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Load Forecasting in Central Java using ANFIS (Adaptive Neuro-Fuzzy Inference System)

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Abstract: The need for electrical energy that continues to increase must be balanced with the provision of adequate electrical energy. Therefore we need an electric power system that is reliable but still economical. The amount of electrical energy consumed must be the same as the electrical energy generated. The amount of electrical energy demand from consumers cannot be determined with certainty, therefore it is necessary to have an electric load forecasting. In this research, the ANFIS (Adaptive Neuro-Fuzzy Inference System) method is used to perform forecasting. The data used are historical data of daily peak load in Central Java from 2010 to 2016. The MAPE value is used as a benchmark in this forecast. The forecasting results will be compared with the forecast results using the load coefficient method. From the forecasting results, the absolute average error percentage obtained is 1.88%. The MAPE from ANFIS forecasting is 0.04% smaller than the MAPE forecasting results using the load coefficient method.

Keywords: ANFIS, load forecasting, MAPE

I. INTRODUCTION

In line with the times and advances in science and technology, the need for the availability of electrical energy is increasing. The increase in demand for electricity must be balanced with the provision of electrical energy by the providers of electrical energy in order to achieve the stability of the electric power system and be able to meet the large consumer needs for electrical energy.

The power generated or produced must always be the same as the power consumed by the electricity users, which is technically generally referred to as system load. If the amount of electrical energy generated and sent is lower or insufficient to meet the needs of consumers' electrical energy, it can cause an overload which will result in blackouts that are detrimental to consumers. Conversely, if the amount of electrical energy generation is much greater than the demand or need of consumers, it can result in a waste of energy so that the electricity supply company can suffer losses. Strategies and methods are needed for adjustments between power generation and demand. In order to achieve an adjustment between power generation and demand, the electricity provider must know the load or demand for electrical power for some time in the future by forecasting electrical loads [1].

Previous research on short-term load forecasting has been carried out, among others, by using the fuzzy logic method for forecasting the daily short-term load forecasting model [2]. In addition, a forecasting method using artificial neural networks (ANN) has also been used to forecast electric load [3]. The ANFIS method, which is a combination of fuzzy logic and artificial neural networks, has also been used in previous studies for the electric load forecasting model [4].

Therefore, in this research, forecasting the daily peak load will be carried out use ANFIS (Adaptive Neuro-Fuzzy Inference System).

II. ANFIS LEARNING

ANFIS learning uses a hybrid learning rule that combines the Least Squares Estimator (LSE) method to determine the consequent value in the forward flow and Error Backpropagation (EBP) in the backward flow to improve the premise parameter [5]. LSE is a method used to determine the linear relationship of data where the sum of the squares of the distance between the points and the regression line being searched must be as small as possible, while EBP is a supervised training method or in the sense that it has a target to be sought. The EBP method is done by propagating the error value backwards from the output layer to the input layer [6].

The first stage in ANFIS training is a progression. This stage consists of 5 layers according to the ANFIS architectural drawing in Figure 1.[7]

The first layer consists of a fuzzification process where the input and target data are mapped in their membership degrees. In the second and third layers, an inference process is carried out which is used to determine the fuzzy rule using Sugeno inference. At the fourth layer, the process of searching for the consequent value is carried out using the Least-Squares Estimator (LSE). And at the fifth layer, a summary process of the two outputs is carried out at the fourth layer.

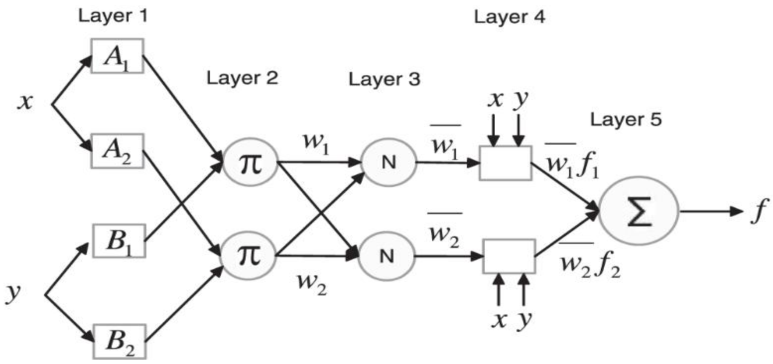


Figure 1. ANFIS architecture

After the output value of the multiple layers is obtained, it is compared with the actual output target. The difference between the output value and the actual target output is called an error. If the error value is greater than the previously set goal value, then the backward flow stage is carried out using EBP to check for any errors on each layer. One step in the direction of learning a back and forth path is called an epoch. This back and forth path phase will stop if the set number of iterations (epochs) is reached or if the network error value has been equal to or less than the predetermined goal value.

III. ANFIS IMPLEMENTATION

The first paragraph The design of the daily peak load forecasting program using ANFIS uses 8 input variables, namely peak load on day D, peak load on days H-1, H-2, H-3, H-4, H-6, H-7, and 1 the output variable is peak load forecasting for day H + 1.There are three stages carried out in system design, namely: training, testing, and forecasting stage.

Training Stage

At the training stage, the initial step taken is taking historical data then determining the form of inputs-targets to form training data in the form of input and target data. After that, the next step is to enter the training parameter values, namely: radius, squash factor, accept ratio, reject ratio, epoch, and goal. Then the training was carried out. This training is carried out with the aim that the system being designed can recognize the target. After networking training is done, the final step is network storage. This network storage is done so that the network that has been created can be used in the testing and forecasting stages. If you want to retrain with a different training parameter value, the user can reset it, then repeat from the stage of determining the training parameter value.

Testing Stage

After the training stage, the next stage is network testing. In this testing phase, the first step taken is taking the test data, then selecting the network that was created earlier in the training phase. After that, the test is carried out. The output of this test is in the form of daily peak load (MW) and error values. After the test results come out, the next step is to compare the value of the daily peak load from the test results with the actual or actual peak load. Good or bad test results can be seen from the resulting RMSE and MAPE values. If the userwant to retest with a different network, then the user can reset and then choose another network again.

Forecasting Stage

After carrying out the network testing phase, the next step is forecasting testing. At the forecasting stage, the first step taken is to select the network for the prediction that has been made. After that, the input data is the amount of peak load today (H), days H-1, H-2, H-3, H-4, H-5, H-6, and H-7. After all data is entered, then do forecasting. The result of this forecast is the value of tomorrow's peak load (H + 1). If the user wants to do the forecasting again, he can do a reset then re-select the network and input data input.

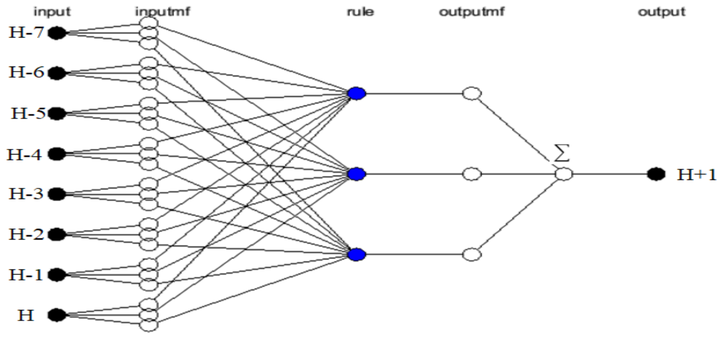


Figure 2. ANFIS structure with peak load input.

IV. RESULT AND ANALYSIS

Training Stage Result

The network variations used in the design of this program is 25 networks. The number of training data used was ±2000 data taken from the period 2010 to 2015. Figure 3 show the daily peak load in Central Java (2010-2015). Figure 4 below is the result of training for Network_1, and Network_11, namely the level of conformity of the output with the target in the form of R.

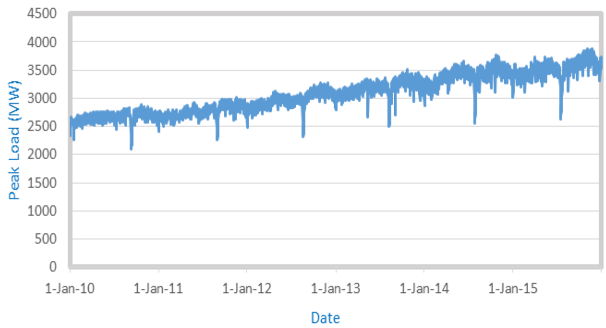


Figure 3.The daily peak load in Central Java (2010-2015).

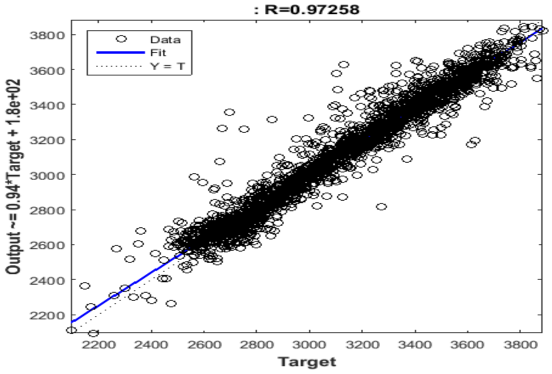
Testing Stage Result

The test data used in designing the daily peak load forecasting program uses data taken from January to June 2016. This test is carried out using the best training result network, namely Network_24. The results of testing the test data using these networks are shown in Table 1.

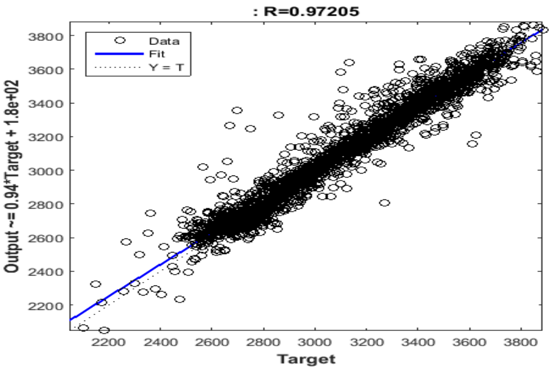
Table 1. Network_24 Testing Results

Network Name	Test result	
	RMSE (MW)	MAPE (%)
Network_24	101.07	2.04

From Table 1 it can be seen that the RMSE value and the MAPE value generated by the network are 101.07MW for the RMSE value and 2.04% for the MAPE value. These values show good results so that the network can be used for the next stage, namely the forecasting stage. Test results networks that have the same RMSE and MAPE values will later produce the same forecast value.



Network 1



Network 11

Figure 4. R value of training results for Network_1 (top) and Network_11 (below)

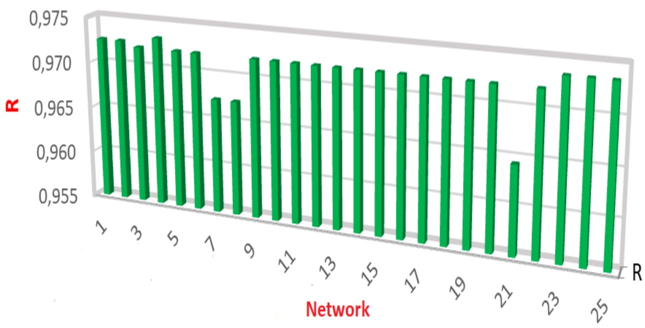


Figure 5. Graph of R Value of Training Results

Forecasting Stage Result

The data used in this forecasting stage is the peak load data for the period June-July 2016 to predict the peak load data for the period 1-9 July 2016. The network used for this forecasting stage is Network_24. The results of forecasting daily peak loads using this network are shown in Table 2.

Based on Table 2, it can be seen that the results of daily peak load forecasting using Network_24 are expressed in MW units.

Forecasting Comparison Between ANFIS and Coefficient Method

ANFIS forecasting results will be compared with forecasting with the load coefficient method and the actual load to determine the magnitude of the error that occurs. Table 3 will present the results of ANFIS forecasting and the forecasting of the load coefficient method of the actual load.

Table 2. Forecasting Results using Network_24

Date	Peak Load Forecasting Results (MW)
1 July 2016	3900
2 July 2016	3897
3 July 2016	3898
4 July 2016	3720
5 July 2016	3629
6 July 2016	3691
7 July 2016	3719
8 July 2016	3900
9 July 2016	3829

Table 3. Comparison of Forecasting Results

Date	Forecasting Results (MW)		Actual Load(MW)
	ANFIS	Coeff Method	
1 July 2016	3900	3872	3841
2 July 2016	3897	3900	3890
3 July 2016	3898	3900	3820
4 July 2016	3720	3718	3751
5 July 2016	3629	3509	3695
6 July 2016	3691	3849	3803
7 July 2016	3719	3848	3930
8 July 2016	3900	3888	3879
9 July 2016	3829	3940	3765

Based on the table, it can be seen the comparison of the ANFIS forecasting results with the forecasting of the load coefficient method against the actual load. In ANFIS forecasting, the MAPE value is smaller, namely 1.88% when compared to the forecasting result of the load coefficient method with a MAPE value of 1.92%. However, both have produced good forecasts according to the standard, namely the MAPE value for short-term forecasting is ± 2%. The comparison of the ANFIS forecasting results with the load coefficient forecasting of the actual load can be seen in Figure 6.

From the comparison graph Figure 6, it can be seen that both the peak load from ANFIS forecasting and load coeffisien forecasting already have a trend that is almost the same as the actual peak load..

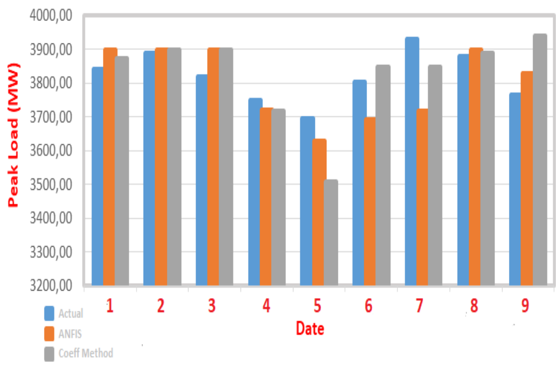


Figure 6. Graph Comparison of ANFIS Forecasting and Load Coefficient Forecasting with Actual Load.

V. CONCLUSION

The design of a daily peak load forecasting program using ANFIS was successfully realized. This design consists of 3 stages, namely the training, testing, and forecasting stages. At the training stage, the data used are daily peak load data for the period 2010 to 2015. From the training results using 25 variations of the parameter values, it is found that Network_24 is the best network that produces an R value of 0.97 with an error value on the last epoch of 79.03 MW.

In the testing phase, the data used is the daily peak load data for the period January to June 2016. From the test results using Network_24, it is obtained that the RMSE value is 101.07 MW with a MAPE value of 2.04% for the network. This value shows good results so that the network can be used for the next stage, namely the forecasting stage.

At the forecasting stage, Network_24 is used to predict the daily peak load on July 1-9 2016. From the forecasting results, the MAPE value is 1.88%. This value is smaller than the MAPE value forecasted by the load coefficient method, which is 1.92%, but both have produced good forecasts according to the standard, namely the MAPE value for short-term forecasting is ± 2%.

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REFERENCES

[1] Hadi Saadat, Power System Analysis, PSA Publishing, 2010.
[2] M. Malekizadeh, H. Karami, M. Karimi, A. Moshari, M.J. Sanjari, Short-term load forecast using ensemble neuro-fuzzy model, Energy, 2020.
[3] Hamed H. H. Aly, A proposed intelligent short-term load forecasting hybrid models of ANN, WNN and KF based on clustering techniques for smart grid, Electric Power Systems Research, 2020.
[4] Sasan Barak S. Saeedeh Sadegh, Forecasting energy consumption using ensemble ARIMA–ANFIS hybrid algorithm, International Journal of Electrical Power & Energy Systems, November 2016.
[5] Jang, J.S. Roger, Sun, Chuen-Tsai, dan M. Eiji, Neuro-Fuzzy and Soft Computing, USA: Prentice-Hall International, 1997.
[6] Lin, Chin-Teng dan Lee, George, Neural Fuzzy Systems, London: prentice-hall, 1996.
[7] Cheng, Ching-Hsue dan Wei, Liang-Ying, One Step-Ahead ANFIS Time Series Model for Forecasting Electricity Load, Optim Eng, Vol.11, pp. 303-317, 2010.

