting is the neural network. There are many advantages of using the neural network. The neural network has the possibilities to use a great number of input variables that affect the price and low errors of forecast under high volatility of considered time series [9]. The conventional model did not have the abilities that neural network have where the neural network has the ability to learn complex and nonlinear relationship [5]. Neural network shows an accurate prediction even in volatile situations [5]. This final year project developed short-term electricity price forecasting by using an artificial neural network (ANN) to forecast the future price for 24 hours ahead or one week ahead.

1.4 Project Objective

The main objective of this project is:

1. To analyze the correlation between forecast input and future price by using correlation analysis.
2. To perform sensitivity analysis of a the neural network by varying learning rate, momentum rate, and the number of the hidden neurons.
3. To develop neural network electricity price forecasting model.

1.5 Project Scope

The scopes and limitations of this project are:

1. Neural network model is developed in MATLAB software as a price forecasting method.
2. Sensitivity analysis of neural network is performed by varying learning rate, momentum rate and number of hidden neuron.
3. The future electricity price are predicted for 24 hours ahead.
4. Short-term electricity price forecasting model using neural network is examined on the Ontario energy market.
5. The objective function of this project is mean absolute percentage error (MAPE).

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CHAPTER 2

LITERATURE REVIEW

2.1 Introduction

There are many methods for electricity price forecasting. The common methods that were used by researchers are time series, data mining and simulation method. The most popular time series method is autoregressive integrated moving average (ARIMA) method. However, neural network is widely used as it can work under non-linearity conditions.

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2.2 ARIMA Model

Time series model also can be classified as an old traditional method to predict electricity price. The most common used by the researchers in the linear model is autoregressive integrated moving average (ARIMA) which were introduced by Box and Jenkins. It is a stochastic process that is built into time series data to get more understanding of the data and predict the future series [23].

ARIMA is used to capture linear patterns in the data. The advantage of ARIMA is the flexibility but its major limitation is it can only capture linear correlation. The approach of linear models to a complex real-world problem is not suitable. Other researchers stated although some modification has been implemented with non-linear models such as neural network, the results of using them for general forecasting problems is limited [3].

Based on the literature review, ARIMA model has been used to predict gas, oil and load forecasting in power system. Norwegian, Spain and California used this method to predict their electricity price [23]. For Californian power market also the ARIMA was used to forecast daily averages prices based on historical data was done [23].

ARIMA model was developed for the Australian national electricity market [10]. A case study presented with the historical data in 2006 to forecast the next 168 hours or one-week electricity prices. It was tested on different seasons; summer, fall, winter, and spring. The mean absolute percentage error produced are 10.46% to 16.06%.

Furthermore, in ARIMA model, the future value of a variable is assumed to be linear function of several past observations with random error. ARIMA model also has been tested for the Czech Republic electricity market in 2014. The mean absolute percentage error (MAPE) was 11.41% [3].

Generally, due to the complex pattern existing in price series and also inherent limitations, just a part of price signal's features can be captured by ARIMA. This model has been tested on Spain electricity market on four different seasonal; summer, fall, winter, and spring. The model was examined in 2002 and the mean absolute percentage error (MAPE) resulted from 6.71% to 21.86%.

From the literature review, ARIMA model is less appropriate to be implemented in the real-world problem because it can only capture linear pattern instead of a non-linear pattern.

2.3 Neural Network Model

The most popular artificial intelligence method is neural network. Many researchers use this method as the neural network has the capability to predict price accurately even in the volatile situation [1, 8, 11, 12, 15, 16, 18, 19]. Artificial neural network (ANN) was inspired by human nervous system which can be handle complex system with the adjustment of the weights in the iterative learning process [12]. Neural network consists of three layers that consist of input layer, hidden layer and output layer [6]. Feed Forward Neural Network (FFNN) is the most preferred neural network type and usually used in the short term electricity price forecasting [5, 6, 12, 16].

Based on the previous researches, neural network can give many advantages in price forecasting where it can deal with a great number of input variables that affect the price and resulted in low error although under high volatility [9]. Furthermore, neural network also can be trained by historical data of a time series in order to capture the characteristics of the time series [7] however, other researchers observed that neural network does not have mechanism to avoid local minimum [14].

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Furthermore, neural network able to resolve indeterminate relation between input and output variables, approximate complex nonlinear functions and can implement multiple training algorithms. Neural network requires huge data but can face over-fitting when huge data are trained.

Besides, in the learning process of the neural network, there is the relationship between input and output according to the set of inputs and corresponding output that have been given [6]. Furthermore, one of the researchers have conducted the Principal Component Analysis (PCA) during the data preparation process because the dimension of the input vector is large but components of vectors are highly correlated [7]. Other than that, the accuracy of the price forecasting can be determined by using Mean Absolute Percentage Error (MAPE).

In [5], neural network has been performed in New England is with hourly historical data of temperature, demand and natural gas price. The neural network is trained with data from 2007 to 2011 and tested on data 2012. During the training, 28 hidden neurons for the hidden layer is used. It has been observed that during the testing, the average mean absolute percentage error (MAPE) is 9.14% and demand data is the most important variable affecting the electricity price [5].

In [12], researchers utilizes various parameter such as weather, population, economic and demographic data in RBFN model. The model presented is less complex and produces satisfactory results.

Based on the research that using the neural network on the Ontario energy market during summer, the researchers developed six forecast models that represent six types of input where the input are the price of past 14 days, demand and price for 14 days and, demand for the previous day. The learning rate and momentum rate are varied from 0.05 to 1 with the step of 0.05. The number of hidden neurons are varied for 2,5,10 and 15. The MAPE was 18.74% where the input are price and demand of the previous day. The number of hidden neuron is 2, learning rate and momentum rate are 0.6. The researchers state that the selection of input data is the most important in forecasting [18].

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In particular, other researchers also use neural network on the Ontario with 13 inputs including previous day average load, load from same hour and same day of the previous week, previous day average price and price for same hour of the previous day for. Data from 2007 to 2011 of Ontario energy market were tested and the resulted MAPE is 13.29% [19].

To capture chaotic character of price, an optimum neural network is developed in California market [23]. Combination of feature selection technique and neural network is used to remove the non-stationary and time variance in price behavior. The model is examined on Pennsylvania, Jersey, Maryland Power Pool or JPM electricity market for forecasting day-ahead locational marginal price (LMP). Another researches used neural network model based on similar days method is used for predicting day ahead electricity price in JPM electricity market.

In addition, authors in [23] developed neural network model with four layered perceptron with one input layer, two hidden layers and one output layer. Levenberg-Marquardt back propagation method is used that illustrates its high capability and performances. Meanwhile, recurrent neural network (RNN) is applied to eliminate complex and rough fluctuations in price in New York. The result shows high accuracy with less computation time [23]. To get a better performance, the number of hidden neuron need to be reduced if during the training of neural network it shows a good performance but during the test of neural network it shows a worse performance [5] while other researchers stated that number of hidden layers can be increased to get best results [1].

The selection of the input is the important thing to forecast the price. The input that always used is demand and price which is the most variable affecting the electricity price. Most of the time, neural network is forecasting with minimum possible error and high absolute error at one or two instances may occur but the effectiveness of neural network remains good most of the time. Conclusively, previous research showed that using neural network can give less mean absolute percentage error (MAPE) in the prediction of price forecasting compared to time series model.

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2.4 Fuzzy Logic

In 1965, fuzzy set was introduced by Lofti Zadeh. The characteristic of fuzzy system is a mathematics calculus to translate the subjective human knowledge of the real processes. Linguistic terms were applied in the fuzzy system. Other speculative and mathematical methods cannot use the linguistic terms [21]. The researchers state that the fuzzy inference mechanisms consist of three stages where the first stage is fuzzyfication which is values of the numerical inputs are mapped by a function according to the degree of compatibility of the respective fuzzy sets. Meanwhile, the second stage is fuzzy system processes the rules in accordance with firing strengths of the inputs. The third stage is defuzzyfication where the resultant fuzzy values are transformed again into the numerical value.

Fuzzy neural network has been used in Australian New-South Wales electricity market to test the forecasting model [2] where past demand, price and weather are selected as input feature. The resulted MAPE were 8% to 21%.

Adaptive Neuro-fuzzy Inference System (ANFIS) has been carried out on Spanish energy market where four seasonal week were tested. The MAPE were range from 6.41% to 19.8%.

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Other than that, the Fuzzy Neural Network has been tested for Spanish energy market in 2002 data. It was tested four weeks on four different seasonal; summer, fall, winter, and spring. The MAPE range is 4.8% to 10.7%.

Based on the literature review, it shows that the fuzzy system has some disadvantages. Instead of easy interpretation of the results because of the natural rules representation, the fuzzy system is unable to generalize or it only answers to what is written in its rule base. Meanwhile, fuzzy system depends on the existence of an expert to determine the interference logical rules [23].

2.5 Conclusion of Overall Literature Review

Through the literature review, the ARIMA model can only be used for linear data and it is not suitable for the real situation in deregulation of energy market where the price are volatile and non-linear. Besides, neural network are the good tools to forecast the electricity price as it shows low error compared with the other methods such as time series and fuzzy logic. Therefore, this project are proposed to use neural network as the method of electricity price forecasting.

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CHAPTER 3

METHODOLOGY

3.1 Introduction

This chapter discusses on the theory of neural network and flowchart of the developed neural network model.

3.2 Theory of Neural Network

The theory of neural network is discussed in this section.

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Artificial neural network is a computational system that inspired by the structure, ability to learn and method to learn by the human brain. One of the neural network model is multilayer perceptron (MLP). Neural network consists of input, output and hidden layer. Each layer contains specific number of computational elements called a neuron [13]. The neuron inside the neural network operates in parallel where the model of neural network consists of three simple elements which are a set of weights, an adder for summing the input signals and activation function for limiting the amplitude of the output of neuron [5]. Neural network has many advantages for price forecasting where it has possibility to use huge number of input variables that affect the price and resulted in low error although under high volatility [9].

There are many types of neural network such as radial basis function (RBF), feed forward neural network (FFNN) and recurrent neural network (RNN). The radial basis function is derived from the theory of function approximation. The characteristics of the radial basis function (RBF) are contains of two layer feed forward networks, the hidden nodes implement Gaussian function and the output layer implement linear summation functions. Furthermore, radial basis function (RBF) are very good at interpolation.

Meanwhile, recurrent neural network (RNN) can analyze the data dynamically over time and can forecast the next sequence of the element in the data series. For the input of the recurrent neural network (RNN), the previous output data can be used as the input. Furthermore, the decision of the recurrent neural network (RNN) depends on the decision that the network gained from the previous moment. Therefore, the current output of the network depends on both current input and previous output. The input and output of the recurrent neural network (RNN) need to be in the three dimensional which is different for output in feed forward neural network (FFNN) that need to be in two dimensional.

Conventionally, feed forward neural network can be defined as the connection between units that do not form in a loop. Feed forward neural network has an input, output layer, and at least one hidden layer. There is no theoretical limit on the number of hidden layers but usually, the researchers set one or two for the hidden layer.

Feed forward neural network is the most preferred neural network type and usually used in the short term electricity price forecasting [5, 6, 12, 16]. FFNN uses supervised learning algorithm. It consists of the number of the neurons that organized in a layer. Each neuron in certain layer is connected to each neuron to the next layer and no feedback connections.

In neural network, the activation function is used as a decision maker at the output of a neuron. The neuron determined the linear on non-linear decision boundaries based on the activation function. Furthermore, to prevent the output neuron to become very large due to cascading consequence, the neural network has the normalization. There are three types of activation function that quite used in the neural network which are sigmoid, tanh, and rectified linear unit (ReLU).

Sigmoid can be interpreted maping in the x-axis to values between 0 and 1 while tanh maps the value between 1 and -1. Moreover, in the rectified linear unit (ReLU), it allows only positive value while the negative value are mapped to the zero.

There are five algorithms to train the neural network. The algorithms are gradient descent, Newton's method, conjugate gradient, quasi Newton and Levenberg-Marquardt. The simplest training algorithm in neural network is gradient descent, which also known as steeper descent. The first order method in this training algorithm is obtained information from gradient vector. There are two steps in training process of gradient descent. First, computed the training gradient direction next, found a suitable training rate. The disadvantage of this training algorithm where it required many iterations for functions.

Newton's method can be described as second order algorithm. Main function of this algorithm is to direction by using second derivatives of loss function. The first process in the Newton's method is obtained first Newton's training direction and then find a suitable training rate.

Conjugate gradient is the training method between gradient descent and Newton's method. It drives by the desire to accelerate the slower convergence in the gradient descent.

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The quasi Newton method are being using to improve the weakness that have in the Newton's method. It calculated the Hessian matrix directly and evaluate the inverse and build up the approximation of the inverse Hessian at each iteration of algorithm. This method only required the information of the first derivatives of the loss function.

The Levenberg-Marquardt algorithm known as the damped least square method that work with the loss function which has been taken from the sum of squared error. It work with the gradient vector and Jacobian matrix. Therefore, it is very fast when training neural network which need to measure the error. The first step in this method is to calculate the loss, the gradient and the Hessian approximation. Then the damping parameter is adjusted to reduce the loss at each iteration.

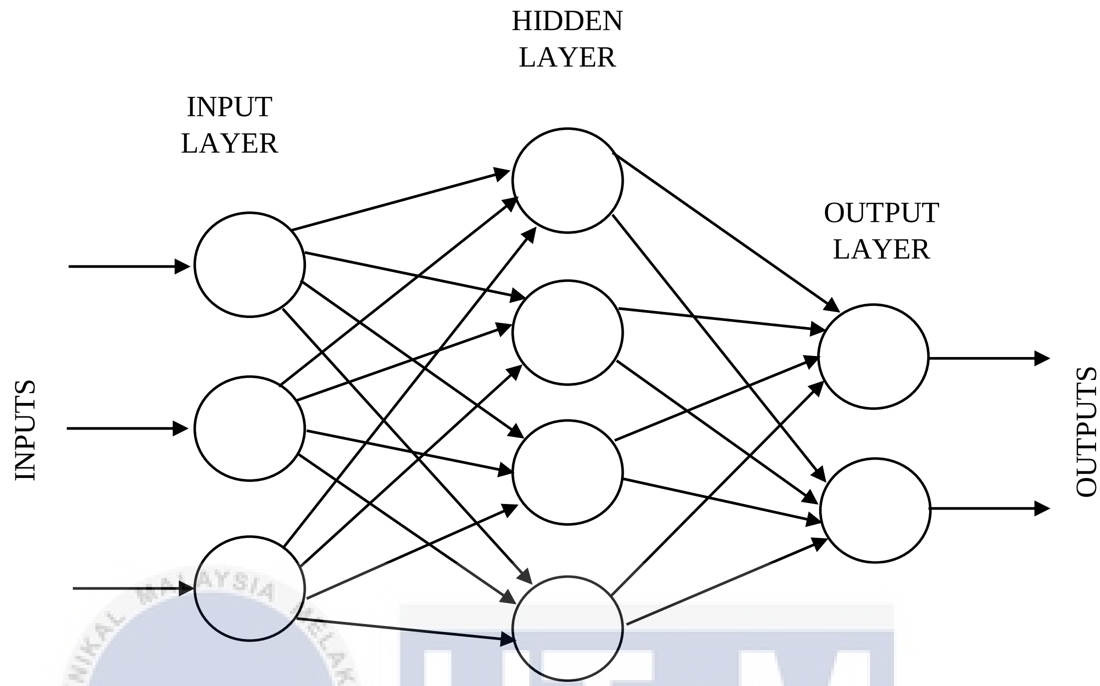

Figure 3.1: The Three Layer of Feed Forward Neural Network

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3.3 Flowchart of Neural Network Forecast Model

3.3.1 Data Collection

In this proposed project, the data that be used in this project are retrieved from the website; http://www.ieso.ca/. The data is publicity for the researchers. Data of 2008 and 2009 are used in this project for training and testing.

3.3.2 Correlation Analysis

After obtaining data from the IESO website, correlation analysis is performed. Correlation analysis is performed to study the strength of the relationship between the two variables. In this project, the correlation analysis is performed between price and demand for past 7 days before the forecast day. The correlation analysis was performed by using MATLAB software.

The syntax *corr2* has been used to conduct the correlation analysis. In correlation analysis for demand data, the data analysis is performed for 7 days which are d-1 is demand a day before the forecast day, d-2 is demand two days before the forecast day and d-3 is demand three days before the forecast day. While d-4 is four days before the forecast day, d-5 is five days before the forecast day, d-6 is the demand six days before the forecast and d-7 is demand seven days before the forecast day.

For the price data, the analysis also is performed for 7 days which are p-1 is price a day before the forecast day, p-2 is price two days before the forecast day, p-3 is price three days before the forecast day and p-4 is the price four days before the forecast day, p-5 is price five days before the forecast day, p-6 is price six days before the forecast day and p-7 is price seven days before the forecast day.

The range of the values of the correlation coefficient is -1 and 1. The correlation coefficient approaches 1 indicates higher correlation where the correlation shows it approached to -1 also shows higher correlation but in a negative way.

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3.3.3 Learning Rate, Momentum Rate and Hidden Neuron

Varying the learning rate, momentum rate and number of hidden neurons is the next step after the correlation analysis was performed. Learning rate is defined as how quickly a network abandons old beliefs for new ones. High learning rate means the network changes its mind quickly.

Besides, momentum rate is the measures how much the past step affects the next step. It also prevents the system from converging to a local minimum. These can help to increase speed of the convergence but setting the momentum too high can create a risk of overshoot which can cause the system become unstable. Too low momentum also can slow down the training of the system. The number of the hidden neuron is inside the hidden layer. In deciding the number of the hidden neurons, using too few neurons will result under lifting. Under lifting occurs where are too few neurons in hidden layer to adequately detect the signals in complicated data set while using too many neurons will result over fitting.

In addition, there is no proper formulation through which number of neurons in the hidden layer of a feed-forward neural (FFNN) can be finalized. Besides, FFNN has low learning rate and higher possibility to trap in local minima. In contrary to this fact, radial basis function (RBFN) has comparatively less chances to trap in local minima and has fast learning rate.

Based on the previous research, it is stated that in the training phase, the weight and biases of the neural network are well altered to reduce the performance of the network function. The first step in training the neural network is set the number of the hidden neuron to one and increase it one by one to increase the performance network [8]. In this process, 70% of the data is used for training sequence and 30% data are used for validation purpose. There are two categories in the learning process which are supervised learning and unsupervised learning. Supervised learning is a set of training data with proper network behavior while unsupervised learning is the weights and biases are modified only to improve the input.

To speed up the learning process, there are parameters that can be modified which are learning rate and momentum because back propagation easily turns to merge slowly [18]. However, some researchers did not varied the number of the hidden neurons, learning rate and momentum rate [19].

3.3.4 Training and Testing

There are three datasets known in neural network. There are training set, validation set and test set. Training set is a set of examples used for learning, where the target value is known. For validation set, it is a set of examples used to tune the architecture of classifier and estimate the error. Besides, test set used only to assess the performance of a classifier. It is never used during the training process so that the error on the test set provides an unbiased estimate of the generalization error.

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Neural network needs to be training thus, it can recognize the pattern of the data. During the training, neural network gets the extensive number of contribution with comparing yields esteems which help the system to take in an association amongst sources of info [11]. The neural network in this project is trained with Levenberg-Marquardt back propagation method. After undergoing the training process, the neural network can predict the future electricity price. Besides, the neural system can recognize likenesses in inputs, despite the fact that a specific information may never have been seen already.

After neural network undergo training process, it must be testing before the model are being used to forecast electricity price in energy market. Testing is the process where the knowledge that obtained by the neural network through training process is tested by applying new data that it has never seen before. The network should be able to generalize and have an accurate output for the unseen data.

3.3.5 Mean Absolute Percentage Error

There are also many methods to figure out the accuracy of the price forecasting which is mean absolute percentage error (MAPE), mean absolute error (MAE) and RMS error (RMSE). In addition, mean absolute percentage error (MAPE) is the most common measure of forecast error.

$$MAPE = \frac{1}{N}\sum_{t=1}^{N}\left|\frac{At - Ft}{At}\right| \times 100\%$$

$$MAE = \frac{1}{N}\sum_{t=1}^{N}|At - Ft|$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{t=1}^{N}|At - Ft|^2}$$

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Where:

A_t = actual value of price at hour t

F_t = forecast value of price at hour t

N = number of hour for forecasting

In this project, only mean absolute percentage error is being calculated to figure out the accuracy of the forecast price. The model can be used when the results of the mean absolute percentage error (MAPE) shows the least error.

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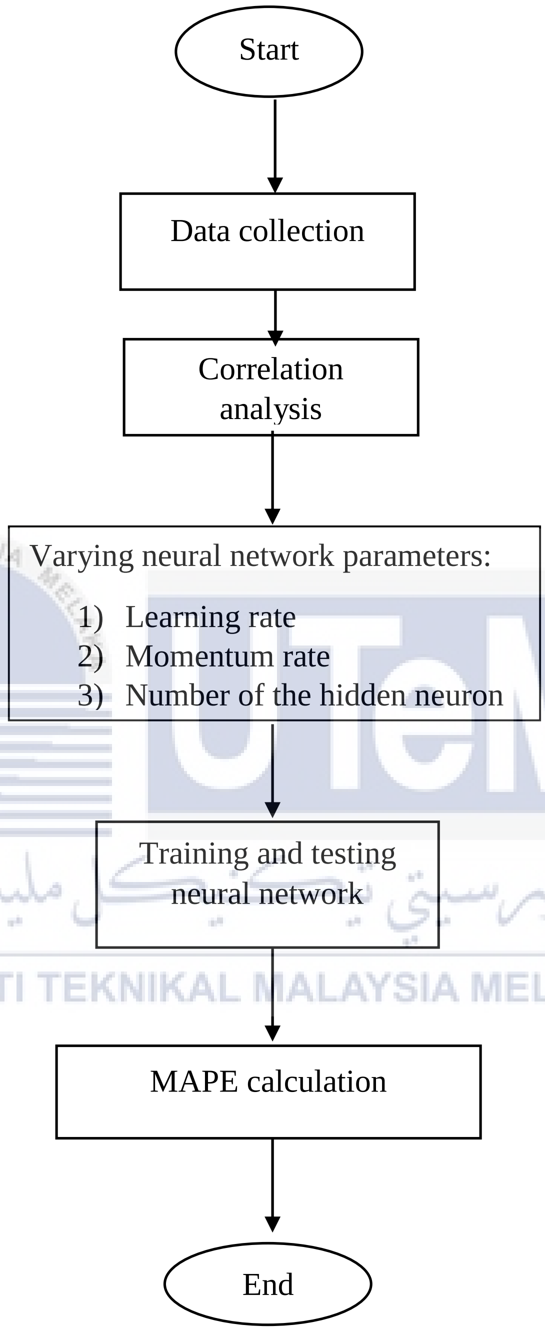

Figure 3.2: Flowchart of overall methodology

3.4 Conclusion of Overall Methodology

As a conclusion, in order to select the feature of the neural network, correlation analysis need to be performed to observe the strength of the input and output variables. Parameter of neural network such as learning rate, momentum rate and the number of the hidden neuron are need to be varied to get better accuracy in price forecasting. The neural network need to undergo training and testing process. The method used for the training process in this project is supervised learning and Levenberg-Marquardt algorithm due to fast learning process. The mean absolute percentage error is being calculated to figure out the accuracy of the forecast price.

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CHAPTER 4

RESULT AND DISCUSSION

4.1 Introduction

This chapter discusses the results of correlation analysis, training and testing of neural network. All results are compared with the existing methods.

4.2 Correlation Analysis

Correlation analysis was conducted to study the strength of the relationship between the two variables. In this project, the correlation analysis is performed between the price and demand for past 7 days before the forecast day. For d-n means, day before forecasting day and *d* means the forecasting day. The range of the correlation coefficient is -1 and 1.

Table 4.1: Correlation between the feature and target

Feature	Target
Demand (d-n)	Price (d)
Hourly price (d-n)	Hourly price (d)

Table 4.2: Correlation coefficient for demand and price for the year 2008 and 2009

Feature (d-n)	Correlation Coefficient			
	Demand 2008	Demand 2009	Price 2008	Price 2009
d-1	0.9495	0.9723	0.5771	0.6463
d-2	0.9282	0.8720	0.4624	0.7190
d-3	0.9308	0.8580	-0.2718	0.3067
d-4	0.9648	0.8052	0.6873	0.4894
d-5	0.9539	0.8362	0.5977	0.3278
d-6	0.9540	0.8729	-0.0518	0.7281
d-7	0.9448	0.9136	-0.0959	0.4672

Table 4.2 shows the correlation coefficient for demand and price on the year 2008 and 2009. The correlation coefficient is between -1 and 1. The coefficient of 1 to 0.5 shows a strong correlation. The results show that the demand in 2008 is highly positively correlated. The correlation result between the demand for past 7 days and price on the forecast day also shows that the demand in 2009 is highly positively correlated.

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For the correlation result between the price for past 7 days and the price on the forecast day 2008 shows that there is a correlation on d-1 but low correlation on d-2 and d-3 shows a weak correlation in a negative way. On d-4 and d-5, shows that there is a correlation. But for d-6 and d-7 shows uncorrelated results. The correlation result between the price for past 7 days and the price on the forecast day in year 2009 shows that on d-1 and d-2 have correlation but on d-3, d-4 and d-5 there is a weak correlation but have correlation on d-6 and again weak correlation on d-7.

Therefore, demand will be selected as the input for the training and testing of the neural network as the demand show high correlation compared to the price.

4.3 Neural Network with Cross Validation Techniques

Cross-validation is used to determine the predictive performance of the models and to evaluate the performance of the sample to a new data set known as test data. The importance of cross-validation technique is when to fit a model, it needs to be fitting to a training dataset. Without cross validation technique, the researcher will only have information on how does their model perform to the in sample data. Basically, cross-validation is the technique how does the model perform when it has a new data in terms of accuracy. In this project, the future electricity price in Ontario energy market is predicted for 24 hours ahead. The selected input is past 7 days demand before the forecast day while the output is the price

4.3.1 Training and Testing Period

The training and testing of neural network have been done by using data of the year 2004. The selected input is the demand while the selected output is the price. The training of neural network has been done for 7 weeks and the testing of neural network has been done for one week. The training and testing period of neural network has been summarized in table 4.1.

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To compare with the previous study, there are six forecast models are developed to represent the whole year of 2004. Each model is trained with seven weeks data prior to the forecasting week as shown in table 4.3.

Table 4.3: Training and Testing Period of Neural Network

Training week (7 weeks)	Testing week (1 week)	
March 8 – April 25	April 26 – May 2	Spring low demand
March 15 – 2 May	May 3 – May 9	
June 7 – July 25	July 26 – Aug 1	Summer peak demand
June 13 – Aug 1	Aug 2 – Aug 8	
Oct 25 – Dec 12	Dec 13 – Dec 19	Winter high demand
Nov 1 – Dec 19	Dec 20 – Dec 26	

4.3.2 Normalization and Denormalization

The purpose of the normalization is to improve the accuracy and training of the neural network model. This technique gives an advantage in mapping the target output to the non-saturated sector of tensing function. In this project, the input data which is the demand of year 2004 and the output data which is hourly Ontario electricity price (HOEP) of year 2004 are being normalized. The data are normalized from the range of -1 to 1.

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The formula used to normalize the data is shown as below.

$$x_n = \frac{x_{j} - \left[\frac{x_{\max} + x_{min}}{2}\right]}{\left[\frac{x_{max} - x_{min}}{2}\right]}$$

Where:

x_n= normalized data

x_j= data at the column

x_{max}= maximum value of the data at the column

x_{min}= minimum value of the data at the column

Denormalization is the process to optimize the read performance of data by adding redundant data or by grouping data. In other words, denormalization is the reverse process of normalization. In this project, the denormalization process involved for the output data which is the predicted price (yPredict).

4.3.3 Neural Network Configuration

In this project, the feed-forward neural network (FFNN) with back-propagation has been used to forecast the electricity price. The neurons are arranged feed forward with input units fully connected to neurons in hidden layer and hidden neurons are fully connected in the output layer. Meanwhile, back propagation is the training method where the neurons adapt their weights to learn new things. The learning techniques in this project is supervised learning. Supervised learning is where the output values are known beforehand.

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4.3.3.1 Hidden Layer in Neural Network

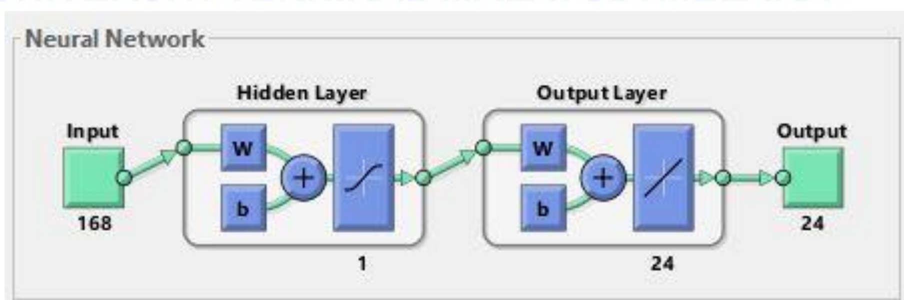

Figure 4.1: Single Hidden Layer

In this project, the hidden layer used is one as shown in figure 4.1. One layer is sufficient to approximate any continuous function. Therefore one hidden layer has been selected to keep the model simple and smooth. However, there is no theoretical limit in the hidden layer but usually, there are just one or two only [24].

4.3.3.2 Activation Function

There is an activation function that been used to transform the activation level of neuron into an output signal. Activation functions of the artificial neurons in hidden layers are necessary in order for the network to be able to learn nonlinear functions. That is why it is important for activation function to be non-linear. Many activation function are being used in neural network. In this project, the tansig and purelin are used as the activation function. Tansig is hyperbolic tangent sigmoid transfer function while purelin is a neural transfer function. Therefore, transfer functions calculate a layer's output from its net input.

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4.3.3.3 Hidden Neuron

There are several problems when many number of hidden neurons are chosen. This can result overfitting. Overfitting can be defined as when the neural network has so much information processing capacity that the limited amount of information contained in the training set is not enough to train all of the neurons in the hidden layers. Besides over fitting, there is also a problem can occur even when the training data is sufficient. An overmuch large number of neurons in the hidden layers can increase the time it takes to train the network. The time taken for the network to train in this project is around six to eight hours.

The selected number of hidden neuron from Week 1 until Week 6 is one. When the bigger number of hidden neurons are selected, the time taken for the neural network for training and testing are too long. So, to avoid the computational burden, the number of hidden neurons is varied from 1 to 2.

The amount of training time can increase to the point that it impossible to adequately train the neural network. Obviously, some compromise must be reached between too many and too few neurons in the hidden layers. There are many rules that can be followed in determining the number of hidden neurons. One of the rules is the number of hidden neurons should be between the size of the input layer and the size of the output layer. Another rule, the number of hidden neurons should be two-third the size of the input layer, plus the size of the output layer and also the number of hidden neurons should be less than twice the size of the input layer [24].

Since in this project need to forecast electricity price for 24 hours-ahead, therefore the number of output neurons is 24. Thus, the number of output neurons is one for each neural network. Thus, this method will be not over fitted since the individual networks are relatively small.

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4.3.3.4 Learning Rate

The learning rate is being varied from 0.1 to 1 with step 0.01. Learning rate can be defined as how quickly a network abandons old beliefs for the new one. Thus, it is very important to balance the intensity of downing the error after epochs. Furthermore, it also gives the effects which are smaller or larger value to the adjustment of preceding weight. High learning rate means the network changes its mind and learn more quickly. However, if the large value is set for the learning rate, the network may not learn very well or not learn at all. Setting high learning rate is improper to the network to learn well [25]. Therefore, setting the value of learning rate to a small value is better but need to find the learning rate that is low enough so that the network converges to something useful but high enough that does not have to spend years training the network.

4.3.3.5 Momentum Rate

Momentum rate can be determined by how much the past step affect the next step. In other words, momentum used to speed up the training but with a reduced risk of oscillating. It also prevents the system from converging to a local minimum and high momentum. If the momentum rate is set to non-zero value, then increasingly greater persistence of former adjustments is permitted in modifying the current modification. This can progress the learning rate in some situations, by helping to smooth out the uncommon conditions in the training set. Setting the value of the momentum rate too small can slowly the training and it might be taken more than hours even days. In this project, the momentum rate is varied from 0.1 to 1 with step time 0.01.

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4.3.4 Cross Validation Result

Table 4.4 shows the results of neural network model with cross-validation technique. Cross-validation in neural network is to split the training set into two which are set of examples to train with and validation set. To train the data, it will use the new training set while prediction on the validation set is used to determine which model to use.

Table 4.4: NN model with Cross Validation Technique

Test week	Selected number of hidden neurons	Regression (R)	Learning rate	Momentum rate	WMAE	WMAPE (%)
Week 1	1	0.73	0.20	0.53	6.97	16.02
Week 2	1	0.77	0.69	0.78	8.08	17.10
Week 3	1	0.81	0.67	0.64	17.03	13.58
Week 4	1	0.91	0.50	0.43	5.56	16.81
Week 5	1	0.65	0.15	0.18	12.06	17.94
Week 6	1	0.66	0.25	0.32	11.30	19.29
Average					10.17	16.79

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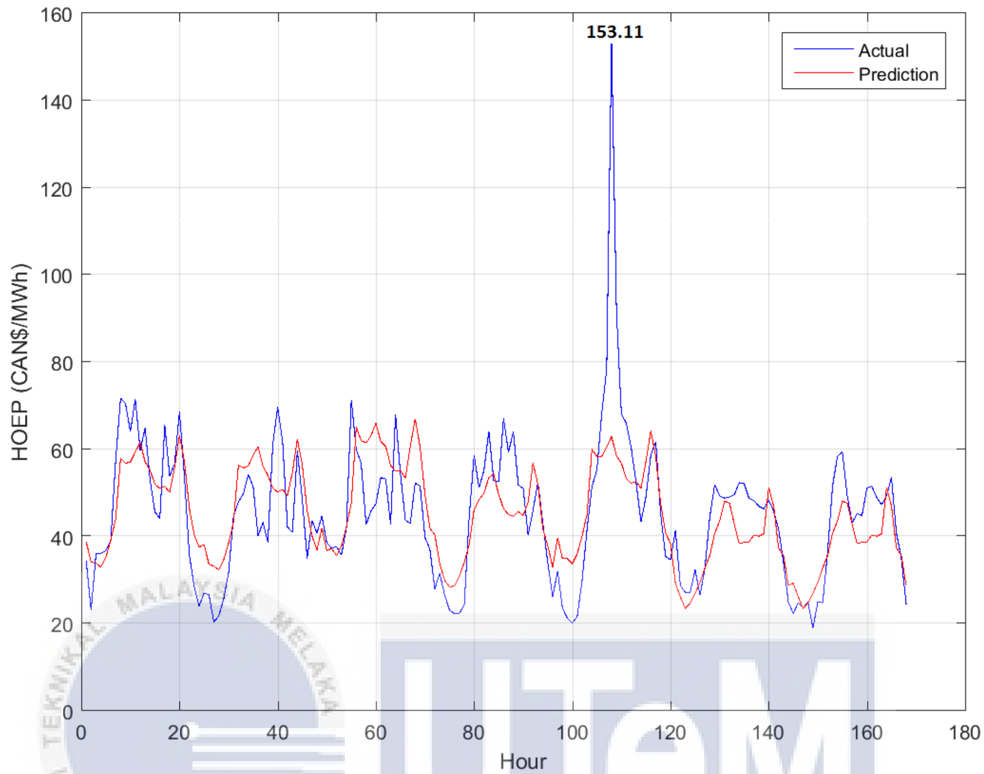

Figure 4.2: Actual and Predicted Price of Ontario Energy Market for Week 1

For week 1, the testing period during the spring low demand (April 26-May 2). The graph shows that on day-1 until day-4 the predicted curve can follow the pattern of the actual price. The actual price on day-1 until day-4 are on the average level which means the price is not too volatile and not too low. But, on the day-5, the predicted curve cannot capture the spike price as the actual price is too volatile. The reason why the price is too volatile because there are many factors that can effected the price such as weather.

Furthermore, the fluctuation of Hourly Ontario Electricity Price (HOEP) arise from a shift in demand, economic activity and supply Meanwhile on the day-6 and day-7, the predicted curve can follow the pattern of actual price as the actual prices on that day are on the average level.

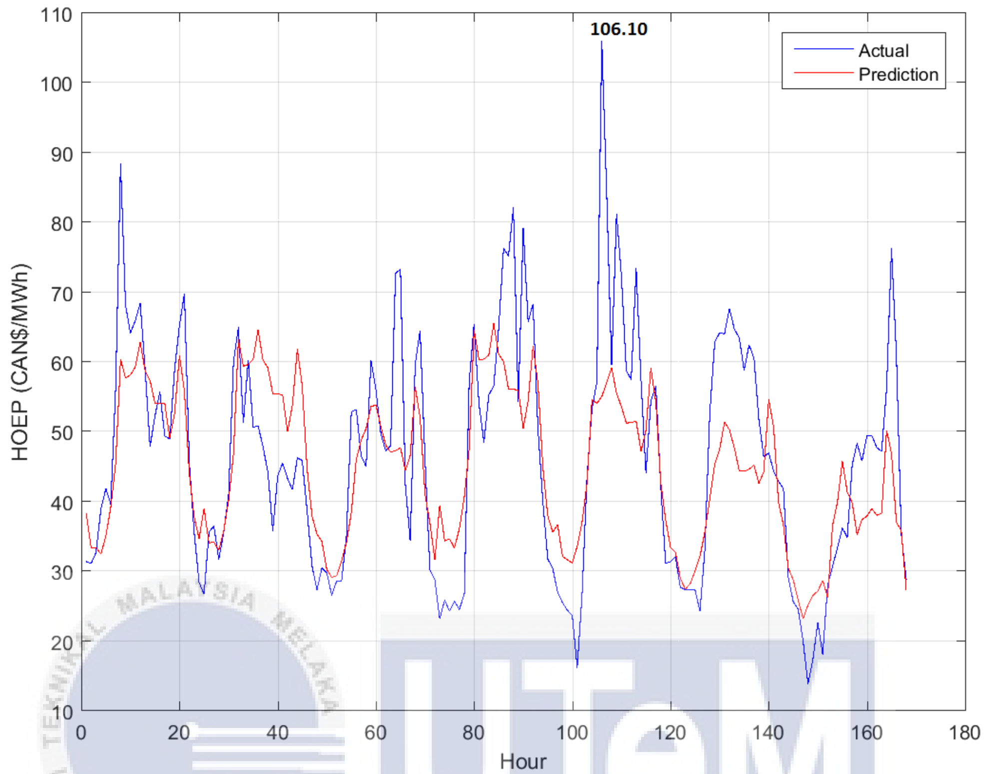

Figure 4.3: Actual and Predicted Price of Ontario Energy Market for Week 2

For week 2, the testing period is on spring low demand (May 3-May 9). Based on the observation in figure 4.3, it shows the forecast price follows the pattern of actual price on day-1 even though on the first hour the actual price fluctuated. But the next hour on the day-1, the predicted curve can follow the actual price curve. On day-3, the predicted curve can follow the pattern of the actual curve. On day-4, the actual price is a little bit high but the predicted curve still can follow the actual pattern.

Meanwhile, on day-5 the actual price curve fluctuated because the price is too volatile. The predicted curve cannot follow the pattern of the actual price. The result on day-6 and day-7 shows that the price is a little bit high and not too volatile but the predicted curve still can follow the actual price pattern. The actual price on day-4 and day-6 are too low. So that predicted price curve cannot follow the pattern of the actual price.

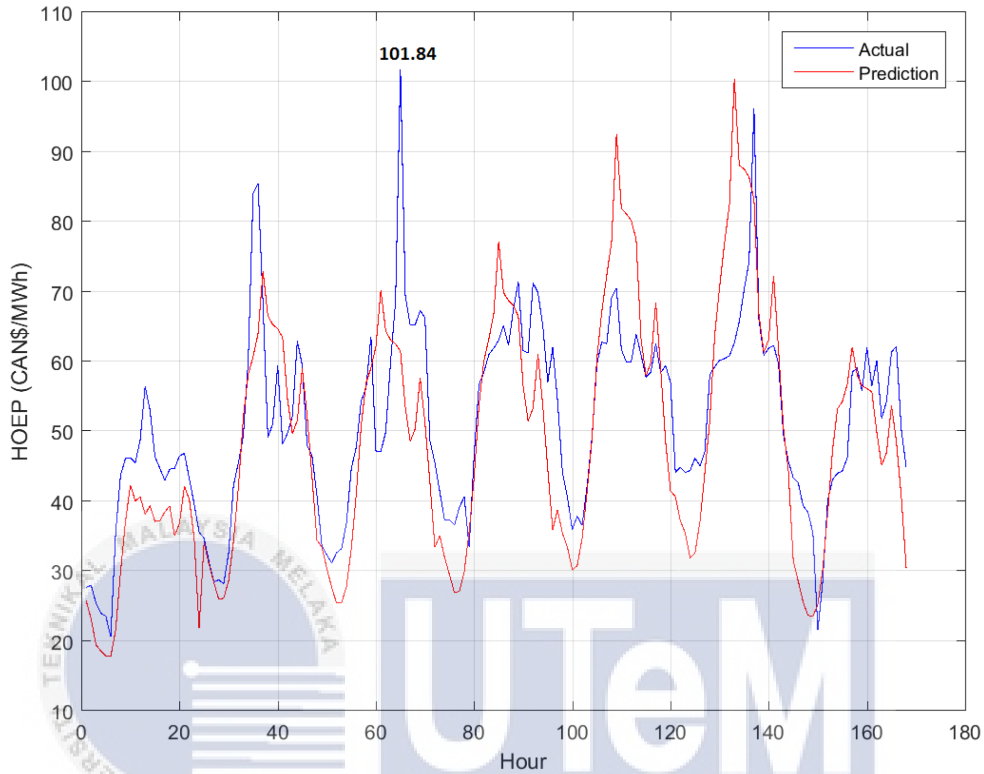

Figure 4.4: Actual and Predicted Price of Ontario Energy Market for Week 3

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The testing period of the Week 3 is falls during the summer peak demand (July 26-August 6). Figure 4.4 shows that the predicted price curve mostly follows the actual curve because mostly the price are on the average level. Based on the observation, on day-1 and day-2 shows that the predicted curve follows the actual curve. On day-3 the predicted curve does not follow the actual price as the actual price are too volatile. The price is too volatile because there are some factors that affect the electricity price. The best result appears in week 3 as the series is not too volatile as other test weeks.

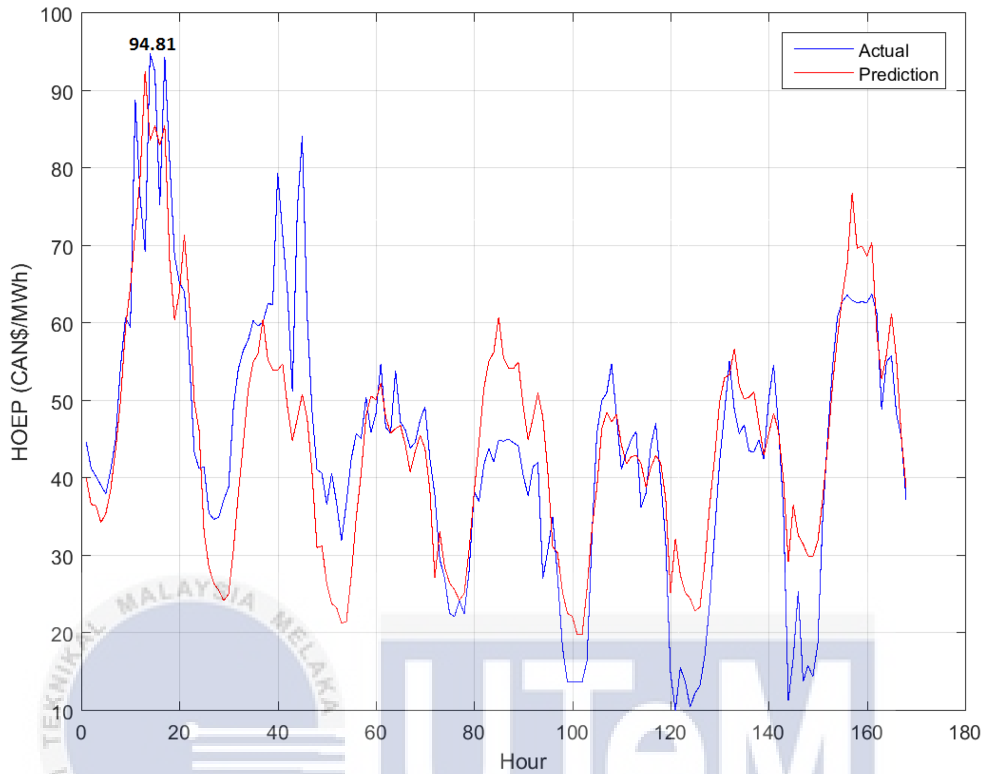

Figure 4.5: Actual and Predicted Price of Ontario Energy Market for Week 4

For Week 4, the testing period is on summer peak demand (August 2-August 8). Figure 4.5 shows that the forecast curve on day-1 can capture the spike price hence shows that neural network can capture the volatility situation. Based on Ontario's monthly market report [25], 2 August was considered as 24 off-peak hours, which known as Civic Holiday statutory holiday. Thus, when demand is too high, the price also becomes high. But, on day-2 the actual price also can be considered as high because the curve not at the average level. That is why the predicted curve cannot follow the pattern of the actual curve.

On day-3, the actual curve shows that the actual curve and predicted curve are at the average level. The predicted curve can follow the pattern of the actual curve. On day-4, the predicted curve shows that it cannot follow the pattern of the actual curve. The predicted curve on day-5 shows that it also cannot follow the actual curve as the actual price is too low. The result on day-7 also shows the same result as on day-6.

During the summer, the electricity price will be high. At low levels of increases consumption, prices will rise at the same rate as the consumption but due to the hot days, the energy demand rises to moderate and then to the extreme level. This situation happened because mostly the consumers will turn on their electrical appliances such as air conditioning to the coolest level. Hence, it will give more difficult to the grid managers to find effective ways to meet demand. At this point, the price will arise and become volatile.

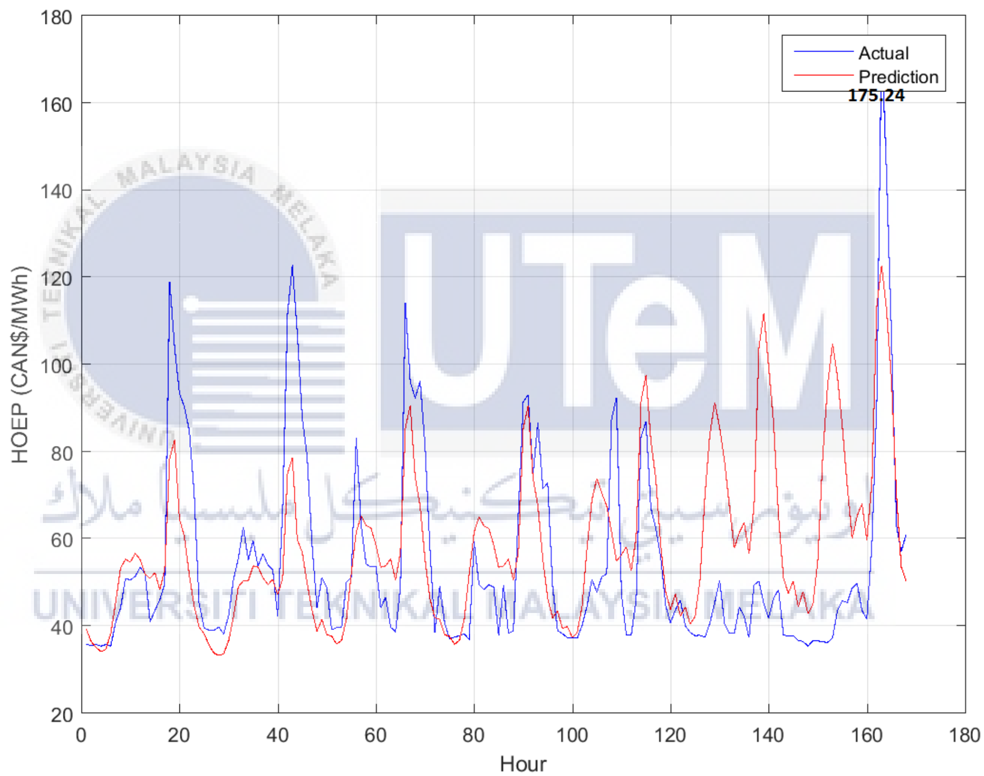

Figure 4.6: Actual and Predicted Price of Ontario Energy Market for Week 5

The testing period for Week 5 during the winter high demand (December 13-December 19). The overall result shows that most of the series of actual price is too low. Based on the observation, the predicted curve on day-1 and day-2 show the curves is at the average level even though the actual price curve is high. On day-3, the predicted curve does follow the pattern of the actual pattern. On day-4, the predicted curve also can follow the actual price pattern.

On day-5, the predicted curve follow the actual price pattern. But on day-6, the actual price is low hence the predicted curve cannot follow the pattern. The result also same goes to day-7 where the predicted curve cannot follow the pattern of the actual price because the actual price is too volatile.

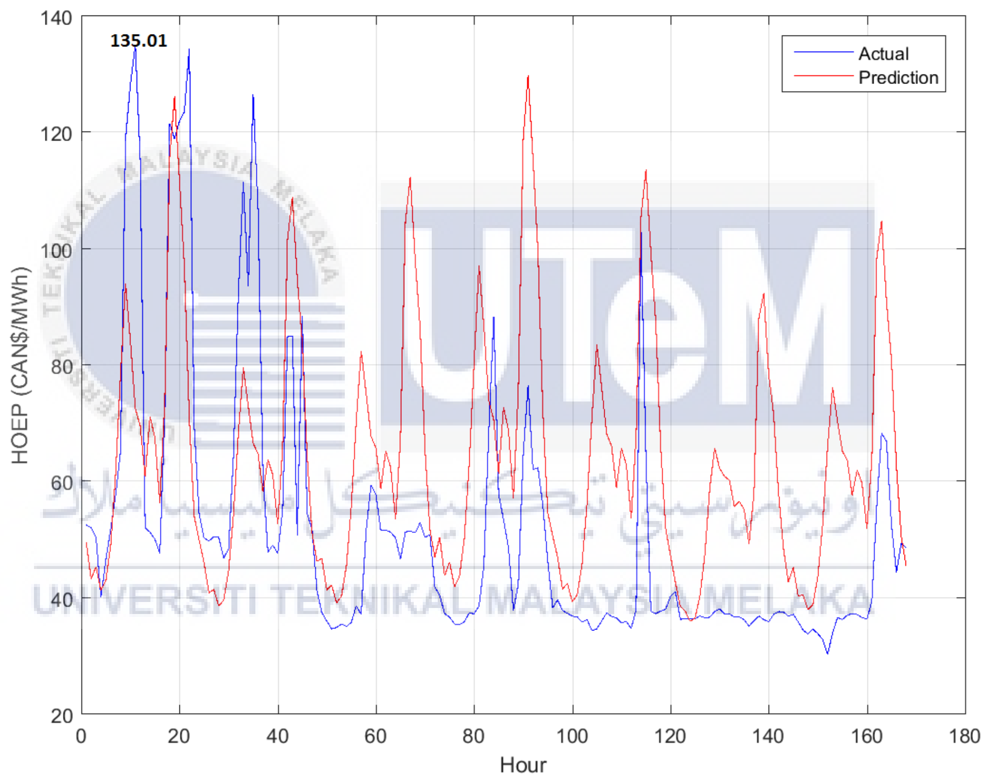

Figure 4.7: Actual and Predicted Price of Ontario Energy Market for Week 6

For week 6, the testing period is on winter high demand (December 20-DDecember26). For figure 4.7, most of the prediction series have too many spikes. This is because there are too high and too low in actual price. On day-1, the price is too high and give effect at the predicted curve. The predicted curve cannot follow the actual pattern.

The price is too fluctuated because of many factors such as temperature and demand. The worst result appears in week 6 which is the average MAPE is 19.29%.

4.3.5 Comparison Method

The developed model of neural network is compared with other existing methods as tabulated in table 4.5. The result shows that the model of neural network in [24] and [25] are not good enough compared with the developed model of neural network with cross-validation which is 16.79%. The other method such as heuristic, multiple linear regression (MLR), wavelet and neural network, ARIMA, and simulation model used by Ontario's Independent Electricity System Operator (IESO) shows that the average MAPE is higher than the developed model of neural network with cross-validation.

Table 4.5: Result of other existing method

Ref.	Year	Method	Test week						Average MAPE
			1	2	3	4	5	6	
Proposed		NN with cross validation	16.02	17.10	13.58	16.81	17.94	19.29	16.79
[24]	2008	Heuristic	21.70	17.80	22.92	37.77	24.60	24.55	24.89
		MLR	16.26	19.23	17.69	20.55	16.73	1854	18.17
		NN	16.56	19.34	17.45	20.27	17.03	19.69	18.39
		Wavelet + NN	15.21	18.62	17.91	18.72	16.61	18.02	17.51

[25]	2006	ARIMA	15.90	18.60	13.60	21.50	15.40	20.80	17.63
		IESO	39.70	30.30	36.90	31.60	60.20	37.30	39.33
		NN							18.80

4.4 Conclusion of Overall Result and Discussion

In this project, the cross-validation technique was used for neural network. Learning rate and momentum rate are varied from 0.1 to 1 with step time 0.01. The neural network in this project used a single hidden layer with number of hidden neuron is 1. The demand has been selected as the input while the price as the output to forecast the 24 hours ahead electricity price forecasting. Neural network gives good result to capture the chaotic situation. In order to show the accuracy of the price forecasting, MAPE has been used. The result of average MAPE is 16.79% which is the best result compared with other existing methods.

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CHAPTER 5

CONCLUSION AND RECOMMENDATION

5.1 Conclusion

Electricity price forecasting is very important in energy market. It is very important for utilities, investors and consumers in order to achieve maximum profit. The short-term electricity price forecasting can be defined as the duration from a few minutes to one week ahead. The price in Ontario energy market is very volatile and challenging for the researcher. Neural network is a good method to forecast electricity price as it major advantages are can capture non-linear pattern and show the least error in (MAPE).

The major issues in order to predict the electricity price are the accuracy. The existing method such as time series method, show low accuracy in price forecasting. In addition, it is also very challenging to predict the price in Ontario energy market as the price are highly volatile and non-linear. Some of the price forecasting methods produced high error because of the sensitivity analysis does not perform properly.

The feature selection for neural network input is important and can be performed by correlation analysis. Correlation analysis is performed to study the strength of the relation between two variables. Furthermore, the number of hidden neurons are varied from one to two. In addition, the learning rate and momentum rate are being varied from 0.1 to 1 with step time 0.01. Then, the sensitivity analysis should be performed to have a better configuration of neural network that leads to a better accuracy in price forecasting.

Most of the time in neural network is forecasting with minimum possible error and high absolute error at one time but the effectiveness of neural network remains good most of the time. The simulation produced accurate prediction even in volatility cases. The average mean absolute percentage error (MAPE) obtained is 16.79% in the year 2004. The neural network cross-validation model to predict the electricity shows better performance than other existing methods.

5.2 Recommendation

Neural network has a great advantage in capture the chaotic character of the price. In this project, neural network shows a good result compared to other existing methods. Neural network gives a better result in short-term forecasting the electricity price on Ontario energy market. The result shows that the predicted curve can follow the actual price curve. Only on the certain time, the predicted curve does not follow the actual curve due to the volatility of the price.

For the future work, the factors such as temperature, humidity and wind velocity can be selected as the input for the short-term electricity price forecasting. In future, neural network can be combined with other forecasting methods such as with fuzzy logic or ARIMA. This combination is known as a hybrid model. Furthermore, the hybrid model can give better accuracy in forecasting the electricity price compared with the stand-alone neural network. Hence, this technique can be an important tool to predict the electricity price and can help the market participants to reduce their risk in purchasing and buying power.

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