Short-term Electrical Load Prediction Using Evolving Neural Network

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Abstract. A short-term electrical load prediction can use an artificial neural network approach. In this paper, an optimized neural network, namely Evolving Neural Network (ENN) has been developed for short term electric load prediction. ENN uses a genetic algorithm to optimize the weighting of neural networks. After the feedforward algorithm, the process continues with optimization, instead of learning process normally applied to the neural network. The proposed algorithm is implemented in MatLab. Data from April 2010 to April 2011 will be used as training data and data in May 2011 will be used as checking data. To evaluate the performance of Evolving Neural Network, Wavelet Neural Network (WNN) is also involved for comparison. The evaluation is conducted by observing the prediction results. Performance measurements are performed by observing errors that occur. The smaller the error value, the better the accuracy. The experimental result shows that the accuracy performance of ENN is better than WNN.

1. Introduction

After a large deficit of electricity in 2008, as several gas and steam power plants can be realized at the end of 2017 in Kalselteng system, there will be a surplus of 100 MW. The growth rate of electricity demand, from 2009 to 2019, is projected more or less 8.96% per year. The peak load will be 807 MW in 2019 [1].

Table 1. Electricity demand forecast of Kalselteng (Barito System)

| Desc.       | Unit | 2009 | 2010 | 2011 | 2012 | 2013 | 2014 | 2015 | 2016 | 2017 | 2018 | 2019 |
|-------------|------|------|------|------|------|------|------|------|------|------|------|------|
| Demand      | GWh  | 1,740| 1,886| 2,063| 2,257| 2,470| 2,704| 2,960| 3,233| 3,524| 3,835| 4,176|
| -Growth %   |      | 7.09 | 8.40 | 9.37 | 9.43 | 9.46 | 9.48 | 9.24 | 8.98 | 8.84 | 8.88 |
| Production  | GWh  | 2,070| 2,221| 2,416| 2,629| 2,875| 3,145| 3,440| 3,756| 4,090| 4,448| 4,840|
| Peak Load   | MW   | 372  | 396  | 428  | 462  | 501  | 544  | 591  | 640  | 692  | 747  | 807  |
| LF %        |      | 63.53| 64.01| 64.49| 64.97| 65.46| 65.95| 66.45| 66.94| 67.45| 67.95| 68.46|

Table 1 shows the 2008’s forecast of demand, production and peak load until 2019. This growth is in line with economic growth of Kalselteng (Kalimantan Selatan and Tengah)[2]. By 2019, PLN (state electricity company) will build 1,413 MW of power plants in Kalselteng (see Figure 1), as well as a 150 kV transmission line of 2,606 Kms to achieve the 92 % electrification target in 2019 for the two provinces[1].

In 2016, in normal circumstances, the capacity for Kalselteng was 632 MW with 640 MW peak load. However, electrical power could be reduced in November-December because one unit of PLTU (steam
Asam Asam was undergoing routine maintenance so that rota blackouts were needed to overcome power deficit. In addition, damage interruption of the SUTT (high voltage transmission) of 150 kV, could happen anytime. E.g., occurring in the lane between the Gardu Induk (GI/Substation) Barikin and GI Rantau, caused a blackout in almost the entire Kalselteng region. This disturbance made that the power supply from Bangkanai Power Plant (140 MW) could not be distributed. Power loss of 140 MW cause the voltage frequency in the Kalselteng electrical system to drop, causing some large power plants to suddenly stop operating. For recovery, the plants had to be restarted one by one.

**Figure 1.** Power plant planning in Kalselteng region

Thus, the fulfillment of dynamic power demanded in critical conditions stated above requires prediction of power consumption to maximize distribution. Electrical power can not be stored in a large quantity so it must be provided when absolutely necessary.

Electrical load data is usually recorded by PLN. It is a time series data, so it can be analyzed and predicted using statistics or soft computing approach. Wang Yong, et al [3] proposed a Back Propagation Neural Network (BPNN). They presented an accurate electricity load forecasting algorithm with back propagation neural networks. It contributes to short-term electricity load forecast methodology with a neural network and with weather feature such as max centigrade, min centigrade and weather types. As a result, the electrical load can be predicted more efficiently. But Li Chungui, et al [4], who tested the implementation of BPNN in traffic studies, stated that BPNN is not very accurate because it is possibly premature solution. They proposed the processing of genetic algorithms that determine the value of neural network weights. The result, the traffic can be predicted more efficiently. The approach with genetic algorithms has been applied in other areas, such as rainfall prediction and traffic flow. In addition, Yuhui Wang, et al [5] declared the Wavelet Neural Network is an excellent tool for predicting rainfall and rainfall-runoff. Gao Guorong and Liu Yanping [6] implemented the Wavelet Neural Network (WNN) as an algorithm for predicting the flow of traffic. They claim that WNN is better than BPNN. Lareno [7] proposed ENN for short-time traffic flow prediction. The result, ENN is better than WNN, ANFIS and BPNN. Also, Swastina, et al [8] proposed ENN for short-time rainfall prediction, with the same result: ENN being better than WNN.

Thus, neural network based algorithm has been known and widely used as an algorithm of time-series data prediction. Therefore, in this paper, an Evolving Neural Network (ENN) algorithm is proposed for predicting short-term electrical load.

### 2. Research Method

This research uses an experimental research method, which consists of: (1) Data collection and preparation processing, (2) Proposed method, (3) Experimental results and (4) Evaluation and validation of results.
2.1. Data collection and preparation processing
Electrical load data were obtained from PLN Kalselteng. The data required in this study consist of the load from May 1st, 2010 to May 31st, 2011 for the load at 6:00, 10:00, 14:00, 18:00, 19:00, 20:00, 21:00, 22:00, and 23:00 WITA.

The data obtained from the PLN were in the form of data consisting of various parameters, so that they had to be recapitulated first. As a result, data of this process are data with the following attributes: Time and Load (MW). Each row of data consist of data from 9 selected times. Data had been collected for one year and one month, so that there are 3604 data available.

2.2. Proposed method
The algorithm used is the Evolving Neural Network used to predict the electrical load and Wavelet Neural Network (WNN) as compared algorithm. Data from April 2010 to April 2011 will be used as training data and data in May 2011 will be used as checking data. The evaluation is conducted by observing the prediction results. Performance measurements are performed by observing errors that occur through parameters: Root Mean Square Error (RMSE), Mean Absolute Deviation (MAD) and Mean Absolute Percentage Error (MAPE). The smaller the error value, the better the accuracy.

2.2.1. Evolving Neural Network. Evolving Neural Network is a method of weighting between neurons at different layers using the principle of genetic algorithm (GA). Figure 2a, explains the structure of the ENN algorithm [9]. Chromosome Representation Encoding i.e each gene presents the weights between two neurons in different layers. A chromosome is constructed from a series of genes illustrated in figure 2b. For example, the first gene in the chromosome sequence is W15, the weight that connects neurons 1 and neuron 5. The second gene is W16, the weight of connecting neurons 1 and 6 [10]. And so on.

2.2.2. Wavelet Neural Network. Wavelet Neural Network is a neural network based on wavelet transformation. The WNN combines the multiscale analysis ability of the wavelet transform and the classification capability of the artificial neural network by setting the wavelet function as the transfer function of the neural network. The essence of WNN is to find a group of wavelets in the feature space so that the relationship of complex functions contained in the original signal may be accurately
expressed [11]. Wavelet transformation will be used to correct the weights of relationships between neurons in different layers.

3. Experimental Result and Evaluation

3.1. Structure Test
The experiment to get the best architecture of neural network (without GA or wavelet), indicates structures 9-18-1 and 18-6-1 the lowest RMSE value. Another test performed to get the best architecture for WNN, indicates structures 18-18-1 and 18-32-1.

3.2. ENN
Five important parameters of genetic algorithm according to Suyanto [10], are as follows: crossover type and its value, type of mutation and its value and type of selection, arranged using Taguchi experimental design. The Taguchi experimental design [12] is used for setting parameters. It’s done by calculation of Signal-to-Noise (S/N). The codes and levels for each of the parameters are shown in table 2, as follows:

| Parameter/Code | Level 1 | Level 2 | Level 3 | Level 4 |
|----------------|---------|---------|---------|---------|
| Cross over (A) | 1-Point | 1- Point| 2- Point| 2- Point|
| Mutation (B)   | 1- Point| 1- Point| Shift   | Shift   |
| Selection (C)  | Total   | Total   | Elite   | Elite   |
| Cross over rate (D) | 0.2 | 0.4 | 0.6 | 0.8 |
| Mutation rate (E) | 0.1 | 0.3 | 0.5 | 0.7 |

Figure 3. Convergence profile for semi-seasonal time-series data

According to Pei-Chann Chang et al [9], a convergence profile for semi-seasonal time-series data suggests that the system can converge after 2,000 generations, even for small population sizes, eg 10. However, for fast and smooth convergence of population sizes are found in populations size of 40 or 50, which converges to a steady state after more or less 300 generations (Figure 3).

Therefore, a population size of 50 will be used as the initial population for the experiment. The electrical load data as input and target, three times experiments of genetic algorithm (without neural
network) with 50 populations, then the average S/N ratio calculated at each factor level, the results are shown in table 3 follow:

| Factor | A   | B   | C   | D   | E   |
|--------|-----|-----|-----|-----|-----|
| Level 1| 13.15 | 27.00 | 11.76 | 12.11 | 13.22 |
| Level 2| 10.43 | 18.66 | 12.42 | 15.21 | 16.40 |
| Level 3| 15.28 | 9.84  | 11.69 | 14.44 | 12.21 |
| Level 4| 13.09 | 8.77  | 18.22 | 16.26 | 16.05 |

From Table 4, the best combination of parameter settings can be found as (A) 3 - (B) 1 - (C) 4 - (D) 4 - (E) 2 (in bold). These codes represent two-point crossover, one point mutation, elite selection, crossover rate = 0.8, and mutation rate = 0.3. So the structure of NN used is 9-18-1 and 18-6-1. GA operator: two-point crossover, one point mutation, elitist selection, crossover rate = 0.8, and mutation rate = 0.3. For comparison to WNN, ENN tested to 18-18-1 and 18-32-1. The results are shown in Table 4. Figure 4 shows the best result of the ENN for checking data (May 2011).

| Architecture NN | ENN (MSE) |
|-----------------|-----------|
| Input Hidden-1 Out | RMSE | MAD | MAPE |
| 9 18 1 | 27.40 | 21.24 | 0.1046 (10.46%) |
| 18 6 1 | 19.26 | 11.77 | 0.0614 (6.14%) |
| 18 18 1 | 19.33 | 11.92 | 0.0625 (6.25%) |
| 18 32 1 | 23.35 | 15.13 | 0.0761 (7.61%) |
| Avarage | 22.34 | 15.02 | 0.0762 (7.62%) |

Figure 4. The best result of the ENN (structure 18-6-1)

3.3. WNN
Structure of NN used is 18-18-1 and 18-32-1. For comparison to ENN, WNN tested to 9-18-1 and 18-6-1. The results are shown in Table 5. Figure 5 shows the best result of the WNN.

| Architecture NN | WNN (MSE) |
|-----------------|-----------|
| Input Hidden-1 Out | RMSE | MAD | MAPE |
| 9 18 1 | 33.75 | 26.28 | 0.1211 (12.11%) |
| 18 6 1 | 25.23 | 17.72 | 0.0872 (8.72%) |
| 18 18 1 | 20.86 | 13.23 | 0.0685 (6.85%) |
| 18 32 1 | 22.16 | 14.55 | 0.0731 (7.31%) |
| Avarage | 25.50 | 17.94 | 0.0875 (8.75%) |
3.4. Evaluation
As shown in Table 5 and Table 6, based on MSE, MAD and MAPE, ENN is better than WNN. In Figure 6, smaller error of ENN based on MAPE is 6.14% on 18-6-1 and smaller error of WNN is 6.25% on 18-18-1. Thus, best accuracy performance of ENN based on MAPE is 93.86% on 18-6-1 and best performance of WNN is 93.15% on 18-18-1.

![Figure 5. The best result of the WNN (structure 18-18-1)](image)

4. Conclusion
ENN has been developed for short term electric load prediction and achieved higher precision. Performance measurements were obtained by observing errors that occur through RMSE, MAD and MAPE parameters. Based on RMSE, MAD and MAPE, experimental results show ENN is better than WNN. The best performance of ENN is 93.86% on 18-6-1 and the best performance of WNN is 93.15% on 18-18-1. In general, ENN indicates better accuracy. The Evolving Neural Network (ENN) algorithm approach can be performed to predict short-term electrical load.

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