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Short Term Forecasting of Electricity Load: A Comparison of Methods to Paiton Subsystem East Java & Bali

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Abstract. Electricity consumption in Indonesia is expected to continue to grow by average of 6,5% per year until 2020. Therefore, PT. PLN had to make an effective subsystem that can provide electrical energy based on customer needs. The electrical energy is converted from the mechanical energy and can't be stored. Because of that reason, if the electrical energy isn't channeled properly then PT. PLN will suffer losses. It is necessary to plan a proper distribution system of electrical energy. The aim of this research is to predict short-term electricity consumption for Paiton's subsystem in East Java Indonesia by using ARIMA and Multilayer Perceptron. The best model is measured based on MAPE, SMAPE, and RMSE value in data sample. The result of the analysis shows that Multilayer Perceptron method provides better accuracy rate for electricity consumption forecasting in Paiton subsystem based on peak load compared to ARIMA.

1 Introduction

Indonesia's electricity consumption continues to increase each year in line with the national economic growth. In Indonesia, the electricity market area is divided into three broad areas, Sumatra, Java-Bali, and east Indonesia. According to the statistics data of PT. PLN, electricity sales data in Java-Bali region shows that Jakarta is the first rank, second rank was occupied by West Java, and East Java ranked third [1]. East Java distribution is governed by PT. PLN (Persero) P3B East Java & Bali. There are five areas of distribution subsystems in East Java, namely Krian , Paiton, Ngimbang, Kediri, and Krian-Gresik subsystem. Each subsystem supplies electrical energy in some districts and cities.

The availability of electricity is very essential because it associates with customer satisfaction and company reputation. Therefore, PT. PLN (Persero) P3B East Java & Bali must be effective in providing electrical energy for consumers in each subsystem territory. Prediction of short-term electrical load has an important role in real-time control and security functions of an energy management system. If the results of short-term power load forecasting produces good accuracy, the electrical energy supply to consumers will be optimized [2]. In addition, from each subsystem forecast model, the amount of territory peak of electricity load for each power plant can be known. This can be used to plan daily production in the electric power plants. PT. PLN (Persero) P3B East Java & Bali uses many sources for the production, for example steam power plant that uses coal. The availability of the resources affects the production mechanism of electricity. If the required resource is less than demands, PT. PLN (Persero) P3B East Java & Bali should purchase from third parties in advances and it will take time to get it.

However if the PT. PLN (Persero) East Java & Bali save too much resources, it will affect the inventory capacity and it requires a considerable cost. Previous studies of short-term forecasting electricity consumption with double and seasonal ARIMA and Elman-Recurrent Neural Network (NN) on electricity consumption data in Mengare Gresik shows their limitations in estimating the parameters of the SAS package double seasonal ARIMA model to include the effect of outliers which is the result of outlier detection process [3]. However, one of the difficulties of using NN is determining the appropriate input variables in order to produce the optimal model. Researchers often perform a trial-and-error in determining the optimal configuration of NN. To resolve this issue, lag AR of ARIMA as a determinant variable is used. It will be used in MLP model.

2 Ralated Work

There are many techniques that can be used in electric load short-term forecasting, among which Autoregressive Integrated Moving Average (ARIMA), linear regression, exponential smoothing, and so on. Previous research has also been carried out by Soares and Medeiros that examined Brazil's electricity consumption data by using TLSAR, ARIMA, and NN. The research produces the conclusion that NN method gives results that are not significant. [4]. Another study that also associated with the electrical load has been carried out by Azadeh. This study uses ANFIS method for forecasting long-term electricity consumption in Europe [5]. Related research has also been conducted by Zhang, from literature review performed in this study, several important points can be taken. The NN is able to provide a satisfactory performance in forecasting and there are several factors that can affect the performance of NN [6].

3 Proposed Method

Research of methodology to be implemented consists of data sources, literature, design methods, implementation methods, testing methods, and analysis of the test results. The method used in this research are ARIMA and MLP. Data is analyzed using these three methods, and then the results will be compared to find the most appropriate method for short-term forecasting electricity consumption in Paiton subsystem.

3.1 ARIMA

ARIMA used for short-term forecasting electricity consumption, ARIMA forecasting is believed to be reliable for short-term forecasting [8]. This following steps of ARIMA modeling analysis are used in performing this study [7]:

1. Identify the ARIMA model to the characteristics of the data load electricity in East Java. In this process, the data stationary test in mean and variance. When data is not stationary in the variance, then the Box-Cox Transform process is executed. Whereas if data is not stationary in mean, differencing process is executed. Then identify the model by looking at the ACF and PACF plots.
2. ARIMA models estimate the SAS program package based in the CLS method. Furthermore, the testing is done using a statistical t-test.
3. Model fitting test with white noise test.
4. If residual test does not meet the normal distribution assumption, then the next step should be done to detect outlier.
5. Create forecast data out samples based on models.

6. Determining the value of MAPE, SMAPE, and RMSE for each model, then choosing the best model based on the smallest value of MAPE, SMAPE, and RMSE.

3.2 Multilayer Perceptron

After forecasting using ARIMA, we perform subsequent analysis using MLP. Multilayer perceptron has one or more layers located between the input layer and output layer. Generally, there are weights that located between two adjacent layers. Network with many layers can be more difficult than a single layer coating, with more complex learning as in Figure 1.

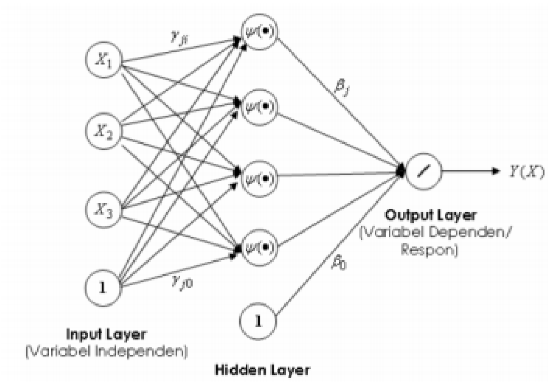


Figure 1. Architecture Multilayer Perceptron

MLP Process has two processes, feedforward and backpropagation. In the feedforward stage, the input signal is given to the network. The neuron in each layer compute the output. At this stage, the weights in the network are not changed. At the stage of backpropagation all weights will be changed based on the error corrected network. Weights are improved to make the resulting output closer to the desired output. Backpropagation algorithm is an algorithm that processes operations relatively fast and does not require a large training data [9].

Input in this study based on the lag AR of ARIMA method. This form is commonly called autoregressive neural network. The illustration of 3 lag input can be seen in Figure 2.

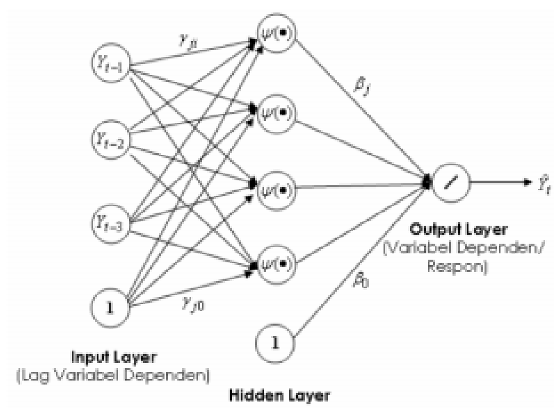


Figure 2. Architecture Autoregressive Neural Network

Common forms of architecture AR-NN model is the same as ARIMA (p,0,0) which the transfer function of a past event $(y_{t-1}, y_{t-2}, \ldots, y_{t-p})$ is shaped nonlinear. While the ARIMA model (p,0,0) form of the function is a linear function. So, it often referred as the MLP model of nonlinear autoregressive model [9].

The following steps of the process are used in MLP method in this study.

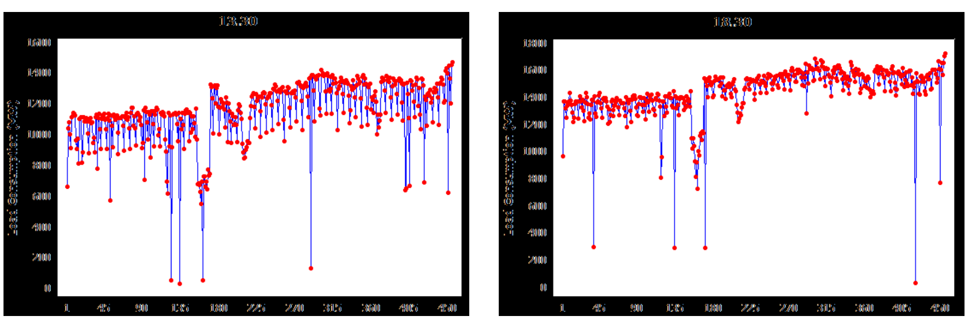
1. Make the determination based on the input variable lag AR of ARIMA models that have been determined.
2. Determine the number of neurons in the hidden layer. Weight values for each neuron in the input layer, at random between -1 and 1.
3. Then do the feedforward process to obtain the value of the output neuron. For each neuron used bipolar sigmoid activation function.
4. Conducting the process of backpropagation is useful for fixing the weights on each neuron

These measures are taken to obtain a model with maximum performance.

4 Experimental Result

4.1 Data Sets

The data used in this research is secondary data obtained from PT. PLN (Persero) P3B East Java &Bali. It is consist of electricity consumption data per half hour from January 1, 2014 to March 31, 2015. Modeling was performed to Paiton subsystem when peak load occurs every shift in PT. PLN (Persero) P3B East Java & Bali. Paiton subsystem peak load occurs at 13.30, 18.30, 22.30. Data is divided into two data, data from January 1, 2014 to February 28, 2015 as in sample data and data from March 1, 2015 to March 31, 2015 as out sample data. Time series plot of the data in Paiton subsystem can be seen in figure 3.



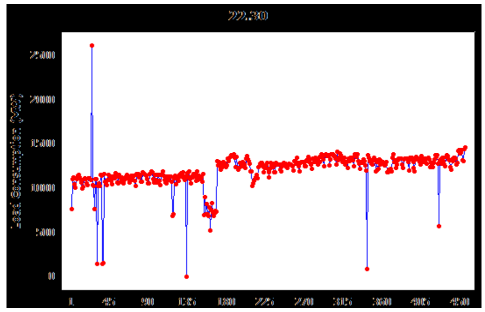


Figure 3. Time Series Plot of Paiton Subsystem, (a) is Paiton 13.30 Hours, (b) is Paiton 18.30 Hours, (c) is Paiton 22.30 Hours.

4.2 Forecasting Electricity Loads using ARIMA

In this study, the implement ARIMA using SAS software. Based on an analysis using Box-Cox transform, the result data is already stationary in variants because of rounded value between UCL and LCL. ACF and PACF plot indicate that the data has a seasonal pattern 7, because lags dies down every 7, 14, 21, 28. However, the data has not been stationary in mean because there's still slow lag down. If differencing 1, then the result data is stationary in mean. ACF and PACF plot can be used for prediction models.

The next step is to test the assumption of residual white noise. The results of this test showed that the models already meet the assumptions of residual white noise because p-value > 0.05. After that, we need to test the normality. the models generated from ARIMA method, although it has already been added outlier not all residual has normal distribution, This is because the data is in the leptokurtic form. Table 1 is a table of result model from ARIMA methods with added outlier by calculating MAPE, SMAPE, and RMSE of out sample's data. The resulting models are Paiton 13.30 is $(0,1,1)\,(0,1,1)^7$, Paiton 18.30 is $(0,1,[1,2,3])\,(0,1,1)^7$, Paiton 22.30 is $(0,1,[1,8])\,(0,1,1)^7$. Calculation of MAPE, SMAPE, and RMSE model can be seen in Table 1.

Table 1. The Result of ARIMA Model with Outlier Detection

Modeled Time	MAPE	RMSE	SMAPE
13.30	8.14	143.94	6.83
18.30	22.2	350.71	24.95
22.30	8.68	149.5	6.93

4.3 Forecasting Electricity Loads using MLP

The first step in MLP method is to determine the input variables. Input variables are selected based significant AR's lag from ARIMA model. Input for MLP method in Paiton 13.30, 18.30 and 22.30 are $y_{t-1}, y_{t-7}, y_{t-8}$. The next step is to determine the number of units in hidden layer neuron. The data used in this method is same as in sample and out sample's data used in the ARIMA method. In this forecasting, we perform experiment using the number of units in the hidden layer neuron (maximum of

10 neurons), one hidden layer, one neuron output, and then added each one bias neuron in the hidden layer and output layer with constant value 1. First, weight values for each neuron in the input layer, at random between -1 and 1. Then, we do the feedforward process to obtain the value of the output neurons in the output layer. For each neuron, we used bipolar sigmoid activation function. After that, backpropagation process that is useful to renew the weights on each neuron. These measures are taken until all input are executed and produced models forecasting the maximum. The results of experiments that have been carried out, using a hidden layer neuron 1 to 10, the results of experiments with MLP method can be seen in Table 2. Architecture model of Paiton 13.30 is NN(3,10,1), Paiton 13.30 is NN(3,10,1), and Paiton 22.30 is NN(3,6,1).

Tabel 2. Result of Experiments with MLP Method

Number of Neuron in Hidden Layer	Input Based On Lag AR	13.30			18.30			22.30		
		MAPE	RMSE	SMAPE	MAPE	RMSE	SMAPE	MAPE	RMSE	SMAPE
1	1, 7, 8	10.60	169.24	9.78	8.85	178.68	8.12	8.50	149.86	7.19
2	1, 7, 8	10.59	168.96	9.76	9.67	180.83	9.09	7.95	148.86	6.62
3	1, 7, 8	10.33	165.05	9.40	8.48	177.87	7.67	7.70	146.24	6.35
4	1, 7, 8	10.44	170.42	9.50	8.44	176.39	7.62	7.83	147.34	6.47
5	1, 7, 8	10.74	174.53	9.89	8.62	176.78	7.83	7.68	145.90	6.29
6	1, 7, 8	10.30	166.03	9.32	7.92	169.36	7.01	7.60	145.57	6.19
7	1, 7, 8	10.35	171.18	9.43	8.22	173.68	7.37	7.62	145.22	6.20
8	1, 7, 8	10.40	164.53	9.54	8.73	173.59	7.99	7.66	145.54	6.21
9	1, 7, 8	10.10	166.70	9.13	8.11	172.07	7.23	7.63	145.02	6.20
10	1, 7, 8	10.06	163.92	9.09	7.75	166.65	6.83	7.60	146.20	6.15

5 Conclusion

Based on the analysis and discussion that has been done, the conclusions drawn from this study are as follows:

- It is concluded that the characteristic of the electricity consumption in Paiton' subsystem between 2014 and 2015 which is calculated every half-hour. For each subsystems that have a different total power consumption, Paiton's subsystem highest load is at 18:30 in 1430,58 MW, and the lowest load is at 24:00 in 934,65 MW.
- In general, the result of the best model using MLP method produces a value that is more accurate than the ARIMA method. Two of three models show that the MLP method has the smallest RMSE, MAPE, and SMAPE value compared with ARIMA

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