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Electricity price forecasting using artificial neural network: activation function selection

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ABSTRACT – Electricity price forecasting has been center of studies in the energy and financial market. The price forecasting is important to the market participants to avoid major losses in financial. Using the test market of Ontario, this approach will forecast using the neural network model. This approach will be focusing on the selection of hidden neuron and the activation function (hyperbolic tangent and logistic) of the neural network, and their effect on the Mean Absolute Percentage Error. This study is expected to be an important research on the selection of activation function of the neural network in the electricity price forecasting.

1. INTRODUCTION

Internationally, numerous acts pushed the governments to deregulate their energy industry in their countries. The fact that many nations had gained their motivation due to gather external investment and cash flow through the privation of the state-owned utilities, while the other first world countries, had the goal to create the competition for the overall of the traditional industry [1]. In a competitive energy market, just like the other commodities, the electricity also can be 'bought' and 'sold' at market prices. However, the risk hold by the market participants (producer, retailer, and trader) has increased as the extreme price volatility had forced the producer and the consumer to avoid not only the opposed to the volume risk but also to the price movements [2].

Price forecasting plays a crucial role in the modern electricity industry as to help the independent generators in setting up an excellent bidding pattern and scheming physical bilateral contracts, market prices stoutly influence the decision on investing new generation facilities in the long run [3].

Past researches have proposed many models for the electricity price forecasting such as Feed Forward Neural Network [4], Fuzzy ARTMAP network [5], Recurrent Neural Network [6], ARIMA-GARCH [7], etc. The artificial neural network models had gained author interest, as it is easy to implement, less time consuming and had reasonable accuracy as mentioned in [8]. However, forecasting the electricity price can be a bit challenging as the price itself depends on many variables such as fuel, weather, wind etc. Therefore, in modelling the neural network needs to detail in order to improve the accuracy of the forecasting.

2. METHODOLOGY

The test market for the electricity price forecasting is the Ontario electricity market [9]. The training period used is 49 days as referred from the previous researcher [10] for a fair comparison. The historical demand and Hourly Ontario Energy Price (HOEP) is considered as the input variable. The suitable input is selected based on the correlation analysis between the variable. For the neural network training, three activation functions are tested in a single hidden layer, which is the logistic function and the hyperbolic tangent function. The equation (1), (2), and (3) represent the hyperbolic tangent function, logistic function and hyperbolic tangent sigmoid 1.7159 respectively.

$$\boldsymbol{S(x) = \tanh(x) = \frac{e^{x} - e^{-x}}{e^{x} + e^{-x}}} \quad (1)$$

$$\boldsymbol{S(x) = \frac{1}{1 + e^{-x}}} \quad (2)$$

$$\boldsymbol{S(x) = 1.7159\ \tanh\left(\frac{2}{3}x\right)} \quad (3)$$

The normalization for the hyperbolic tangent function is [-1, 1] while the logistic function is [0, 1]. The hidden neuron in the hidden layer was varied from 1 until 2, the learning rate and momentum rate was varied from 0.01 until 1. The output layer for both sets of activation function is a pure linear function. The best Mean Absolute Percentage Error (MAPE) from the matching hidden neuron, learning rate, and momentum rate is calculated for each activation functions. Equation (4) shows the MAPE formula.

$$\text{MAPE} = \frac{100}{N} \times \sum_{t=1}^{N} \frac{\left| P_{actual_t} - P_{forecast_t} \right|}{P_{actual_t}} \quad (4)$$

Where the notation of N is the number of hours, P_{actual_t} is the actual HOEP at hour t and $P_{forecast_t}$ is the forecasted HOEP at hour t.

3. RESULTS AND DISCUSSION

Table 1 shows the hidden neuron, learning rate, momentum rate, time and MAPE for the hyperbolic tangent activation function for six different weeks that represent the winter, summer and spring seasons while Table 2 shows for the logistic activation function. Table 3 shows the hyperbolic tangent with $1.7159\ \tanh\left(\frac{2}{3}x\right)$ function. The learning rate and momentum rate have the variety of range between 0.01 until 1.

The learning rate is the part of the error gradient, where the weights need to be modified. Bigger the learning rate can accelerate the convergence process; however, it may generate an oscillation across the minimal. The momentum rate resolved the fraction of the change in previous weights that need to be applied to calculate the new weights [11]. The average MAPE for the hyperbolic tangent function is 14.82% with 11.92 seconds of operation time while the logistic function is 14.95% with 12.93 seconds of operation time. The average MAPE for the hyperbolic tangent $1.7159\ \tanh\left(\frac{2}{3}x\right)$ functions is 15.08% with 12.74 seconds of operation time

Table 1 The neural network with the hyperbolic tangent function.

Test week	HN	LR	MR	Time (s)	MAPE (%)
1	1	0.90	0.36	0.83	14.76
2	2	0.25	0.40	2.08	15.62
3	1	0.08	0.59	0.86	13.97
4	2	0.59	0.12	4.10	13.93
5	2	0.99	0.48	3.24	13.77
6	1	0.63	0.50	0.81	16.85
Average					14.82

Table 2 The neural network with the logistic function.

Test week	HN	LR	MR	Time (s)	MAPE (%)
1	1	0.17	0.76	1.22	15.00
2	2	0.15	0.37	2.16	15.70
3	2	0.71	0.03	1.84	13.29
4	2	0.51	0.76	2.72	14.61
5	2	0.20	0.43	4.28	14.05
6	1	0.72	0.08	0.72	17.04
Average					14.95

Table 3 The neural network with the tanh 1.7159 function.

Test week	HN	LR	MR	Time (s)	MAPE (%)
1	1	0.52	0.82	1.51	15.14
2	2	1.00	0.35	2.10	15.79
3	2	0.18	0.25	1.53	13.69
4	1	0.82	0.91	1.23	15.25
5	2	0.4	0.39	4.60	13.78
6	1	0.63	0.49	1.77	16.85
Average					15.08

4. CONCLUSION

The activation function does not give significant changes in the performance of the neural network, as the percentage difference between the functions is less than one percent. The total time (s) recorded for both functions also having not much difference. However, from this research, the hyperbolic tangent activation functions gave the more accuracy and less time computation compared to the logistic activation functions. The hidden neuron in the hidden layer gave the significant changes for the performance of the neural network models. This study is expected to be an important research on the selection of activation function of the neural network in the electricity price forecasting.

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