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Membership Function Comparative Study on Load Forecasting using ANFIS Framework

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Abstract— Electrical load is always different from time to time. Thus, the supply of electrical energy is also dynamic followed the changes in load. Good operation of power system must be able to serve the electrical demand with good quality. This research aimed to apply the ANFIS to predict the electrical load required by customers in every single day. The output of this study can be used as a reference for managing the schedule of power plant that serve the load. Load forecasting in this study is a short-term load forecasting which uses historical data of electrical load from the distribution area of Central Java and Special Region of Yogyakarta Indonesia, as a ANFIS input. The historical data then modeled using MATLAB to get the corresponding output. The result show that ANFIS forecasting with trimf membership function produce smallest MAPE when compared with other membership function type that is 1.4624%. Based on these data it can be stated that ANFIS can be applied to forecast the short-term electrical load which uses historical data of electrical load as a ANFIS input with the best membership function is trimf.

Index Terms— ANFIS, forecasting, historical data, load, MAPE, membership function, short-term.

1 Introduction

Electrical load is changeable at any time. Thus, the supply of electrical energy is also dynamic followed the changes in load. Long-term load forecasting performed to anticipate the increase of electrical load in the next year, while short-term forecasting performed to determine the scheduling of generators (unit commitment scheduling) that will operate to serve the load, maintenance scheduling, and for system security. Short term forecasting is required by producers to derive their strategy for electrical market. Forecasting with good data will produce better prediction. It can be seen from the difference between the values of forecasting with the actual data.

Electrical load forecasting research either in the short term forecasting, medium term forecasting and long term forecasting has been done before. Statistical method for short term forecasting such as linear regression model [1], [2], exponential smoothing [3] and the model autoregressive integrated moving average [4], [5] has been performed.

Soft computing method include artificial neural network [6], fuzzy modelling [7] are widely used for forecasting approach. A comparative study between artificial neural network and ANFIS method [8] show that the use of ANFIS produce lower mean average percentage error than neural network. Research using ANFIS with variation of the input number [9], show that use more number of input will produce more accurate forecasting data. It can be seen from the value of magnitude and error value. ANFIS which use backpropagation method for training data [10], has been done before. The result of this research show that ANFIS is the best method for electrical load forecasting.

In general, forecasting is a method that is done by knowing the pattern data based on the data that have been there before. One method that can be used is adaptive neuro fuzzy inference system (ANFIS). ANFIS have the ability of adaptive neural network and fuzzy system. The problem of ANFIS that must be considered is the training and checking data for updating the membership function parameter. In this research, we try to find he best type of membership function which have the smallest mean absolute percentage error (MAPE) between actual data and forecasting data.

2 Adaptive Neuro Fuzzy Inference System

Adaptive neuro fuzzy inference system (ANFIS) is a hybrid system from adaptive neural network and fuzzy logic. Adaptive neural network method provides the capability of learning and adapting the parameters of the fuzzy rule base. Adaptive neural network can eliminates the deficiency of conventional fuzzy system where the researcher must set up a membership function value both input and output membership function.

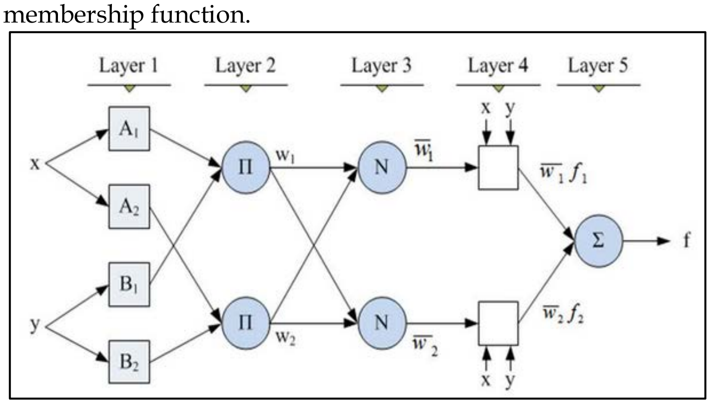

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Fig. 1. ANFIS Structure [11]

Figure 1 shows an ANFIS structure composed of five layer with two input x and y and one output f. Each layer contains several nodes which describes the node function. Square node indicates an adaptive network while circle node indicates a fixed nodes.

In layer 1, all the nodes are adaptive network. There are two fuzzy parameters A1-A2, and B1-B2. The output of layer 1 which called fuzzyfication layer is given by:

$$O_{1.i} = \mu Ai\,(x), i = 1,2 \quad (1)$$

$$O_{1.i} = \mu Bi - 2\,(y), i = 3,4 \quad (2)$$

x and y value is the input for each node. The membership function for A and B describes by type of membership function.

In layer 2, each nodes are fixed nodes which computes the strengths of the rules. Output of the layer 2 is given by:

$$\boldsymbol{O_{2,I} = w_i = \mu_{A_i}(x)\Delta\mu_{B_i}(y), i = 1, 2} \quad (3)$$

or,

$$w_1 = \mu_{A_1}(x) AND \mu_{B_1}(y) \quad (4)$$
$$w_2 = \mu_{A_2}(x) AND \mu_{B_2}(y) \quad (5)$$

In layer 3, each nodes labeled N are also fixed nodes. The output of this layer called normallized firing levels. The outputs is given by:

$$O_{3,i} = \overline{wi} = \frac{wi}{w1+w2},\ i = 1,2 \quad (6)$$

In layer 4, each nodes is adaptive network which computes the contribution of each rules. The outputs of this layer are given by:

$$O_{4,i} = wi\ f\ i = wi(pi\ x + qi\ y + ri) \quad (7)$$

In layer 5, which the last layer is the summation of all incoming signals from the previous layer. The output is given by:

$$O_{5,i} = \sum_i \overline{w_i}\, fi = \frac{\sum_i w_i f_i}{\sum_i w_i} \quad (8)$$

In this paper, ANFIS is trained by a hybrid learning algorithm which combined least squares method and the gradient descent method [12]. Each membership functions type in this study is compared to find the best type of membership function which generate the better MAPE.

3 Load Forecast Model

The research data used in the study are daily electrical load from Central Java and Yogyakarta Distribution area in December 2014 - June 2015. The daily electrical load is composed from every 30 minutes data. So, in one day is consist of 48 data. Total data used in this research is 1000 data. The data set into two parts. First group consist 900 data used for training and second group consist 100 data used for checking data.

3.1 Membership Function

Different type of membership function used to find the best forecasting result. The membership function type used in this research are trimf, trapmf, gbellmf, gaussmf, pimf, and dsigmf. Each membership function have a different equation that used in fuzzyfication process at layer 1. The equation each membership function defined as follows:

1. Triangular-shaped membership function (trimf)

$$f(x; a, b, c) = \begin{Bmatrix} 0, & x \ll a \\ \frac{x-a}{b-a}, & a \ll x \ll b \\ \frac{c-x}{c-b}, & b \ll x \ll c \\ 0, & c \ll x \end{Bmatrix} \quad (9)$$

2. Trapezoidal-Shaped membership Function (Trapmf)

$$f(x; a, b, c, d) = \begin{Bmatrix} 0, & x \ll a \\ \frac{x-a}{b-a}, & a \ll x \ll b \\ 1, & b \ll x \ll c \\ \frac{d-x}{d-c}, & c \ll x \ll d \\ 0, & d \ll x \end{Bmatrix} \quad (10)$$

3. Generalized bell-shaped membership function (Gbellmf)

$$f(x; a, b, c) = \frac{1}{1+\left|\frac{x-c}{a}\right|^{2b}} \quad (11)$$

4. Gaussian curve membership function (Gaussmf)

$$f(x; a, c) = e^{\frac{-(x-c)^2}{2a^2}} \quad (12)$$

5. Phi-shaped membership function (Pimf)

$$f(x; a, b, c, d) = \begin{Bmatrix} 0, & x \ll a \\ 2\left(\frac{x-a}{b-a}\right)^2, & a \ll x \ll \frac{a+b}{2} \\ 1 - 2\left(\frac{x-b}{b-a}\right)^2, & \frac{a+b}{2} \ll x \ll b \\ 1 & b \ll x \ll c \\ 1 - 2\left(\frac{x-c}{d-c}\right)^2, & c \ll x \ll \frac{c+d}{2} \\ 2\left(\frac{x-d}{d-c}\right)^2, & \frac{c+d}{2} \ll x \ll d \\ 0, & x \gg d \end{Bmatrix} \quad (13)$$

6. Difference between two sigmoidal function membership function (Dsigmf)

$$f(x; a, c) = \frac{1}{1+e^{-a(x-c)}} \quad (14)$$

3.2 ANFIS Model

In this study, ANFIS system has four input and one output. Each input has two membership function so that formed 16 rules of ANFIS shown in Figure 2. Inputs are historical load from the same day on previous week while output is forecasted load. The structure of inputs consist four data sets (D=4) with delay is 48 step (Δ=48) and the predicted value, P = 48. Based these data can be structured data as follows:

[x(t-144), x(t-96), x(t-48), x(t), x(t+48)]

The ANFIS model in this study consist of six steps:
Step 1: Pre-processing data (grouping data every single day)
Step 2: Load training data (900 data)
Step 3: Training data with 500 Epoch
Step 4: Data prediction

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Step 5: Load checking data (100 data)
Step 6: MAPE calculation

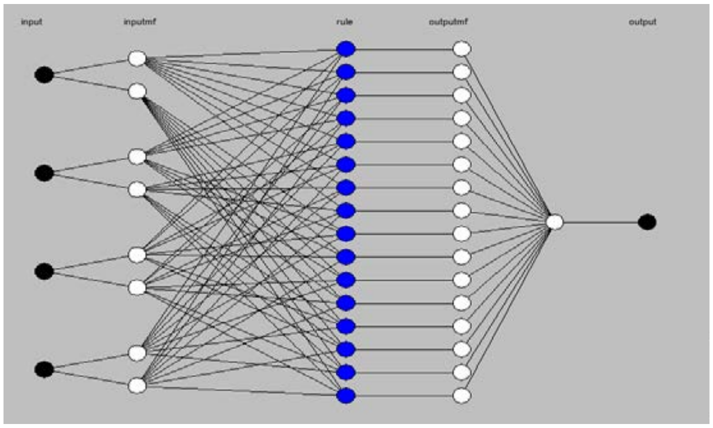

Fig 2. ANFIS Model

3.3 Model Accuracy

The accuracy of short term electrical load forecasting result computed with mean absolute percentage error (MAPE) defined as follows:

$$MAPE = \frac{1}{n}\frac{\sum_{i=1}^{n}|X_t - F_t|}{X_t}x100\%$$

Where,
Xt is the actual value of electrical load and *Ft* is the predicted value. The smallest value of MAPE indicates the best forecasting method.

4 Result and Discussion

The ANFIS approach is applied to forecasting next week electrical load in Central Java and Yogyakarta Distribution area. Load forecasting is computed using historical data from December 2014 to June 2015. Different type of membership function used to find the best forecasting result. Table 1 present the MAPE for each membership function in this research.

TABLE 1
Comparative MAPE Result

Day	MAPE (%)					
	trimf	trapmf	gbellmf	gaussmf	pimf	dsigmf
Monday	1.0043	1.0163	1.0210	1.0288	0.9805	1.0145
Tuesday	1.1830	1.2051	1.1977	1.2159	1.2356	1.2056
Wednesday	1.8640	1.8040	1.8318	1.8374	1.7378	1.7839
Thursday	1.3426	1.3305	1.4152	1.3628	1.3336	1.3540
Friday	1.2965	1.3139	1.3570	1.3536	1.3840	1.3559
Saturday	2.0940	2.0079	1.9872	1.9969	2.0194	2.0018
Sunday	1.2842	1.2858	1.3897	1.3637	1.3585	1.3344
Average	1.4384	1.4234	1.4571	1.4513	1.4356	1.4357

From Table 1, it can be seen that trapmf has the smallest MAPE 1.4234%, while gbellmf has the largest MAPE 1.4571%. From this data it can be stated that trapmf is the best type of membership function for electrical load forecasting in this research. Figure 3-9 shows the daily actual load curve in red, while forecasted result with trapmf membership function type in blue.

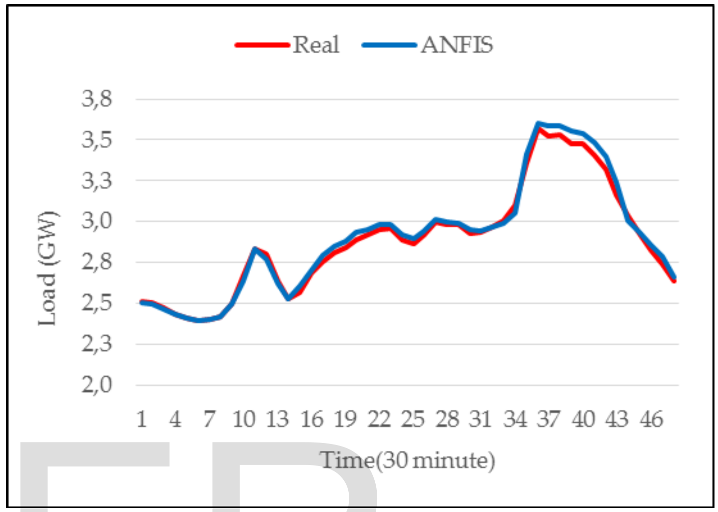

Fig. 3. Comparison of actual load and predicted load with anfis in monday

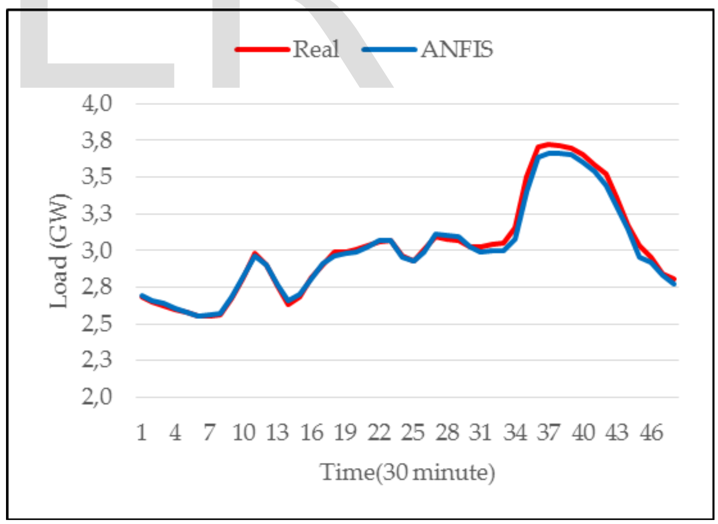

Fig. 4. Comparison of actual load and predicted load with anfis in tuesday

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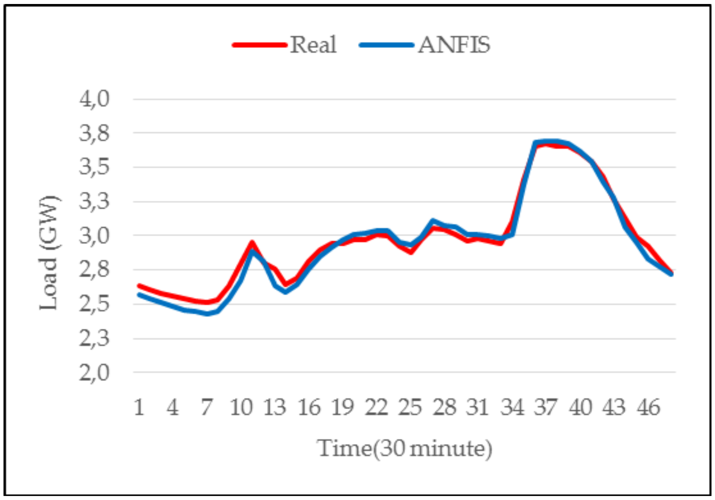

Fig. 5. Comparison of actual load and predicted load with anfis in wednesday

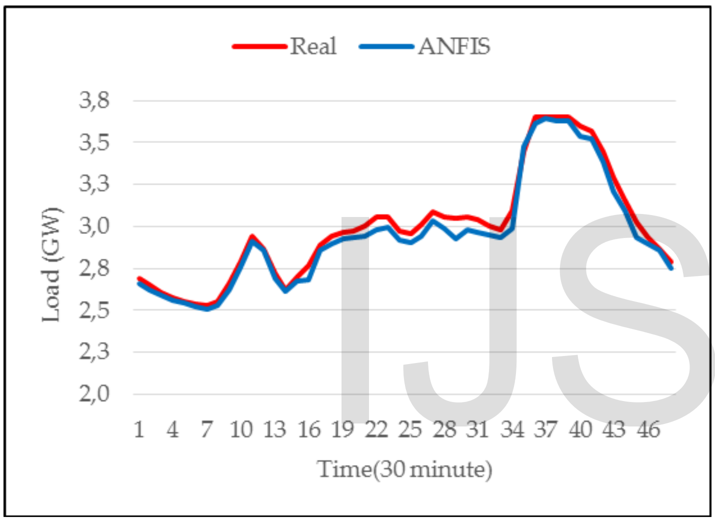

Fig. 6. Comparison of actual load and predicted load with anfis in thursday

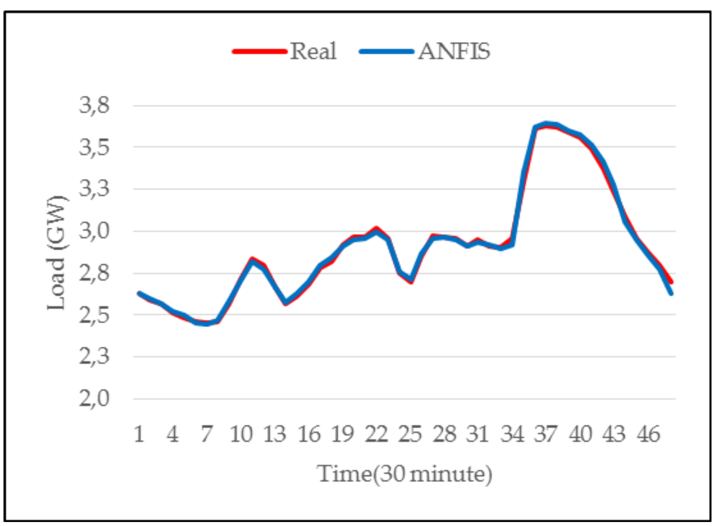

Fig. 7. Comparison of actual load and predicted load with anfis in friday

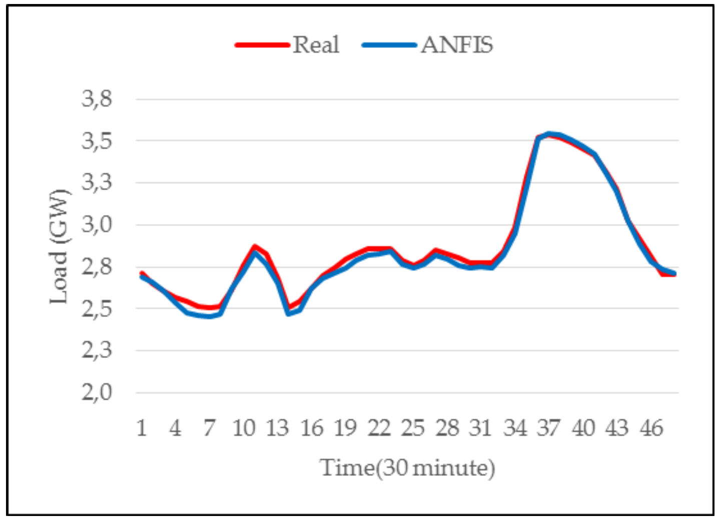

Fig. 8. Comparison of actual load and predicted load with anfis in saturday

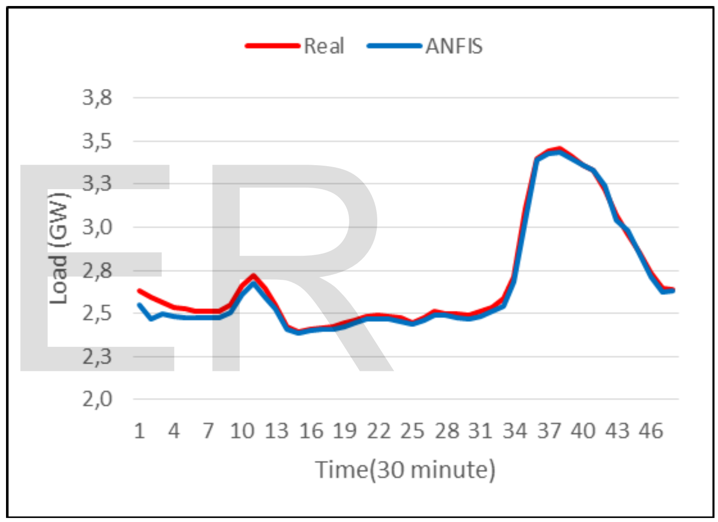

Fig. 9. Comparison of actual load and predicted load with anfis in sunday

5. Conclusions

This paper present a comparative study of ANFIS for short term load forecasting. The different membership function used to find the best type of membership function which have the smallest mean absolute percentage error (MAPE) between actual data and forecasting data. The result show that ANFIS with trapmf membership function has the smallest MAPE 1.4234%.

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