The Impact of Influence Range Fuzzy Subtractive Clustering Modification to Accuracy Anomalous Load Forecasting

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Abstract. Short term load forecasting (STLF) has an important role for reliability and economic operation of electrical power system. In this paper, fuzzy subtractive clustering (FSC) method is used in STLF of electrical power system for special days in anomalous load conditions. These anomalous loads occur during national holidays. This method is applied on dataset of Region 2 Java-Bali to forecast the load demand on half-hour in national holidays (anomalous load). The proposed methodology has been to decrease the forecasted error value. Finally, the result shows that FSC implementation for STLF of regional load have more accuracy and better outcomes.

1. Introduction
Electricity needs from year to year increase, the power system operation is needed to meet the public demand for electrical energy. The key to achieving safe, reliable, efficient and low-cost supply of electric energy as well as improving the economy of the future is energy management system (EMS), which is one of its functions is forecasting [1][2].

Load forecasting is an operations and planning future electric industry which plays an important role in the electric utility [3]. Load forecasting techniques can be divided into three categories: short therm load forecasting, mid term and long term load forecasting load forecasting [4]. In this research, using the technique of short term load forecasting (STLF). STLF predict the load for 1 hour and then to 1 week ahead [5].

Forecasting for the electrical load is divided into normal loads and loads of anomalies. Normal load is a load on the load kerjasedangkan anomalies are a burden on special days, such as public holidays and long weekand [14]. In many load forecasting applying artificial intelligence (AI). AI consists of expert systems (ES), artificial neural network (ANN) and genetic algorithm (GA) [4]. Such as Artificial Neural Network has the advantage that tolerate strange patterns, have the ability adatif, etc [8].

One of the state-owned electricity industry, namely the State Electricity Company (PLN) perform load forecasting (forecasting load) which is the first step of the Electrical Power Supply Business Plan (RUPTL) applied to each business unit PLN. Firms Listrik Negara (PLN) have to operate the power system to provide electric power required by the consumer. If the power is generated and transmitted is greater than the needs of consumers, the PLN will have technical and economic losses due to the waste of resources that should not be held, and otherways.

The technique used for short-term load forecasting No 5 ie multiple linear regression models stochastic time series models such as exponential smoothing, ARMA, Box-Jenkins ARIMA, regression, and the transfer function (dynamic regression) [9] , model of expert systems, state space models, general exponential smoothing models and neural network models (JST)[10].

The method used for load forecasting by the author of fuzzy subtractive clustering (FSC). This method is calculating data points are entered into the cluster according to the distance.

2. Method

Electric load data used by the authors for this study based on a national holiday electrical load PLN Persero P3B Java-Bali Region 2 APB Cigereleng 2008 to May 2015. While the data used holiday by the Joint Decree of the Minister of Religious Affairs, the Minister of Labour and Transmigration and Minister of Administrative Reform and Bureaucratic Reform of the Republic of Indonesia. Here are some numbers decree on national holidays and leave together from 2008 to 2015, show in **Table. 1**.

Table 1. Number of Surat Keputusan (Sk) National Holiday 2008-2015

SK.TAHUN	NOMOR SK
2008	NOMOR 1 TAHUN 2008 NOMOR KEP.24/MEN/II/2008 NOMOR SKB/01/M.PAN/2/2008
2009	NOMOR 4 TAHUN 2008 NOMOR KEP.115/MEN/VI/2008 NOMOR SKB/06/M.PAN/6/2008
2010	NOMOR 1 TAHUN 2009 NOMOR SKB/13/M.PAN/8/2009 NOMOR KEP.227/MEN/VIII/2009
2011	NOMOR 03 TAHUN 2011 KEP.135/MEN/V/2011 SKB/02/M.PAN-RB/5/2011
2012	NOMOR 7 TAHUN 2011 NOMOR 04/MEN/VII/2011 NOMOR SKB/03/M.PAN-RB/07/2011
	NOMOR 2 TAHUN 2012 NOMOR KEP.28/MEN/I/2012 NOMOR SKB/01/M.PAN-RB/01/2012
2013	NOMOR 5 TAHUN 2012 NOMOR SKB.06/MEN/VII/2012 NOMOR 02 TAHUN 2012
2014	NOMOR 5 TAHUN 2013 NOMOR 335 TAHUN 2013 NOMOR 05/SKB/MENPAN-RB/08/2013
2015	NOMOR 16 TAHUN 2014 NOMOR 310 TAHUN 2014 NOMOR 07/SKB/MENPAN-RB/09/2014

Research conducted with the theme forecasting load (load forecasting) require some support to optimize the results. Some devices needed is a device (hardware) and software (software). (Hardware) used is 1 set laptop with specs Operating System Windows 7 Ultimate 64-bit (6.1, Build 7601); ADM Processor E1-2100 APU with Radeon (TM) HD Graphics (2CPUs), ~ 1.0GHz; Memory 2048MB RAM. While software (software) used is Matlab R2009a, Microsoft Office Excel 2013, MathType ver. 6.9, Mendeley Desktop ver. 1.13.8.0, and Microsoft Office Visio 2007.

This study uses data load from PLN Persero P3B Java-Bali Region 2 APB Cigereleng data and national holidays Joint Decree of the Minister of Religious Affairs, the Minister of Manpower and Transmigration and the Minister of Administrative Reform and Bureaucratic Reform of the Republic of Indonesia in 2008 until May 2015 . Data collected electrical load created plots so that the characteristics of the load can be identified as anomalous load or normal load. To further convince him compare with normal load characteristics of sample plots on weekdays.

Anomalous load (*short term load forecasting*) which aims to find the electrical load required at the predetermined or known to the target. Short-term load forecasting electricity load anomaly using fuzzy subtractive clustering method (FSC). In this study has defined procedure. The stages of research can be seen in the flowchart shown in Fig.1.

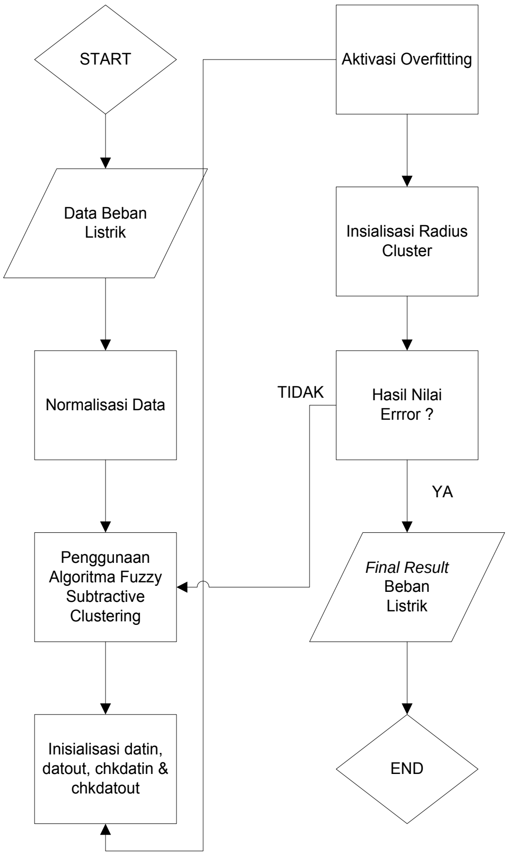

Figure 1. Flowchart Short Term Load Forecasting (STLF)

The stages of the research in accordance with the specified flowchart is as follows:

- Collected the electrical load of PLN Persero P3B Java-Bali Region 2 APB Cigereleng in national holidays from 2008 to May 16, 2015.
- Perform data normalization of our data collection electrical load. Normalization of data is modified or organize a table with insertion or deletion anomaly that caused the error [11]. Normalization of data is a step to transform into (0.1) that aims the team to narrow the distance between 0 and 1. The interval data used in this study was 0.1 to 0.9. Data normalization equation [12]:

$$y = \frac{0.8(x-a)}{b-a} + 0.1 \qquad (3.1)$$

Whrere :
y = the value of the normalization
x = the value of the electric load data
a = the minimum value of the electric power load data

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b = the maximum value of the electric power load data

Once the input data is normalized and get a result, then the input data didenormalisasi by the following equation:

$$z = \frac{(y-0.1)(b-a)+0.8a}{0.8} \quad (3.2)$$

Where:
y = the value of the normalization
z = the value of the results of normalize
a = the minimum value of the electric power load data
b = the maximum value of the electric power load data

- Using Fuzzy Subtractive Clustering Algorithm (FSC) is a step in the matlab script settings by doing plot the data to produce output.
- Initialization Datin, datout, chkdatin and chkdatout is a step in altering the matlab script to the method of data collection used electrical load
- Overfitting is a step to reduce the error generated by the training data are limited but the complexity of the input and output relationship[13]. In this study overfitting can be detected when checkhing errors while training error increases steadily declining.
- Optimization of error results in the short-term load forecasting using fuzzy subtractive clustering method to change some parameters including radius cluster called influence range, input and epoch.
- Initializes influence anatar value range with 0.1 up to 0.9, in this study influence range is limited to the value of 2 digits behind the comma (eg: 0.12).

3. Pattern of Load Characteristics

In general, anomalies load characteristics differ with the load weekdays. Load characteristic weekday show similar patterns and repetitive, because the utility electrical load averaged together. While the load characteristic anomalies shows a pattern inconsistent, because utility erratic electrical load, for example Eid under review has electrical load is low compared to other national holidays. Due to the vast majority of Muslims in Indonesia, so many people who celebrate it. Usually industrial activity stopped for a while and the workers take time off from work a few days. **Fig.2** shows the electrical anomaly load patterns for ± 8 years is different every year due to the added or decreased load electricity used by affected from external factors such as population growth.

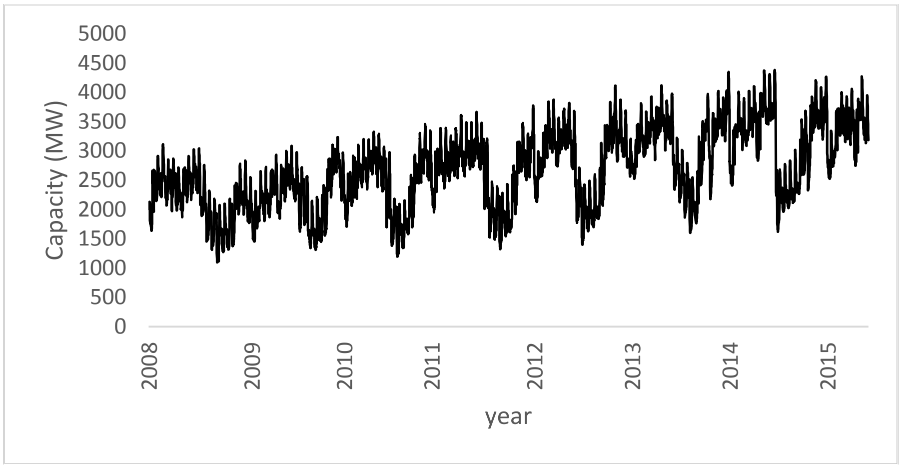

Figure 2. Graphics Load National Holidays Year 2008- May 2015

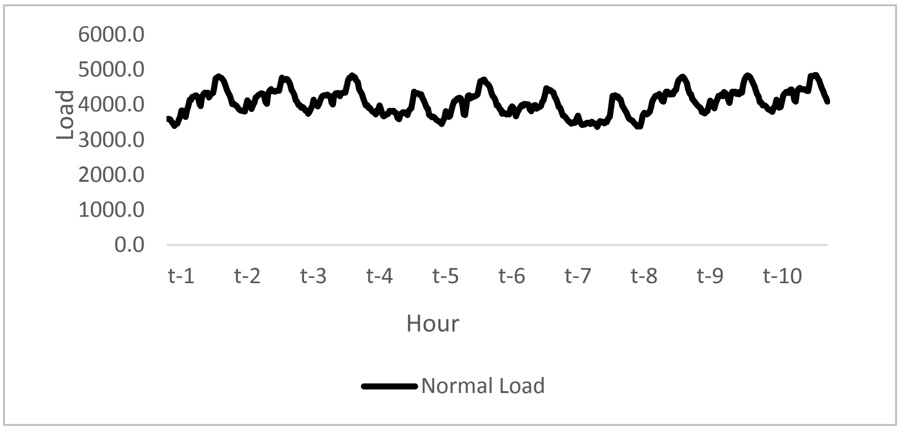

Figure 3. Graphics 10 Load Weekdays Sample Year 2014

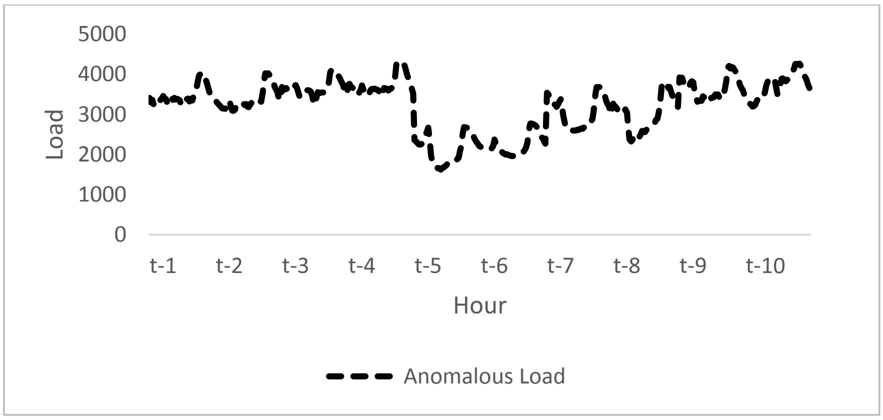

Figure 4. Graphics 10 Load National Holidays Sample Year 2014

Table 2. 10 Date sample Anomalous and Normal Load

	Anomalous Load	Normal Load
	Date	
1	14 January	12 Mei
2	31 March	13 Mei
3	18 April	14 Mei
4	27 Mei	15 Mei
5	28 July	16 Mei
6	29 July	17 Mei
7	17 August	18 Mei
8	5 October	19 Mei
9	25 October	20 Mei
10	26 December	21 Mei

Differences in the pattern load with load weekday anomaly shown in Fig.3 and Fig.4. On the national holiday has the highest peak load reached 4308.5 MW, while on weekdays reached 4842.6 MW. As well as the minimum burden on national holidays reached 1620.8 MW, while on weekdays reached 3367.3 MW.

From the minimum load value on a national holiday with weekday has a difference of 1746.52 MW, while the peak load has a difference of 941.2 MW. In addition, the average load on the national holiday of 3202.7 MW and on weekdays at 4084.3 MW. From a review of the characteristics of the burden on national holidays and weekdays are basic considerations in this study.

4. Result

The study short-term power load forecasting with fuzzy subtractive clustering method (FSC) using a total of 133 electric load data on a national holiday by the data history from 2008 until 2015. In the data all tepatya 133 dated May 16, 2015 is the target electrical load and a day Isra Mi'raj Prophet Muhammad. So that the proper output will approach the target value of electrical load. In this study using 10 to 50 training data and checking the data with previous data that has been normalized.

Table 3. Forecastig Accuracy 30 Input and Radius Cluster = 0.5

Input	RMSE (MW)	Forecasting Accuracy (%)
30	373.0651	88.83011069

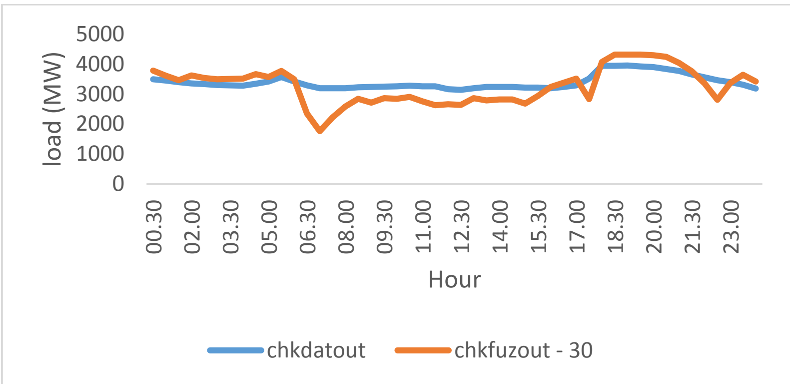

Figure 5. Comparison Chart Actual Load and Forecast Load with Different Input , Influence range = 0.5

Judging from Fig.5 obtained from research lerning input 40 and the central cluster radius used 0.5 produces the value of forecasting accuracy 88.8301%, the value of the average error is 11.1698%. The average error value generated exceeds the maximum value of the standard error of PLN 5%,. If the error generated exceeds PLN standards, may result in power losses. Thus, in the energy planning, which should PLN can save energy per year but will suffer losses both economically and technically. So needed optimization.

Based on the research that has been done the value of forecasting accuracy is not satisfactory because much of the maximum value of PLN standard error is 5%, so as to optimize and generate better value must change the value of the parameter settings. In this study the optimization calculation, setting parameters used are the input parameters, parameters and parameter epoch cluster radius.

4.1. Parameter Input

Input parameter is a trial in which the conversion of the learning value of the input data (learning data input). In studies learning data input digunakana between 10 to 50 (in increments of 10). With the setting value of learning data input to produce their comparative value of forecasting accuracy that can be seen in Table IV. , The highest accuracy of forecasting value of 88.8301% and an average error of 373.0651 MW with 30 input so that it can be concluded that the greater the learning input data is then the higher the value of forecasting accuracypada Fig.6 which shows the difference in load forecasting accuracy by learning input Data between 10 and 60. the output (chkfuzout) using the method of FSC (Subtractive Fuzzy Clustering) which is close to the target actual load, then the output results (chkfuzout) the results obtained in its calculations.

Setup parameters input learning between 10 and 60 inputs have different time duration to get the output in the calculation using the FSC (Subtractive Fuzzy Clustering). Learning more and more the longer the duration of data input is needed, as the sample taken with learning input data is membutahkan duration of 40 ± 10 minutes while learning input data requires a duration of 60 ± 45 minutes.

Table 4. Optimization of Forecasting Accuracy with Radius Cluster = 0.5

Input	RMSE (MW)	Forecasting Accuracy (%)
10	934.0676	72.0066
20	444.0062	81.8202
30	373.0651	88.8301
40	582.9978	82.4031
50	513.6250	84.7245
60	790.0281	76.0881

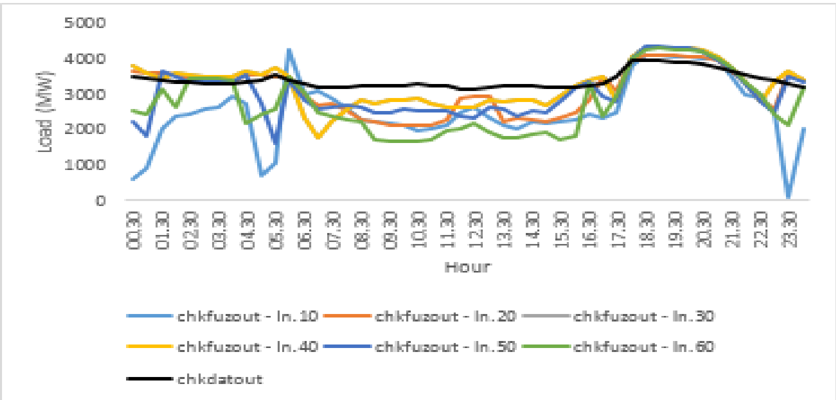

Figure 6. Comparison Graphics Actual Load And Load Forecasting with Various Input,

Influence Range = 0.5

4.2. Parameter Radius cluster

Parameter radius cluster or influence a range of 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. Due to learning the results of the data input 30 to produce the best forecasting accuracy between 10 and 60 input data, the input learning 30 learning data is used as input for the conversion parameter cluster radius. The results of load forecasting is almost close to the target, which has a cluster radius forecasting accuracy and the average error smallest is 0.6 to 90.3482% forecasting accuracy and 323.6582 MW so that the value of the error generated at 9.6517%. Because best results of forecasting accuracy by learning input 30 and radius 0.6 cluster, the cluster radius optimization study 2 decimal places using the parameters and limits the cluster radius between 0.61 up to 0.69.

Table 5. Optimization of Forecasting Accuracy with 30 Input and Radius Cluster 0.61 until 0.69

ra	RMSE (MW)	Forecasting Accuracy(%)
0.61	241.973029	92.77976513
0.62	233.519079	93.03270922
0.63	343.02018	89.98685577
0.64	257.904316	92.26687895
0.65	256.470731	92.310917
0.66	275.449019	91.72399983
0.67	418.070822	87.39658466
0.68	406.007807	87.76153715
0.69	397.717319	88.01224939

As a result the value of the load forecasting accuracy is getting better as shown in Table V. with cluster radius 0.62 to 93.0327%. And the average discount MW and error 233.5190 6.9672% error value. In studies radius parameter setup of the cluster, if the cluster radius values smaller then the duration required for the longer and the smaller the radius value cluster does not affect the value of the more ugly the resulting accuracy.

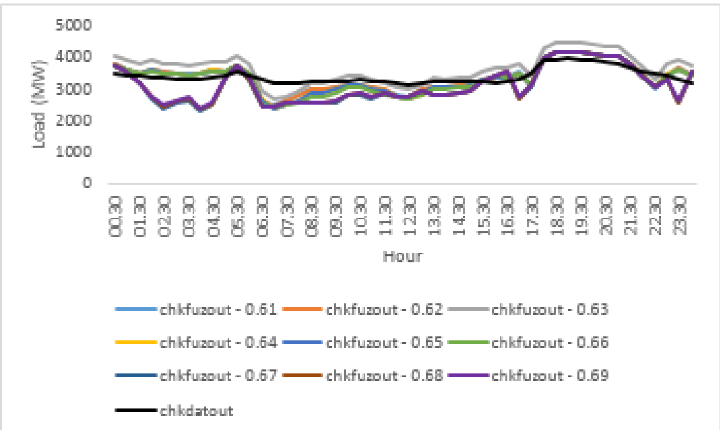

Figure 7. Comparison Graphics Actual Load and Load Forecasting with 40 Input and Radius Cluster 0.61 until 0.69

4.3. Parameter Epoch

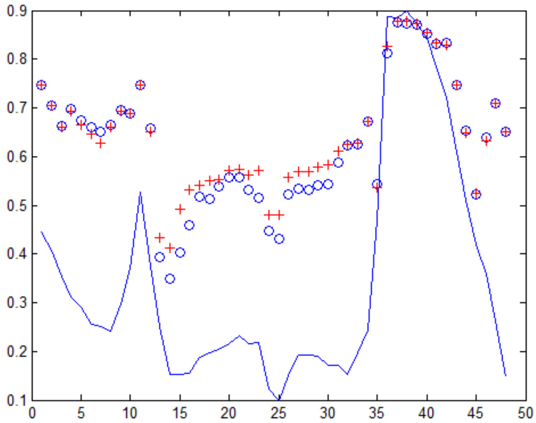

Figure 8. Graphics Optimization of Load Forecasting with 30 Input and Radius Cluster 0.62 with epoch 10

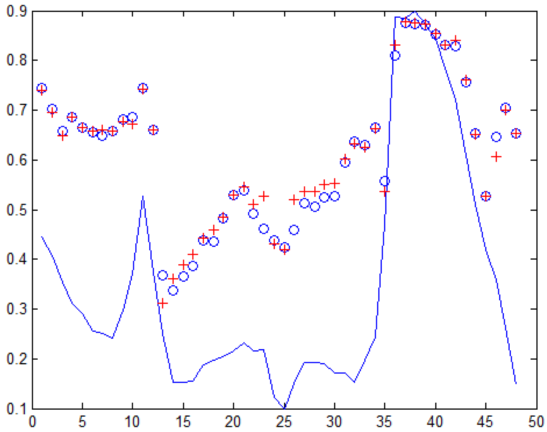

Figure 9. Graphics Optimization of Load Forecasting 30 Input and Radius Cluster 0.62 with epoch 100

Setup parameters penilitian mrupakan epoch in the initial setup of the epoch value by 20 to 100. The setting value of the epoch in the study do not affect the optimization of the value of the error, because the value of the error when the epoch changed from 20 to 100 fixed at 6.9672%. Judging from Fig.7 and Fig.8, setup epoch value indicates the ratio in a script that is operated by means of optimization marked lingakaran ('o') and how to overfitting the plus sign ('+') is red so that if two markers close to the target, the results of error gets smaller and better forecasting accuracy.

The study load forecasting can use a variety of methods. To determine the value of forecasting accuracy in this study did a comparison with the method of time series load coefficient. Comparison with actual load or a target between load coefficient method and fuzzy subtractive clustering (FSC) is intended to determine which method is better. Load coefficient calculation method is konvensinal to determine the load forecasting. Due to that, the sample used the learning input 30 and cluster radius 0.62 for each method.

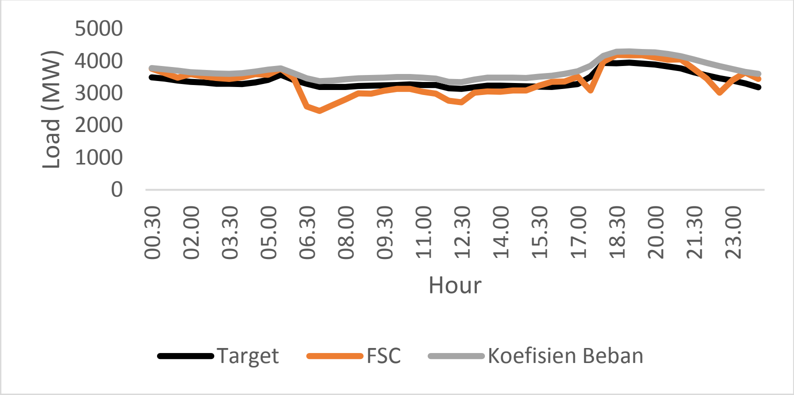

Figure 10. Comparison Graphics Load Coeffiicient and FSC with Actual Load

FSC method has advantages in learning abilities that can solve complex problems without formulating funsinya but using potential point or degree of membership and the results are semi deterministic data output so that the trial process is performed several times the output will not match exactly. While the load coefficient method is deterministic output results so that if done several times the output will be the same but have the function of so many rules or formulas used in this study. So the use of FSC method in this study resulted in a better error because the system better learning.

Table 6. Deficiency and Advantages FSC Method and Load Coefficient

FSC (*fuzzy subtractive clustering*)	Koefisien beban
Kekurangan: Data bersifat semi deterministik	Kelebihan: Data bersifat deterministik
Kelebihan: Kemampuan belajar yang dimiliki metoda FSC , sehingga tidak perlu untuk merumuskan fungsinya, sehingga cocok untuk STLF yang merupakan permasalahan yang rumit dan tidak diketahui fungsinya .	Kekurangan: Memiliki kaidah atau fungsi dalam pemecahan masalah *short term load forecasting (STLF)*.

The exact method used to study short-term load forecasting can save costs (cost) so that the company did not suffer huge loss. Judging from Table.VII is the most cost-effective method of Fuzzy Subtractive Clustering (FSC), which has been optimized Rp 373,630,526.7 but those not optimized Rp 596,904,176.4, so the difference of Rp 223,273,649.7. Then optimizing methods greatly affect the cost savings incurred.

Table 7. Cost Comparison Load Coeficient Method and FSC

Metode	Eror (MW)	Cost (Rupiah)
Koefisien Beban	293.1065	468,970,456.5
FSC	373.0651	596,904,176.4
FSC (Optimasi)	233.5191	373,630,526.7

5. Conclusion

Characteristics of the load anomaly patterns show inconsistent, because utility erratic electrical load, for example Eid under review has electrical load is low compared to other national holidays. Due to the vast majority of Muslims in Indonesia, so many people who celebrate it. Usually industrial activity stopped for a while and the workers take time off from work a few days.

Short-term load forecasting (STLF) using fuzzy subtractive clustering method (FSC) prior to conducting research with learning optimized input 30 produces a value of 88.8301% accuracy so that the average error obtained MW 373.0651 and 11.1698% error value.

Parameter setting for short term load forecasting optimization (STLF) using fuzzy subtractive clustering method (FSC) which consists of three input parameters, cluster radius or influence range and epoch. In this study the impact of changing radius search of a cluster or influence range. With the optimization in this study resulted in accuracy by learning the value of input 30, cluster radius is 0.62 and the epoch 20 93.0327%, so it has an average error of 233.5190 MW and 6.9672% error value. So the optimization in this study was very influential in optimizing the value of forecasting accuracythat has not been optimized with an optimized at 6.5983%.

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