Short Term Load Forecasting for Weekends in Indonesia: Comparison of Three Methods

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Abstract. This paper compares the three methods used for short-term load forecasting on the electrical system in Indonesia. The three methods are coefficient load method, single exponential smoothing, and fuzzy subtractive clustering that in optimization using adaptive neuro fuzzy inference system (ANFIS). The experiments were conducted on seven data of electric load on a weekends in October 2014. The result of simulation showed that single exponential smoothing method is more precision in electrical load forecasting for weekends in Indonesia.

1. Introduction

Short Term Load Forecasting (STLF) is an electrical load prediction tool for a few hours a week [1]. STLF has an important role in managing the operation of the power system [2]. Errors in the prediction of the load can increase operational costs [3]. Based on conservative estimates, reduced prediction error of 1% at 10,000 MW electric power system can save up to \$1.6 million per year [4]. By plotting the scheduling and planning of power supply, the reliability and operation of stable power can be maximized and also can improve security on electrical equipment, and reduce operational costs [5] [6].

In its application, it is required a method to produce load forecasting. Several methods can be used such as time-series approach such as load coefficient method, statistical method such as exponential smoothing method, decomposition, and linear regression, and also artificial intelligence methods such as fuzzy logic, neural networks, and particle swarm optimization [7]. On the other hand, it can be combined from two or three of these methods [8].

Load coefficient method is used by the Indonesian power company in load forecasting. In this method, to determine the coefficient is using loads of the past and the peak load [9]. Exponential smoothing is a method of calculating the predictive calculation repeat continuously using the latest data. Robustness and accuracy of this method has led to the use of this method can be widely in many applications [10]. Single exponential smoothing is used if the data was not significantly affected by the trend and seasonal factors [11]. Adaptive Neuro-Fuzzy Inference System (ANFIS) is forecasting method that combines learning and modeling of neural networks and fuzzy logic in adaptive inference systems. Neural networks deal with imprecise data is by training, while the fuzzy logic can handle the uncertainty of human cognition [12] [13]. By contrast intelligence techniques such as ANFIS employing fuzzy rules can model the qualitative aspects of human knowledge and reasoning processes without employing precise quantitative analyses [14].

Several studies have been done on electric load forecasting by different methods. Comparison between load coefficient methods with artificial neural networks for forecasting produce data on artificial neural network method is closer to the target than by using the load coefficient [15]. Double seasonal exponential smoothing method also has a high degree of accuracy compared to using load coefficient method, but these methods is only recommended for weekday load, it is not recommended for the holidays [16]. Comparison between artificial neural network method with ANFIS generate that using ANFIS method has a more accurate result than the method of artificial neural network on every day except long holiday in 2012 [17]. There is also a short-term load forecasting research on holidays using neural networks to produce a small error on Friday compared to Saturday and Sunday [18]. Therefore, the aim of this study to compare the results of short-term load forecasting with three methods on weekends in Indonesia to get the smallest error value in electric load forecasting.

2. Methods
Short-term load forecasting can be using several methods. In this study using the load coefficient method, single exponential smoothing and FSC-ANFIS. The processed data is obtained from the load divider center area III West Java, Indonesia.

2.1. Load coefficient
To create a forecasting model with load coefficient method is developed by an algorithm as follows: [19]

1. Compiling data of the past loads at t hour on the day (h-1), (h-2), (h-3)... (hn), here in after denoted Xt (h -1), XL (h-2), ..., Xt (hn). Where t = 00:00 - 24.00, and h holidays are observed.

2. Determine the peak load for each load at the (h-1), (h-2), ..., (h-n), for a holiday that is observed.

$$Y_{th} = \left[\frac{1}{5} \left(\frac{X_{t(h-1)}}{X_{maks(h-1)}} + \frac{X_{t(h-2)}}{X_{maks(h-2)}} \ldots + \frac{X_{t(h-5)}}{X_{maks(h-5)}} \right) \right] \times$$
$$\underbrace{}_{\bar{\alpha} = \text{the average coefficient}}$$

$$\left[\frac{1}{4} \left(\frac{X_{t(h-1)}}{X_{(h-2)}} + \frac{X_{t(h-2)}}{X_{(h-3)}} \ldots + \frac{X_{t(h-4)}}{X_{(h-5)}} \right) \right] \times X_{maks(h-1)}$$
$$\underbrace{}_{\bar{\beta} = \text{average growth}}$$

(1)

The average error (%) obtained by the following formula:

$$\varepsilon = \frac{1}{n} \sum_{i=1}^{n} \frac{|y(i,t) - \hat{y}(i,t)|}{y(i,t)} \times 100\%$$

(2)

Y_{th} = estimate of the load on the hour (t) day (h)
ε = average error (%) load estimates
n = the number of hours (n = 00:00 - 24:00)
y (i,t) = the actual load (MW)
$\hat{y}(i,t)$ = load forecasts (MW)

Accuracy of the result is the degree of closeness calculation results with actual value. By doing the usual statistical calculation accuracy values obtained as follows:

$$\text{Accuracy} = 100\% - \text{error \% value}$$

(3)

2.2. Single exponential smoothing

Exponential Smoothing (ES) is a simple prediction method based on historical data [20]. The general form of the functions of exponential smoothing forecast involves a set of adaptive coefficients [21]. There are several types of exponential smoothing that is single exponential smoothing, double exponential smoothing and seasonal exponential smoothing. This study used Single Exponential Smoothing.

This method is used if the data is not influenced by the trend and seasonal factors. Used for time series data that follows the stationary pattern. The main advantage of the exponential smoothing method is their provision, which allows the implementation of rapid and efficient techniques along with descriptive and inferential statistics [22].

The general forms used to calculate forecasting are: [19]

$$\hat{Y}_{t+1} = \alpha Y_t + (1-\alpha)\hat{Y}_t \qquad (4)$$

$\hat{Y}_{t+1}$ = an approximate value for the next period

α = a smoothing constant
Y_t = new data or a real value in period t
$\hat{Y}_t$ = average smoothing until the period t-1
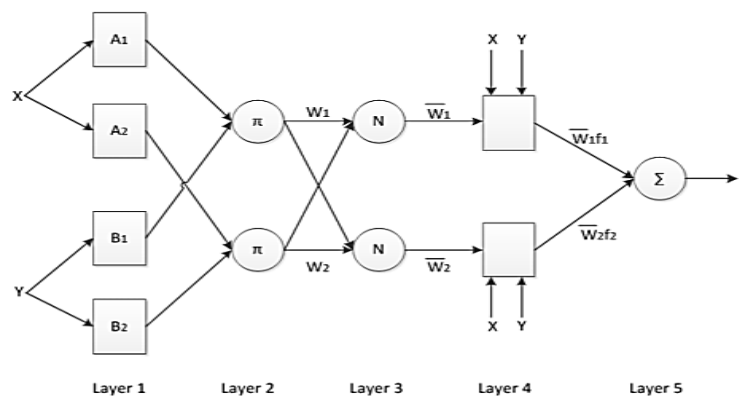
From the equation above, can also be written as:

$$\hat{Y}_{t+1} = \hat{Y}_t + \alpha.e_n \qquad (5)$$

$$\text{with } e_n = (Y_t - \hat{Y}_t) \text{ (error for n period)} \qquad (6)$$

From the form of this equation can be seen that the estimates produced by this method is the previous estimate of plus adjustments for errors that occurred in the recent estimates.

2.3. ANFIS (Adaptive Neuro Fuzzy Inference System)

ANFIS (Adaptive Neuro Fuzzy Inference System) is one system in the neuro-fuzzy group formed from a combination of two soft computing, that is artificial neural networks and fuzzy logic [23] [24]. Neural networks and fuzzy system are widely used in a variety of issues such as the identification system, the data time series prediction, classification and control. ANFIS in the working process using a hybrid learning algorithm, which combines the method of Least Square Estimator (LSE) and Error Back Propagation (EBP). In the structure of ANFIS method EBP is performed in layer-1 and layer method LSE in the layer-4 [25] [26]. ANFIS structure forms are already widely known is shown by Figure 1. In this structure, the fuzzy inference system applied is fuzzy inference model of Takagi-Sugeno-Kang Order 1 [26].

Figure 1. ANFIS Structure

As shown in Figure 1 ANFIS system consists of five layers, consisting of layers that are adaptive and fixed layers. The parameters of the membership function fuzzy non-linear nature of the output of the system is in the 1st layer. At this layer is used EBP to renew its parameters, while the parameters that are linear to the output currently on the 4th layer. In this layer is used LSE method to update the 4th layer parameters. Mechanism of ANFIS structure can be explained with the following explanation [27] [28].

Layer 1: Membership function parameters can be approximated by the following function:

$$\mu A_i(x) = 1/(1+[\llbracket((x-c_i/a_i)]\rrbracket ^2) \tag{7}$$

$\{a_i, b_i, c_i\}$: the set of parameters
$\mu(x)$: degree of membership

Layer 2: The output of layer-2 is the product of the degrees of membership of the first layer:

$$W_1 = \mu A_1 * \mu B_1 \tag{8}$$
$$W_1 = \mu A_2 * \mu B_2 \tag{9}$$

Layer 3: Results from the output of the 3rd layer is known as the normalized firing strength:

$$\acute{W} = W_i/(W_1+W_2) \tag{10}$$

With i = 1, 2.

Layer 4: Each neuron in each layer 4 is node adaptive to an output:

$$\acute{W}_1 Y_1 = (\acute{W}_1 X_1)p_1 +(\acute{W}_1 X_2)q_1 +r_1 \tag{11}$$

P_i, q_i, r_i are the parameters on these neurons.

Layer 5: At this layer is the sum of all inputs:

$$Y' = \sum w_i y_i \tag{12}$$

In doing forecasting with ANFIS, then the output of layer 5 is divided by the data.

$$\text{The results of the data-1 forecaster} = \sum \acute{W}_i y_i/x_2 \tag{13}$$

2.4. Fuzzy subtractive clustering

Fuzzy subtractive clustering method relatively unsupervised clustering method in which the number of cluster centers is not known. This method uses data as a candidate of the center of the cluster, so the computational load depends on the amount of data and is independent of the dimension data. The number of cluster centers is sought is determined through the iterative process to search for points with the highest number of neighbors.

The basic concepts of subtractive clustering are to determine the areas within a space (variable) which has a high density of the dots around it. Point with the highest number of neighbors would have to be the center of the group. The point that has been at the center of this group will then be reduced density. Furthermore, it will be elected another point that being a neighbor to be the center of most other groups. This will be repeated until all points tested.

To create a forecasting model with Fuzzy Subtractive Clustering compiled by an algorithm as follows [29]:

1. Input data to be in clustering: X_{ij} with i = 1,2, ..., n; and j = 1,2, ..., m.

2. Set value :
    a. r_j *(influence range)*
    b. q *(squash factor)*
    c. Accept_ratio
    d. Reject_ratio
    e. Xmin
    f. Xmax

3. Normalization:

$$X_{ij} = \frac{X_{ij} - X\min_j}{X\max_j - X\min_j}, i = 1,2,...,n; j = 1,2,..m$$

(14)

4. Determine the potential beginning of each data points:
   a. i = 1
   b. working up to i = n
   - Tj = Xij; j = 1,2,…m
   - Initial potential: if m = 1, then

$$D_i = \sum_{k=1}^{n} e^{-4\left(D_{k1}^2\right)}$$

(15)

   if m > 1, then

$$D_i = \sum_{k=1}^{n} c^{-4\left(\sum_{j=1}^{m} D_{k2}^2\right)}$$

(16)

   - i = j + 1

5. Find the point with the highest D:
   a. m = max [Di; I = 1,2,…,n]
   b. h = i; such that Di = m

6. Determine the center of the cluster and its potential to reduce the points around:
   a. Center = []

$$D'_k = D_k - D_{c1} * e\left(-\frac{\|x_k - x_{c1}\|}{(r_b/2)^2}\right) \quad \text{b.}$$

(17)

7. Return the center of the cluster of forms normalized to its original shape. Centerij = Centerij * (Xmaxj - Xminj) + Xminj

8. Calculate the value of sigma cluster:

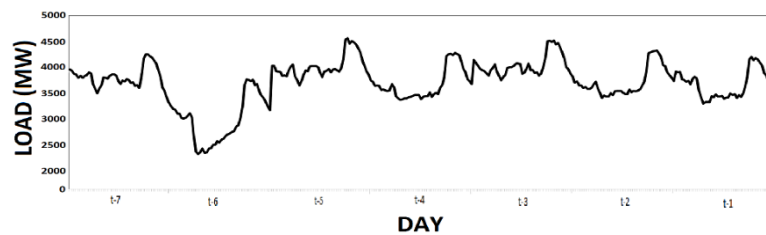$$\sigma_j = r_j\left(\frac{X\max_j - X\min_j}{\sqrt{8}}\right)$$

(18)

9. Calculate the degree of membership:

$$\mu_{ki} = e^{-\sum_{j=1}^{m}\frac{(X_{ij}-C_{ij})^2}{2\sigma_j^2}}$$

(19)

3. Results and discussion

Load forecasting restricted to predict the electrical load on Saturday and Sunday in October, 2014. From the data obtained, analyzed the data of the electrical load is the actual load data on a seven-day weekend in October 2014 by adding one the next day as a comparison value. Furthermore, the load of the day is divided into 48 variables called half-hour load, on weekend in October which is dated 4, 5, 11, 12, 18, 19 and 25. The result of the data is in the forecast with load coefficient method, smoothing single exponential and FSC-ANFIS. After the predicted value obtained is then compared with the actual load data to measure how much the value of errors in each method.
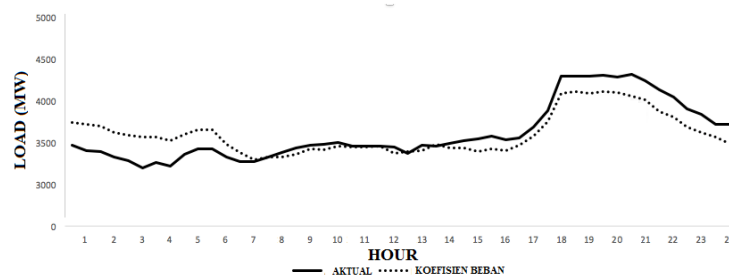
Figure 2. Graphic of load on weekend

In general, the load of the holiday shows similar and repetitive patterns. While on a national holiday has a different electrical loads. It can be seen on t-1 (October 25, 2014) which is a new year of Hijra has a similar load to the load on the weekend. While on t-6 (October 5, 2014) which is the feast of Eid al-Adha has a low electrical load compared to the electrical load at the other weekend. This is because the majority of the population in Indonesia are Muslim, so the use of electrical load is relatively small [30].

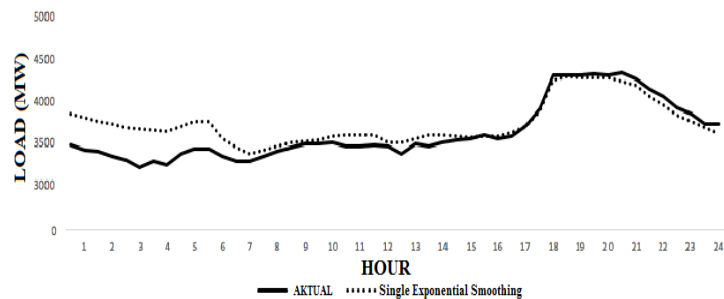*3.1. Short term load forecasting with load coefficient method*
Load coefficient method using the data load and peak load for the previous gain coefficient alpha (α) and beta (β). Calculations on the forecasting using Microsoft Excel software. This calculation results obtained from the average value of error of 4.34%. Comparison of the data for the actual load forecasting results in this method is presented in Figure 3.

Figure 3. Comparison of data from load coefficient method with actual load data

3.2. Short term load forecasting with single exponential smoothing method
In forecasting with a single exponential smoothing method is using Zaitun Time Series software. This software provides a comparison of the alpha value that will be selected by the MSE value of the data entered. Thus it can be determined the value of alpha = 0.1, by reference to the smallest MSE value. This calculation results obtained from the average value of error of 3.87%. Comparison of the data for the actual load forecasting results in this method is presented in Figure 4.

Figure 4. Comparison of data from single exponential smoothing method with actual load data

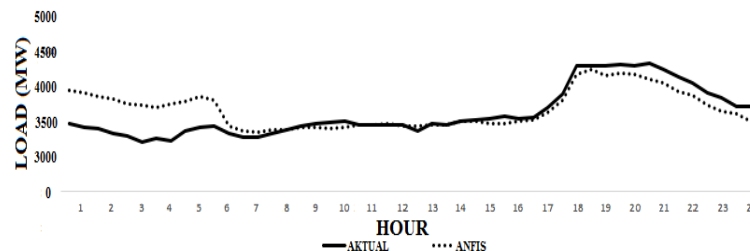*3.3. Short term load forecasting with FSC-ANFIS method*
In forecasting the load with FSC-ANFIS method using MATLAB software. In this method, first of all do clustering with FSC method, after it was optimized using ANFIS method. In practice, it takes on a cluster radius parameter FSC method for generating optimal value.

6

Cluster radius parameter or influence range is setting values cluster radius between 0.1 up to 0.9. Changing the cluster radius parameter optimization learning is done after the data input is obtained. Because the available data are only 7, then the learning input 7 data is used as input for parameter learning cluster radius.

Table 1. Radius cluster parameter

GENFIS (CLUSTER)	Total Residue		Error %	
	FSC	ANFIS	FSC	ANFIS
0.10	8623.48	8704.56	4.97%	5.02%
0.15	8623.48	8748.70	4.97%	5.05%
0.20	8623.47	41291.41	4.97%	23.81%
0.25	8623.47	10614.61	4.97%	6.12%
0.30	8496.06	10726.53	4.90%	6.19%
0.35	8458.64	50445.38	4.88%	29.09%
0.40	8485.64	10844.11	4.89%	6.25%
0.45	8234.84	8211.53	4.75%	4.74%
0.50	8222.31	8221.55	4.74%	4.74%
0.55	8216.60	8207.13	4.74%	4.73%
0.60	8289.59	8288.26	4.78%	4.78%
0.65	8286.51	8287.69	4.78%	4.78%
0.70	8298.02	8304.53	4.79%	4.79%
0.75	8293.95	8296.83	4.78%	4.79%
0.80	8287.33	8291.67	4.78%	4.78%
0.85	8299.48	8299.08	4.79%	4.79%
0.90	8229.81	8236.18	4.75%	4.75%

From the following data, cluster 0.55 is selected because it has the smallest error value that is 4.73%. Comparison of the data for the actual load with forecasting results in this method is presented in Figure 5.

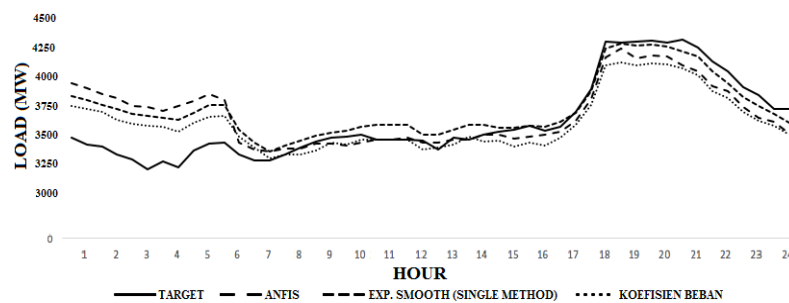**Figure 5.** Comparative data of ANFIS method with actual load data

3.4. Comparison of load coefficient, single exponential smoothing, and FSC-ANFIS with actual load
From the simulation results of three methods that have been discussed, the obtained value forecasting results of each method and the value of its error. Comparison of error in each method is presented in Table 2, as well as the comparison of forecasting results are presented in Figure 6.

Table 2. Comparison of error of Load Coefficient, single exponential smoothing and FSC-ANFIS

cluster	Residue			Forecasting error accuration (%)		
	FSC-ANFIS	Exp. Smooth	Load coefficient	FSC-ANFIS	Exp. Smooth	Load coefficient
0.55	8207.13	6718.61	7528.75	4.73%	3.87%	4.34%

Figure 6. Comparison of three methods to target (actual load)

4. Conclusion

In this research has been conducted comparison of three methods for short-term load forecasting. The smallest error value obtained was 3.87% with a Single Exponential Smoothing method. The result is not linear with previous related studies, where artificial intelligence method for generating an error value is greater than the load coefficient method and the single exponential smoothing.

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