SHORT TERM ELECTRICITY PRICE FORECASTING USING NEURAL NETWORK

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ABSTRACT. This paper presents neural networks applied for short term electricity price forecasting in Ontario energy market. The accuracy in electricity price forecasting is very crucial for the power producer and consumer. With the accurate price forecasting, power producer can maximize their profit and manage short term operation and long term planning. Meanwhile, consumer can maximize their utilities efficiently. The objective of this research is to develop models for day ahead price forecasting using back-propagation neural network during summer. Six models were developed representing six types of inputs. The result shows that 24 models representing 24 hours ahead price forecasting with price and demand inputs gives better result compared to other five models due to unique model developed for each hour rather than a model for a day with mean absolute percentage error (MAPE) of 18.74%.

Keywords: short term electricity price forecast, neural network, day ahead forecast, MAPE

INTRODUCTION

Electricity price forecasting has become an integral part of power system operation and control. Developers, generators, investors, traders and load serving entities need to know future electricity prices as their profitability depends on them. In other word, generation companies can maximize their profits by bidding effectively and hence bulk electricity customers can optimize their load schedules. Furthermore, accurate price forecasting is important for players to purchase bulk amounts of power during spot pricing of electricity (Singhal & Swarup, 2011). Overestimation in price forecasting leads unnecessary spinning reserve and even 1% increase in forecasting error implies £10 million increase in operating cost (Pai & Hong, 2005).

In a pool-based electric energy market, producers submit to the market operator selling bids consisting in energy blocks and their corresponding minimum selling prices. Meanwhile, consumers submit to the market operator buying bids consisting in energy blocks and their corresponding maximum buying prices. In turn, the market operator clear the market using an appropriate market clearing procedure that results in hourly energy prices and accepted selling and buying bids.

However, forecasting electricity prices is a complex task because price series is a non-stationary, high frequency (Amjady & Daraeepour, 2009a) and highly volatile series with non-constant mean, variance and significant outliers (M. Shahidehpour, 2002) as well as calendar effects. Other than that, generation side may face with unexpected outages while transmission lines may experience congestion that creating electrical imbalance (Amjady & Daraeepour, 2009). Furthermore, there is more uncertainty in price forecasting (Angelus, 2001) rather than load forecasting since price forecasting involves forecasting both supply and demand (Amjady & Daraeepour, 2009b). Many factors cause for price spikes such as volatility in load and fuel price as well as power import to and export from outside the market through long term contract (Singhal & Swarup, 2011).

RELATED WORKS

Many methods have been applied in price forecasting ranging from statistical method to production-cost technique which dealing with linear and non-linear models. However, some of the statistical techniques only cater linear patterns which are not suitable for price or load forecasting. For example, ARIMA ignores many factors influencing load (Pai & Hong, 2005; (Stevenson, 2011), (Niu, Liu, & Wu, 2010), (Rodriguez, Member, & Anders, 2004), , (Bastian, Zhu, Banunarayanan, & Mukerji, 1999), (Garcia, Contreras, Member, Akkeren, & Garcia, 2005), (Zareipour et al., 2006), (Nogales, Contreras, Conejo, & Member, 2002), (Conejo, Contreras, Espı, & Plazas, 2005). In addition, price series is highly volatile due to sudden outage, rainfall and temperature variations (Singhal & Swarup, 2011). Other linear methods are multivariate time series models such as Dynamic Regression (DR) and Transfer Function (TF) (Zareipour et al., 2006 & Conejo et al., 2005), Multiple Linear Regression (MLR) (Conejo et al., 2005), Auto Regressive (AR) (Crespo Cuaresma, 2004) and game theoretic model (Bunn, 2000). Neural network could cater for non-linear pattern of price series as presented in (Amjady & Daraeepour, 2009a)&(Angelus, 2001).

Some researchers reported that it is difficult to forecast price during summer as its volatility compared than other three seasons (Amjady & Daraeepour, 2009a), (Vahidinasab, Jadid, & Kazemi, 2008). With the feature selection algorithms of modified relief (MR) and mutual information (MI) applied for neural network, the MAPE obtained for summer is 4 - 8% (Amjady & Daraeepour, 2009a). (Amjady & Keynia, 2009) reported a MAPE of 8.62% when apply an improved Mutual Induction (MI) to Cascaded Neuro-Evolutionary Algorithm (CNEA). Other researchers presented a modified Levenberg Marquardt training algorithm to improve learning rate and fuzzy c-mean (FCM) to cluster daily load pattern into three clusters (peak, normal and off-peak hours) with the MAPE of 8.4% during summer (Vahidinasab et al., 2008). An optimization algorithm called as Particle Swarm Optimization is applied for Support Vector Machine to forecast price during summer shows good performance with MAPE of 9.25% rather than other three methods; ARIMA, Generalized Regression Neural Network (GRNN) and SVM-PSO (Niu et al., 2010).

Other than that, forecasting electricity price with neural network by (Zareipour et al., 2006) shows an average MAPE of 18.8% during spring, summer and winter. Meanwhile, (Conejo et al., 2005) and (J.P.S. Catalão, Mariano, Mendes, & Ferreira, 2007) reported a MAPE of 18.14% and 11.4% respectively when apply neural network to forecast electricity price during summer. All of them use price and demand as training input except for (J P S Catalão, Mariano, Mendes, & Ferreira, 2007) that use only price data. Presented in this paper are approaches of neural network to develop models for day ahead electricity price forecasting in Ontario power market during summer.

NEURAL NETWORK CONFIGURATION AND SIMULATION

Artificial Neural Network (ANN) is one of machine learning methods where computers learn from experience, example and analogy (Negnevitsky, 2005). ANN mimics function and characteristics of human's brain; to recognize pattern and tackle the practical problem with less effort (Rao & Srivinas, 2003). Back propagation neural network is used in this paper where the input is passed layer through layer until the final output is calculated, and it is compared to the real output to find the error. The error is then propagated back to adjust weight and bias in each layer. This paper comprises of six types of forecast models representing six different inputs. The data is normalized to the range [-1, 1] according to the formula:

$$x_n = \frac{x_i - \left[\dfrac{x_{\max} + x_{\min}}{2}\right]}{\left[\dfrac{x_{\max} - x_{\min}}{2}\right]} \quad (1)$$

Where xn is normalized value, xmax and xmin are the maximum and minimum electricity price data. The normalization helps to improve accuracy of training and testing phases (Areekul, Senjyu, Urasaki, & Yona, 2011). For all simulations, Levenberg Marquardt training algorithm is applied due to fast training simulation. The network of three layer is applied which is input layer, single hidden layer and output layer. Transfer function of tansig is used for hidden layer while purelin is applied for output layer. However, back propagation tends to converge slowly. In order to accelerate the learning process, two parameters are adjusted; the learning rate and the momentum. The learning rate and momentum rate are varied from 0.05 to 1 with the step of 0.05. Several numbers of hidden neurons are used; which are 2, 5, 10 and 15.

Case Study 1: 24 Forecast Models with Price Input of Past 14 Days

The past price data from 1st May 2002 till 12th July 2002 is used for neural network training to forecast price for next 40 days which is from 14th July 2002 till 22nd August 2002. The past price of two weeks data is used to forecast the next day electricity price. 24 models representing 24 hours are developed and tested with 2, 5, 10 and 15 hidden neurons.

Case Study 2: 24 Forecast Models with Price and Demand Input of Past 14 Days

The same period as Case Study 1 is applied for Case Study 2 but with the inclusion of demand data.

Case Study 3: 24 Forecast Models with Price and Demand Input of Previous Day

The training input data consist of minimum price on the previous day ($P_{min(d-1)}$), maximum price on the previous day ($P_{max(d-1)}$), price at hour *t* on previous day ($P_{t(d-1)}$), loads of L_{t-3}, L_{t-2}, $L_{t-1}$and L_t, maximum load on the previous day ($L_{max(d-1)}$) and the day type (-1 for weekend and 1 for weekday). The training data is selected from 1st May 2002 till 30th June 2002 to forecast price for the next 40 days which is from 1st July 2002 till 9th August 2002. Each model is tested for 2, 5, 10 and 15 hidden neurons to see the performance and accuracy of each case.

Case Study 4: A Forecast Model with Price Input of Past 14 Days

Same training input of Case Study 1 is applied for Case Study 4 but a model of 336 inputs is developed to forecast day ahead price instead of 24 models.

Case Study 5: A Forecast Model with Price and Demand Input of Past 14 Days

Same training input of Case Study 2 is applied for Case Study 5 but a model of 672 inputs is developed to forecast day ahead price instead of 24 models.

Case Study 6: A Forecast Model with Price and Demand Input of Previous Day

A restructured training input of Case Study 3 is applied for Case Study 6 with 52 inputs; the minimum and maximum price on previous day, the maximum load on previous day, day type as well as 24 hours loads and prices on previous day.

SIMULATION AND RESULT

Each model in Case Study 1 consist of three layers of neural network with 14 inputs in input layer, a hidden layer of 2, 5, 10 or 15 hidden neurons and a node of output layer.

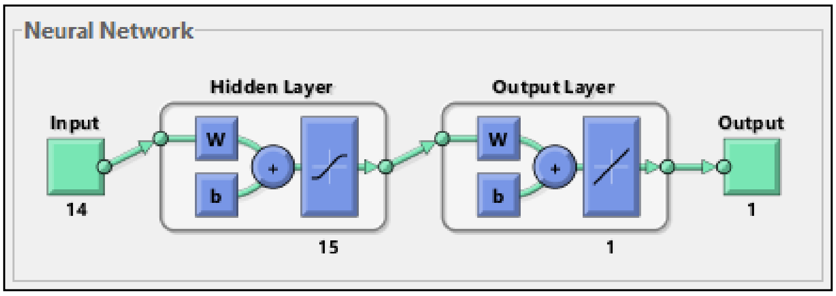

Figure 1. Neural Network Configuration For Case Study 1 With 15 Hidden Neurons

Figure 1 shows an example of neural network configuration with 15 hidden neurons. The average MAPE for all 24 models is 23.03% while the average learning rate and momentum rate are 0.65 and 0.5 respectively with the most applied number of hidden neuron is 2. The average MAPE for Case Study 2 is 23.37%. Most of the models apply 2 hidden neurons with learning rate of 0.7 and momentum rate 0.4. The best model shown by Hour 4 with MAPE of 9.42%; while the worst case shown by Hour 20 with MAPE of 51.1%.

The average MAPE for 24 models of Case Study 3 is 18.74%. The average learning rate and momentum rate are 0.6 while the most applied hidden neuron are among 24 models is two nodes. As the result for Case Study 1 shows the most frequent number of hidden neuron in the model is 2, hence 2 hidden neurons is applied for Case Study 4. The MAPE for the model is 23.88% with learning rate 0.8 and momentum rate 0.15.

As the result for Case Study 2 shows the most frequent number of hidden neuron in the model is 2, hence 2 hidden neurons is applied for Case Study 5. The MAPE obtained from this model is 40.52% with the optimum learning rate and momentum rate are 0.8 and 0.75 respectively. The model is developed with two hidden neurons as it is the most frequent number of hidden neuron in Case Study 3. The MAPE produced is 29.61% with the learning rate and momentum rate are 0.8 and 0.85 respectively.

CONCLUSION

Electricity price forecasting is an essential task in power system operation and planning. However forecasting price during summer is quite difficult compared to other three seasons. This paper presented six models of back-propagation neural network to forecast electricity price for day ahead. As shown in Table 1, the best result is produced by Case Study 3 where the price and demand input of previous day is applied for each 24 models. The worst case is shown by Case Study 5 where price and demand of past 14 days is applied to train the network. The large MAPE is probably caused by large input feed during training phase which is 672 inputs. When comparing Case Study 1 and Case Study 3, the 24 models developed for day ahead shows better result rather than a model representing 24 hours. Different hours have different characteristics and patterns thus the separate models for each hour would give better accuracy. Same goes for Case Study 2 and Case Study 5 as well as Case Study 4 and Case Study 6. Other than that, the inclusion of demand data in Case Study 2 is not improving the forecast accuracy compared to Case Study 1. As a conclusion, the selection of significant input is very important in forecasting. The input must be adequate but too large input should be avoided. The number of hidden neuron must be appropriately selected and two hidden neurons fit for all cases in this paper.

Table 1. Summary for All Six Models

Case Study	No. of Hidden neuron	MAPE (%)	Learning Rate	Momentum Rate
1	2	23.03094	0.65	0.5
2	2	23.36984	0.7	0.4
3	2	**18.7400**	0.6	0.6
4	2	23.88%	0.8	0.15
5	2	**40.52%**	0.8	0.75
6	2	29.61%	0.8	0.85

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