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A VERY SHORT-TERM LOAD FORECASTING IN TIME OF PEAK LOADS USING INTERVAL TYPE-2 FUZZY INFERENCE SYSTEM: A CASE STUDY ON JAVA BALI ELECTRICAL SYSTEM

JAMAALUDDIN[1,2,*], IMAM ROBANDI[1], IZZA ANSHORY[1,2]

[1]Departemen Teknik Elektro Institut Teknologi Sepuluh Nopember (ITS), Surabaya 60111, Jawa Timur, Indonesia
[2]Program Studi Teknik Elektro, Universitas Muhammadiyah Sidoarjo, Jl. Raya Gelam, Candi, Sidoarjo, Jawa Timur, Indonesia
*Corresponding Author: jamaaluddin@umsida.ac.id

Abstract

The process of generation, transmission and distribution of electricity to the customer must be operated properly as they are related to economic problems. One of these planning processes is a very short term forecasting. A very short term load forecasting was done one day before the day of operation that has a planning time interval every 30 minutes. Fuzzy logic is one of the methods in very short term load forecasting. This study used Interval Type-2 Fuzzy Inference System (IT-2FIS) since it has high flexibility. IT-2FIS is the development of the Footprint of Uncertainty (FOU) at IT-1FIS method that has a very flexible advantage in changing FOU, so it is supportive to form the initial processing of time series data, computation, simulation and system model validation. The implementation of IT-2 FIS was on a very short term load forecasting in peak load time. This study found an average of very short term forecasting error rate on the fourth Friday in October 2015 and 2016 is 0.71% when IT-2 FIS was implemented. This result is better than using IT-1 FIS whose average of very short term forecasting error rate is 1.11%.

Keywords: IT-1 FIS, IT-2 FIS, Very short term load forecasting.

1. Introduction

Good forecasting is required in an operational arrangement of a power system. This electrical system operation starts from the generation system, transmission system and distribution system to the customer [1]. This integration is carried out at an electrical agency tasked with forecasting loads and regulating power systems [2-4]. On the forecasting of electrical power, there are at least three kinds of forecasting: long term forecasting, short forecasting and very short term forecasting. Long-term power load forecasting is done at the annual period and is conducted for planning maintenance, replacing tool plants and labour and for planning needs of the fuel operations for one year. Short-term electric load forecasting, i.e., forecasting a daily electricity load to find out the daily peak loads that occur in a year in order to make daily power generation planning for one year. Meanwhile, the forecasting of very short term electric load refers to an electrical load forecasting that is conducted every 30 minutes daily. Jamaaluddin and Sumarno [1] reported that a very short term load forecasting is done one day before the day of loading to plan the electric power generation for the next day. According to Jamaaluddin and Robandi [5], this electrical institute performs a short-term and very short-term forecasting. This load forecasting is needed in relation to the economic problem of generation.

Previous researchers using Fuzzy Logic [6-8] have done optimization of short-term loads forecasting. Present study by da Silva and de Andrade [9] tried to employ Fuzzy logic that is applied for a very short-term load forecasting in peak load time (at 18:00 to 21:30). Other researchers investigated very short-term loads forecasting by using Artificial Neural Network (ANN) and revealed that the Main Absolute Percentage Error (MAPE) was between 0.89% - 1.25% [10]. Another study by da Silva and de Andrade [9] employed Autoregressive Integrated Moving Average Model (ARIMA) and the intelligent system, which has MAPE value between 2.62% - 5.27% and study that using Adaptive Neuro-Fuzzy Inference System (ANFIS) has MAPE results between 10.21% -18.45% [9]. This IT-2 FIS is a development of IT-1 FIS with the excess setting on the FOU that is intended to produce a smaller forecasting error than the other methods.

The study focused on the third plan by planning and setting up the electrical load on an area, in this case, the electrical system in Java and Bali. Java Bali electricity system is the largest electricity system in Indonesia that interconnects all power plants and all loads in Java, Bali and Madura Islands [11-13]. Existing data on the Java Bali electricity system was used as the primary data of this study and the forecasting system that was employed is a very short term forecasting. This very short-term load forecasting has a 30-minute loading data interval that is used as the basis of how much power resources to generate, what generating arrangements that need to be operated, which plants that need to be maintained and which plants that are ready to operate.

2. Fuzzy Logics

The uncertainty concept of the fuzzy type-2 set was first introduced by Zadeh in 1975 as the development of the ordinary fuzzy set concept of "fuzzy fuzzy" or fuzzy type 1. The fuzzy type-1 logic system is often used as the knowledge base to construct rules in a fuzzy logic system (FLS) that is often uncertain. There are three reasons why uncertainty of rules occurred, that cover: [14-16]:

- The words used as antecedents and consequents of the rules may have different meanings to different people.
- Consequents obtained from a poll of a group of experts will often differ on the same rules because the experts are not necessarily all agree on the rules.
- Data training contains a lot of noise

The uncertainty in antecedent or consequent is translated to the uncertainty of antecedent or consequent membership function. Fuzzy logic system type-1 whose membership function is fuzzy set type-1 cannot directly resolve the uncertainty of rule type 2 fuzzy logic system, whereas antecedent or consequent function of fuzzy type-2 set membership is able to overcome the uncertainty of rules. The fuzzy set type-2 themselves have membership levels that are fuzzy.

Levels on the fuzzy set type-2 can be in a subset of secondary membership. Similar to Type-1 FLS, Type-2 FLS also includes FIS membership and defuzzification functions. Based on studies by Liu et al. [17] and Wu and Nie [18], the difference is, before the defuzzification process, there is a type reduction process that has several algorithmic methods such as Mendel Algoritm Kernic (KMA), Mendel Algorithm Kernic Enhance (EKMA), Mendel Algorithm with Initialization (EKMANI) Kernic Mendel, Iterative Algorithm with Stop Condition (IASC) and Enhance Iterative Algorithm with Stop Condition (EIASC).

2.1. Interval type-2 Fuzzy set

An interval of type-2 fuzzy set (IT-2FS) is denoted $\tilde{A}$ with membership function $\mu\tilde{A}$ with $x \in X$ and $u \in Jx \subseteq$. Its characteristic can be recognized in the following Eq. 1 [18, 19].

$$\tilde{A} = \int_{x \in X} \int_{x \in Jx} \frac{\mu\tilde{A}(x,u)}{(x,u)} Jx \subseteq [0.1] \tag{1}$$

x is the primary variable having domain X; $u \in U$, a secondary variable, has a domain Jx for every $x \in X$; Jx is called the primary membership of x. Uncertainty with respect to $\tilde{A}$ is represented by a combination of all primary membership (Jx) called the Footprint of Uncertainty (FOU) of $\tilde{A}$. The equation can be seen as follows:

$$FOU(\tilde{A}) = \bigcup_{\forall x \in X} Jx = \{(x,u); u \subseteq [0,1]\} \tag{2}$$

Jx is an Interval with Eq. (3):

$$Jx = \{(x,u); u \in [\underline{\mu}_{\tilde{A}}(x), \overline{\mu}_{\tilde{A}}(x)]\} \tag{3}$$

$FOU(\tilde{A})$ can be expressed by Eq. (4):

$$FOU(\tilde{A}) = \bigcup_{\forall x \in X} [\{\underline{\mu}_{\tilde{A}}(x), \overline{\mu}_{\tilde{A}}(x)\}] \tag{4}$$

Jx = Primary membership from x.

$\underline{\mu}_{\tilde{A}}$ = Lower Membership Function (*LMF*) from $\tilde{A}$.

$\overline{\mu}_{\tilde{A}}$ = Upper Membership Function (*UMF*) from $\tilde{A}$.

with the graphical description can be seen in Fig. 1.

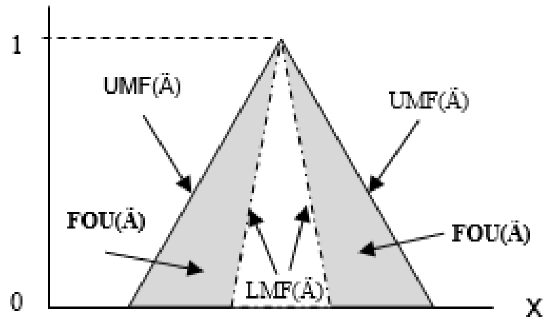

Fig. 1. *FOU* (graycolor), *LMF* (dashed line), *UMF* (solid line).

2.2. Interval type-2 Fuzzy inference system

Fuzzy Inference System (FIS) type-2 is almost the same as FIS type-1, using the same stages. Operation of Fuzzy Inference System type-2 can be seen in the case of giving tip "food" and service at a restaurant as described in Fig. 2.

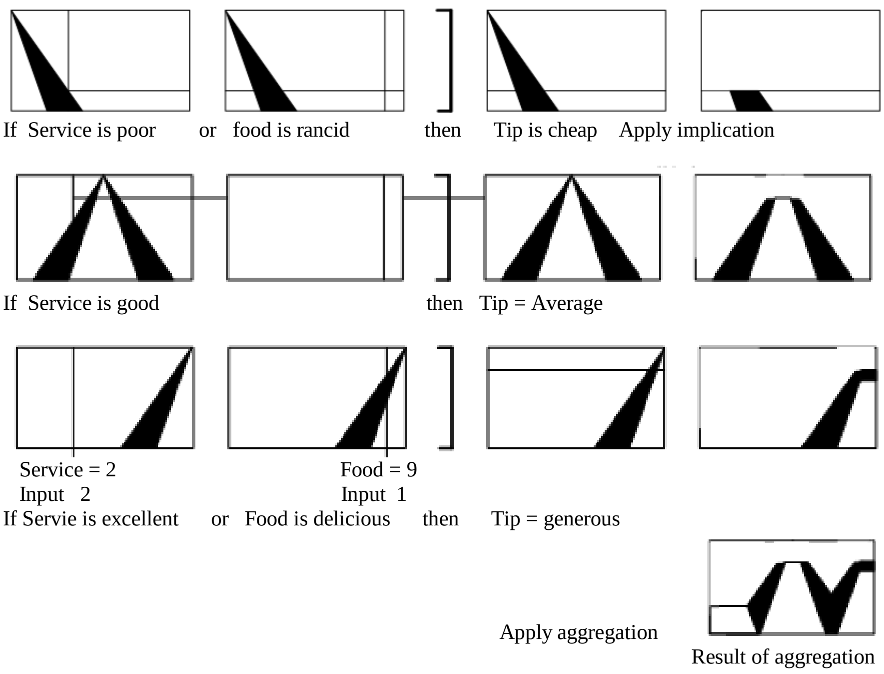

Fig. 2. Fuzzy inference system Mamdani type-2.

2.3. Deffuzzyfication

In Fuzzy Interval type-2, the logic control defuzzification process pass through the type-reducer, which has several algorithmic methods such as (KMA), (EKMA), (EKMANI), (IASC) and (EIASC) [20]. The defuzzification process using centroid on IT-2FLS has been proposed by Mendel Kernic.

3. Research Methods

3.1. Preparation phase

In the preparation phase, it is necessary to prepare the data to be processed, for instance, the load at 17.30; 18.00; 18.30; 19.00; 19.30; 20.00; 20.30; 21.00; 21.30, on the first Friday, the second, third and fourth of October, 2013; 2014; 2015 and 2016, with the following steps:

- Grouping of load data at times as listed above.
- Identifying the load at each time, the first Friday, second and third in the hour of forecasting

$$TD_{(i)} = \frac{\lfloor TD_{(i)F-3} + TD_{(i)F-2} + TD_{(i)F-1} \rfloor}{3} \tag{5}$$

- $TD_{(i)}$ = Time Difference is the average load on the First Friday, Second and Third.

$$LD_{(i)} \cdot TD_{(i)} = \lfloor SD_{(i)} - TD_{(i)} \rfloor \cdot 100 \tag{6}$$

$SD_{(i)}$ is the load at the predicted time.

- Finding the value $TLD_{(i)}$ (The typical Time Load Difference) by calculating the average load of $LD_{(i)}$ on each Friday in October at the hour predicted by the same time last year.
- Calculating *VLD* (Variation Load Difference at Time), which is being forecasted.

$$VLD_{(i)} = LD_{(i)} - TLD_{(i)} \tag{7}$$

3.2. Processing stage

The processing stage was conducted for modelling very short term load forecasting using Interval Type-2 Fuzzy Inference System, which was carried out by using several steps:

- Creating a membership function input interval type-2 fuzzy logic system such as input *X* dan *Y* and output membership function such as Z for time to be predicted with the following conditions:

  X: $VLD_{MAX(i)}$ the same time in the day prior to the forecast time.
  Y: $VLD_{MAX(i)}$ the previous time (adjacent) in the same time type in the forecasting year.
  Z: Forecasting $VLD_{MAX(i)}$ at time to be forecasted.

- Planning the membership function of the type-2 fuzzy logic system interval such as antecedent (*X*, *Y*) and consequent (*Z*) to get the best value of the footprint of uncertainty
- Making fuzzy rules interval type-2 fuzzy inference system (IT-2FIS) as follows:

  IF X is A_i AND Y is B_i THEN Z is C_i
- Implementing the AND operation at the fuzzy inference system type-2 (IT-2FIS)
  - Implementing MIN's implication function on fuzzy rules.
  - Applying MAX composition to each fuzzy rule implication result.
  - Calculating the value of defuzzification through the type reducer using Mendel Kernic Algorithm to get the value of Forecast VLD_{MAX}.

3.3. Phase after processing

The advanced stage is looking for peak load value and forecasting error from Forecast VLD_{MAX}, which was carried out as follows:

3.3.1 Calculating the forecast load difference for the forecasted time

After knowing the value of VLD_{MAX}, the next step is to look for forecasting LD_{MAX} in each year of forecast, using the following formula:

$$LD_{MAX\,(i)} = VLD_{MAX(i)} + TLD_{MAX\,(i)} \tag{8}$$

3.3.2. Calculating forecasting error

After knowing the forecasting value in the year sought, the calculation of errors (*Error%*) in each forecast year is carried out using the following formula:

$$Error\% = \frac{P_{forecast} - P_{actual}}{P_{actual}} \times 100\% \tag{9}$$

$$Error\% = \frac{P_{\max(i)} - MaxSD_{(i)}}{MaxSD_{(i)}} \times 100\% \tag{10}$$

4. Results and Discussion

Explanation of very short term load forecasting method above is one applicable method. However, the above method can be developed using a basic time analysis basis on four days before forecasting day with the same hour, or 4 hours before the forecast hour and so on. In short-term electricity load forecasting, some researchers have used IT-1 FIS and IT-2 FIS in order to get the results of forecasting errors that are smaller compared to other methods. In the short-term electricity load forecasting method, some researchers used different time analysis by using 4 days before the forecast day, there are also those who use other days with the same character as forecasting days [2, 3].

This study used data loading of Java Bali electrical system [11-13, 21] by investigating loads on the first, second, third and fourth Fridays in October 2012 until 2016 at peak load time (at 17.30 to 21.00) to find the value of *TD*, *LD*, and *VLD*. The calculation results are in Tables 1 and 2. The *TD* value is derived from the average value of the sum of the Friday's loads to the first, the second, and the third Fridays. The value of *LD* was obtained from the difference value of *LD* and the prediction of 4th Friday. Table 1 shows the search for *LD* values in 2012 and Table 2 shows the value of *TD* and *LD* in forecasting year 2013.

Table 1. Calculation of *TD* and *TLD* in 2012.

Time	2012 (MW)				*TD*	*LD*
	F-3	F-2	F-1	F		
17.30	18,768.45	19,895.13	20,068.45	19,768.45	19,577.34	0.98
18.00	19,344.00	20,698.57	20,344.00	19,911.00	20,128.86	-1.08
18.30	19,667.00	20,587.89	20,839.00	20,178.00	20,364.63	-0.92
19.00	20,400.00	20,655.77	21,561.00	20,381.00	20,872.26	-2.35
19.30	20,711.00	20,625.11	22,003.00	20,634.00	21,113.04	-2.27
20.00	21,345.00	20,359.19	22,421.00	20,960.00	21,375.06	-1.94
20.30	21,625.00	20,123.86	22,594.00	21,321.00	21,447.62	-0.59
21.00	20,987.30	19,644.05	21,707.14	20,907.14	20,779.50	0.61
21.30	20,266.36	19,256.62	21,266.36	20,261.36	20,263.11	-0.01

F = Friday will be forecasted; F-3 = First Friday; F-2 = Second Friday; F-1 = Third Friday.

Table 2. Calculation of *TD* and *TLD* in 2013.

Time	2013 (MW)				*TD*	*LD*
	F-3	F-2	F-1	F		
17.30	21,068.45	21,304.92	21,868.45	21,568.45	21,413.94	0.72
18.00	21,344.00	22,145.91	22,044.00	21,811.00	21,844.64	-0.15
18.30	21,467.00	22,132.62	22,239.00	22,378.00	21,946.21	1.97
19.00	21,709.00	22,068.45	22,561.00	22,781.00	22,112.82	3.02
19.30	22,311.00	21,911.98	22,903.00	23,034.00	22,375.33	2.94
20.00	22,645.00	21,807.14	23,121.00	23,760.00	22,524.38	5.49
20.30	21,925.00	21,594.28	23,594.00	23,399.00	22,371.09	4.59
21.00	21,787.30	21,266.36	22,907.14	22,707.14	21,986.93	3.28
21.30	21,466.36	20,695.91	22,766.36	22,261.36	21,642.88	2.86

F = Friday will be forecasted; F-3 = First Friday ; F-2 = Second Friday; F-1 = Third Friday.

After obtaining the value of *TD* and *LD*, *TLD* and *VLD* for 2014 were calculated (see Table 3). *TLD* for 2014 value was obtained from the average value of *LD* in 2013 and *LD* 2012. The value of *VLD* for 2014 was obtained from the difference between *LD* and *TLD* value in 2014. Using the same method, the data gained were used to calculate 2015 forecast using 2016 funds, as shown in Table 4.

Table 3. Calculation of *TD*, *LD*, *TLD* and *VLD* in 2014.

Time	2014 (MW)				*TD*	*LD*	*TLD*	*VLD*
	F-3	F-2	F-1	F				
17.30	21,704.61	22,133.11	22,004.61	22,004.61	21,947.44	0.26	0.85	-0.59
18.00	21,975.00	22,901.87	22,631.00	22,631.00	22,502.62	0.57	-0.62	1.19
18.30	22,181.00	22,821.94	22,812.00	22,812.00	22,604.98	0.92	0.53	0.39
19.00	22,353.00	22,704.61	23,191.00	23,191.00	22,749.54	1.94	0.33	1.61
19.30	22,411.00	22,941.31	23,878.00	23,878.00	23,076.77	3.47	0.34	3.13
20.00	22,767.00	22,779.65	23,974.00	23,974.00	23,173.55	3.45	1.77	1.68
20.30	22,453.00	22,636.61	23,573.00	23,573.00	22,887.54	2.99	2.00	0.99
21.00	21,779.65	22,286.85	23,479.65	23,479.65	22,515.38	4.28	1.94	2.34
21.30	21,586.85	21,548.88	23,186.85	23,186.85	22,107.53	4.88	1.42	3.46

F=Friday will be forecasted; F-3 = First Friday ; F-2 = Second Friday; F-1 = Third Friday.

Table 4. Calculation of *TD*, *LD*, *TLD* and *VLD* by 2015 and 2016.

Time	2015				2016			
	TD	***LD***	***TLD***	***VLD***	***TD***	***LD***	***TLD***	***VLD***
17.30	23.333,39	-2,44	0,49	-2,93	23.123,47	3,35	-1,09	4,44
18.00	23.758,44	-3,44	0,21	-3,65	23.847,61	1,14	-1,44	2,58
18.30	23.845,54	-2,85	1,44	-4,30	23.939,25	1,88	-0,97	2,85
19.00	23.423,50	-0,44	2,48	-2,92	23.769,09	4,75	0,75	4,00
19.30	23.144,19	0,18	3,21	-3,02	23.489,09	6,43	1,83	4,60
20.00	22.782,98	1,84	4,47	-2,63	23.434,67	3,68	2,65	1,03
20.30	22.561,00	4,15	3,79	0,36	23.531,12	0,98	3,57	-2,60
21.00	22.652,07	5,67	3,78	1,89	23.034,78	0,77	4,98	-4,20
21.30	22.107,57	6,67	3,87	2,80	22.556,19	0,93	5,78	-4,84

The obtained *X* value is exactly similar to *VLD* for 2014 and the load per hour during load time, which was predicted in 2015 is *VLD* for 2015. It then becomes consequent or *Z*. In addition, *Y* value will be obtained from VLD value for 2015 at near-close time. For the 2016 forecasting year, the processed value is the *VLD* value of 2015 as the mat lab input on the antecendent *X*, while the value of its output/consequent (*Z*) is *VLD* 2016. The value of *Y* will be obtained in the same way for 2015. After gaining the data in Tables 5 and 6, the next step is to include the formation of Fuzzy basic rules for the forecasting in 2015 and 2016 by using the data input *X*, *Y*, and *Z* whose results shown in Tables 7 to 12. The membership function value was obtained by entering the *X* value in the membership function as listed below and a high membership degree is inputted as the antecedents and its consequence values.

The input variables (*X* and *Y*) and the output variable (*Z*) consist of 11 sets of Fuzzy as follows:

- Negative Very Big (NVB) with a values -6 up to -4
- Negative Big (NB) with a values -5 up to -3
- Negative Medium (NM) with a values -4 up to -2
- Negative Small (NS) with a values -3 up to -1
- Negative Very Small (NVS) with a values -2 up to 0
- Zero (ZE) with a values -1 up to 1
- Positive Very Small (PVS) with a values 0 up to 2
- Positive Small (PS) with a values 1 up to 3
- Positive Medium (PM) with a values 2 up to 4
- Positive Big (PB) with a values 3 up to 5
- Positive Very Big (PVB) with a values 4 up to 6

Table 5. Input data for fuzzy forecasting 2015.

Time	2014	2015	Input		Output
	VLD	***VLD***	***X***	***Y***	***Z***
17.30	-0.5884	-2.9261	-0.5884	-3.6531	-2.9261
18.00	1.1886	-3.6531	1.1886	-2.9261	-3.6531
18.30	0.3903	-4.2956	0.3903	-2.9174	-4.2956
19.00	1.6065	-2.9174	1.6065	-4.2956	-2.9174
19.30	3.1346	-3.0229	3.1346	-2.6334	-3.0229
20.00	1.6822	-2.6334	1.6822	-3.0229	-2.6334
20.30	0.9927	0.3596	0.9927	1.8918	0.3596
21.00	2.3378	1.8918	2.3378	0.3596	1.8918
21.30	3.4576	2.8036	3.4576	1.8918	2.8036

Table 6. Input data for fuzzy forecasting 2016.

Time	2015	2016	Input		Output
	VLD	*VLD*	*X*	*Y*	*Z*
17.30	-2.9261	4.4380	-2.9261	-4.8432	4.4380
18.00	-3.6531	2.5752	-3.6531	4.4380	2.5752
18.30	-4.2956	2.8478	-4.2956	2.5752	2.8478
19.00	-2.9174	3.9985	-2.9174	2.8478	3.9985
19.30	-3.0229	4.5996	-3.0229	3.9985	4.5996
20.00	-2.6334	1.0344	-2.6334	4.5996	1.0344
20.30	0.3596	-2.5978	0.3596	1.0344	-2.5978
21.00	1.8918	-4.2031	1.8918	-2.5978	-4.2031
21.30	2.8036	-4.8432	2.8036	-4.2031	-4.8432

Table 7 reveals that *X* has 2 degrees of membership function and was taken as the value that has the highest degree that is similar to results of Tables 8 and 9 for forecasting year 2015.

The 2016 forecasting has the value of membership function of the value of *X*, *Y*, and *Z* as shown in Tables 10 to 12.

Table 7. Establishment of the basic rules for input value of *X* for 2015.

Time	Value	Membership function (μ)											Sets
	X	*NVB*	*NB*	*NM*	*NS*	*NVS*	*ZE*	*PVS*	*PS*	*PM*	*PB*	*PVB*	*X*
17.30	(0,5884)					0,6115	0,3885						NVS
18.00	1,1886							0,7820	0,2180				PVS
18.30	0,3903						0,6470	0,3530					ZE
19.00	1,6065							0,3810	0,6190				PS
19.30	3,1346									0,8220	0,1780		PM
20.00	1,6822							0,4120	0,5880				PS
20.30	0,9927						0,0178	0,9822					PVS
21.00	2,3378								0,8110	0,1890			PS
21.30	3,4576									0,5934	0,4066		PM

Table 8. Establishment of the basic rules for input value of *Y* in 2015.

Time	Value	Membership function (μ)											Sets
	Y	*NVB*	*NB*	*NM*	*NS*	*NVS*	*ZE*	*PVS*	*PS*	*PM*	*PB*	*PVB*	*Y*
17.30	(3,6531)		0,6720	0,328									NB
18.00	(2,9261)			0,953	0,047								NM
18.30	(2,9174)			0,911	0,089								NM
19.00	(4,2956)		0,2881	0,7119									NM
19.30	(2,6334)			0,622	0,378								NM
20.00	(3,0229)		0,1320	0,868									NM
20.30	1,8918							0,4350	,5650				PS
21.00	0,3596						0,6510	0,3490					ZE
21.30	1,8918							0,7500	0,2500				PVS

Table 9. Establishment of the basic rules for input *Z* value in 2015.

Time	Value	Membership function (μ)											Sets
	Z	*NVB*	*NB*	*NM*	*NS*	*NVS*	*ZE*	*PVS*	*PS*	*PM*	*PB*	*PVB*	*Z*
17.30	(2,9261)			0,9530	0,0470								NM
18.00	(3,6531)		0,6720	0,3280									NB
18.30	(4,2956)		0,2881	0,7119									NM
19.00	(2,9174)			0,9110	0,0890								NM
19.30	(3,0229)		0,1320	0,8680									NM
20.00	(2,6334)			0,6220	0,3780								NM
20.30	0,3596						0,6510	0,3490					ZE
21.00	1,8918							0,4350	0,5650				PS
21.30	2,8036							0,7500	0,2500				PVS

Table 10. Establishment of the basic rules for input *X* value in 2016.

Time	Value	Membership function (μ)											Sets
	X	*NVB*	*NB*	*NM*	*NS*	*NVS*	*ZE*	*PVS*	*PS*	*PM*	*PB*	*PVB*	*X*
17.30	(2,9261)			0,9530	0,0470								NM
18.00	(3,6531)		0,6720	0,3280									NB
18.30	(4,2956)		0,2881	0,7119									NM
19.00	(2,9174)			0,9110	0,0890								NM
19.30	(3,0229)		0,1320	0,8680									NM
20.00	(2,6334)			0,6220	0,3780								NM
20.30	0,3596						0,6510	0,3490					ZE
21.00	1,8918							0,4350	0,5650				PS
21.30	2,8036							0,7500	0,2500				PVS

Table 11. Establishment of the basic rules for input value Y in 2016.

Time	Value	Membership function (μ)											Sets
	Y	*NVB*	*NB*	*NM*	*NS*	*NVS*	*ZE*	*PVS*	*PS*	*PM*	*PB*	*PVB*	*Y*
17.30	(4,8432)	0,8780	0,122										NVB
18.00	4,4380										0,6570	0,3430	PB
18.30	2,5752								0,4850	0,5150			PM
19.00	2,8478								0,2570	0,7430			PM
19.30	3,9985									0,1870	0,8130		PB
20.00	4,5996										0,4782	0,5218	PVB
20.30	1,0344							0,8910	0,1090				PVS
21.00	(2,5978)			0,6940	0,306								NM
21.30	(4,2031)	0,2590	0,741										NB

Table 12. Establishment of the basic rules for input Z value in 2016.

Time	Value	Membership function (μ)											Sets
	Z	*NVB*	*NB*	*NM*	*NS*	*NVS*	*ZE*	*PVS*	*PS*	*PM*	*PB*	*PVB*	*Z*
17.30	4,4380										0,6570	0,3430	PB
18.00	2,5752								0,4850	0,5150			PM
18.30	2,8478								0,2570	0,7430			PM
19.00	3,9985									0,1870	0,8130		PB
19.30	4,5996										0,4782	0,5218	PVB
20.00	1,0344							0,8910	0,1090				PVS
20.30	(2,5978)			0,6940	0,3060								NM
21.00	(4,2031)	0,2590	0,741										NB

From the existing data-membership function, a table of basic rules for the forecasting year of 2015 and 2016 was then made as shown respectively in Tables 13 and 14.

From the basic rules of forecasting, a table conversion of the basic rules of forecasting in 2015 and 2016 for Matlab software code was made, as can be seen in Tables 15 and 16.

Table 13. Basic forecasting rules table for 2015.

X/Y	*NVB*	*NB*	*NM*	*NS*	*NVS*	*ZE*	*PVS*	*PS*	*PM*	*PB*	*PVB*
NVB		NM									
NB											
NM											
NS											
NVS		NM									
ZE			NM								
PVS			NB					ZE			
PS			NM			PS					
PM			NM				PVS				
PB											
PVB											

Table 14. Basic forecasting rules table for 2016.

X/Y	*NVB*	*NB*	*NM*	*NS*	*NVS*	*ZE*	*PVS*	*PS*	*PM*	*PB*	*PVB*
NVB											
NB									PB	PM	
NM	PB								PM	PVB/ PVS	
NS											
NVS											
ZE							NM				
PVS		NVB									
PS			NB								
PM											
PB											
PVB											

Table 15. Conversion table of 2015 basic rules for Matlabsoftware code.

No. of rules	**Antecendent**		**Consequent**	**No. of rules**	**Antecendent**		**Consequent**
	X	***Y***	***Z***		***X***	***Y***	***Z***
1	NVS	NB	NM	**1**	5	2	3
2	PVS	NM	NB	**2**	7	3	2
3	ZE	NM	NM	**3**	6	3	3
4	PS	NM	NM	**4**	8	3	3
5	PM	NM	NM	**5**	9	3	3
6	PS	NM	NM	**6**	8	3	3
7	PVS	PS	ZE	**7**	7	8	6
8	PS	ZE	PS	**8**	8	6	8
9	PM	PVS	PVS	**9**	9	7	7

Table 16. Conversion table of 2016 basic rules for Matlab software code.

No. of rules	**Antecendent**		**Consequent**	**No. of rules**	**Antecendent**		**Consequent**
	X	***Y***	***Z***		***X***	***Y***	***Z***
1	NM	NVB	PB	**1**	3	1	10
2	NB	PB	PM	**2**	2	10	9
3	NM	PM	PM	**3**	3	9	9
4	NM	PM	PB	**4**	3	9	10
5	NM	PB	PVB	**5**	3	10	11
6	NM	PVB	PVS	**6**	3	11	7
7	ZE	PVS	NM	**7**	6	7	3
8	PS	NM	NB	**8**	8	3	2
9	PVS	NB	NVB	**9**	7	2	1

The gained data were processed by using Matlab to obtain the *VLD* error value, for the forecasting year 2015 and 2016 by using IT-1 FIS and using IT-2 FIS. The Matlab results above were then inputted to the *VLD* forecasting value to get the value of the load and its error value. The results of the forecasting on *VLD* and the error value can be seen in Tables 17 and 18.

Meanwhile, the average value for each of the forecasting methods are shown in Table 19. From Table 19, it can be seen that in 2015 and 2016 and with different forecasting methods for forecasting using IT-1 FIS, there was 0.94% increase in forecasting errors in 2015 and 1.27% in 2016. The same thing happened for the use of IT-2 FIS forecasting method showing that there was an increase in forecasting errors in 0.70% in 2015 and 0.72% in 2016. Table 19 also showed that the use of the FIS IT-2 method has a smaller forecasting error value compared to the use of IT-1 FIS since IT-2 FIS provides a greater area of membership with the presence of FOU. This gives higher forecasting accuracy. Graphically, the error forecasting in 2015 can be seen in Fig. 3. In addition, the graphic of the error forecasting in 2016 is shown in Fig. 4. From the the discussion, it can be concluded that the use of IT-2 FIS, which has never been used to forecast very short term loads by determining the electric load on the previous date with the same character on Friday before October forecasting Friday performs forecasting errors that are smaller than using other forecasting methods.

Table 17. Calculation of load and forecasting value of 2015 using IT-1-FIS and IT-2 FIS.

IT-1 FIS - 2015				
Output Forecast	**Forecast *LD***	**Forecast *P*'(MW)**	**Actual (MW)**	**Error (%)**
-3,0000	-2,5090	22.747,96	22.765,20	0,0757
-3,7699	-3,5616	22.912,25	22.940,00	0,1210
-3,4109	-1,9692	23.375,97	23.165,00	0,9107
0,0000	2,4811	24.004,67	23.321,30	2,9302
-1,5823	1,6256	23.520,41	23.187,00	1,4379
-3,3518	1,1181	23.037,73	23.201,40	0,7054
0,0000	3,7949	23.417,16	23.498,30	0,3453
1,6280	5,4072	23.876,90	23.936,65	0,2496
1,0050	4,8749	23.185,29	23.582,91	1,6860
			Sum	8,4620
			Average	0,9402

IT-2 FIS - 2015				
Output Forecast	**Forecast *LD***	**Forecast *P*'(MW)**	**Actual (MW)**	**Error (%)**
-3,0000	-2,5090	22.747,96	22.765,20	0,0757
-3,8301	-3,6218	22.897,95	22.940,00	0,1833
-3,3731	-1,9314	23.384,98	23.165,00	0,9496
0,0000	2,4811	24.004,67	23.321,30	2,9302
-3,0000	0,2079	23.192,30	23.187,00	0,0229
-3,2857	1,1842	23.052,79	23.201,40	0,6405
0,0000	3,7949	23.417,16	23.498,30	0,3453
1,6869	5,4661	23.890,25	23.936,65	0,1939
1,7510	5,6209	23.350,21	23.582,91	0,9867
			Sum	6,3282
			Average	0,7031

Table 18. Calculation of load and forecasting value of 2016 using IT-1-FIS and IT-2 FIS.

IT-1 FIS - 2016				
Output Forecast	**Forecast *LD***	**Forecast *P*'(MW)**	**Actual (MW)**	**Error (%)**
4,0014	2,9141	23.797,30	23.898,27	0,4225
3,0000	1,5628	24.220,31	24.119,00	0,4200
0,0000	-0,9691	23.707,26	24.389,00	2,7953
3,5001	4,2522	24.779,80	24.898,27	0,4758
4,9091	6,7376	25.071,69	24.999,00	0,2908
2,7279	5,3732	24.693,88	24.297,00	1,6334
-3,0000	0,5747	23.666,36	23.761,00	0,3983
-4,0012	0,9756	23.259,51	23.213,00	0,2004
0,0000	5,7778	23.859,44	22.767,00	4,7984
			Sum	11,4349
			Average	1,2705

IT-2 FIS - 2016				
Output Forecast	**Forecast *LD***	**Forecast *P*'(MW)**	**Actual (MW)**	**Error (%)**
4,0851	2,9978	23.816,66	23.898,27	0,3415
3,0003	1,5631	24.220,38	24.119,00	0,4203
0,0000	-0,9691	23.707,26	24.389,00	2,7953
3,5922	4,3443	24.801,69	24.898,27	0,3879
4,3612	6,1897	24.942,99	24.999,00	0,2240
2,6751	5,3204	24.681,50	24.297,00	1,5825
-3,0000	0,5747	23.666,36	23.761,00	0,3983
-4,0006	0,9762	23.259,65	23.213,00	0,2010
-4,7000	1,0778	22.799,30	22.767,00	0,1419
			Sum	6,4927
			Average	0,7214

Table 19. Average comparison of usage IT-1 FIS and IT-2 FIS.

Time	IT-1-FIS		Time	IT-2-FIS	
	2015	2016		2015	2016
17.30	0,08	0,42	**17.30**	0,08	0,34
18.00	0,12	0,42	**18.00**	0,18	0,42
18.30	0,91	2,80	**18.30**	0,95	2,80
19.00	2,93	0,48	**19.00**	2,93	0,39
19.30	1,44	0,29	**19.30**	0,02	0,22
20.00	0,71	1,63	**20.00**	0,64	1,58
20.30	0,35	0,40	**20.30**	0,35	0,40
21.00	0,25	0,20	**21.00**	0,19	0,20
21.30	1,69	4,80	**21.30**	0,99	0,14
Sum	8,46	11,43	**Sum**	6,33	6,49
Average	0,9402	1,2705	**Average**	0,7031	0,7214
Average 2 Years		1,1054	**Average 2 Years**		0,7123

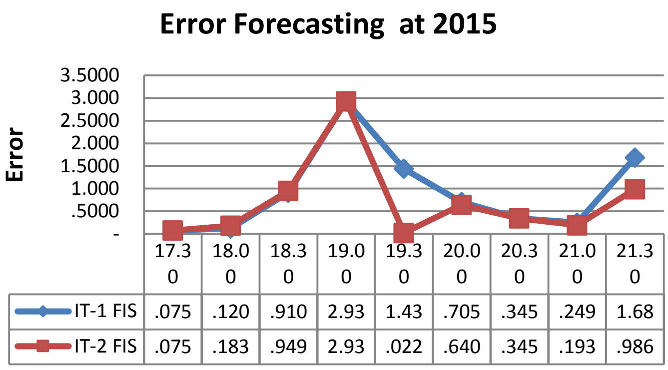

Fig. 3. Error forecasting 2015.

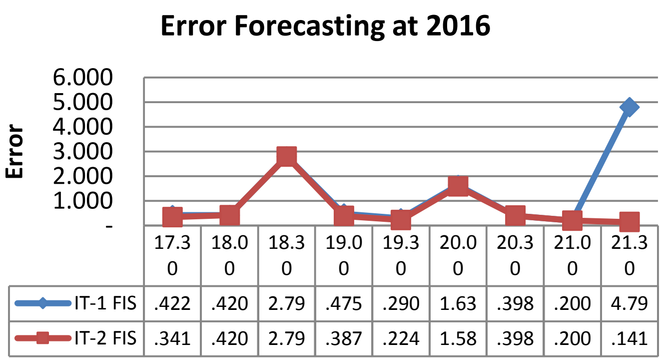

Fig. 4. Graph of forecasting error 2016.

5. Conclusions

From the above analysis, a very short term load forecasting on the fourth Friday on October 2015 using IT-1 FIS obtained the average error is 0.94%, while using IT-2 FIS is equal to 0.70%. In 2016, a very short term load forecasting on the fourth October using IT-1 FIS obtained 1.27% average error while using IT-2 FIS, is equal to 0.72%. The average forecasting error of very short-term using IT-1 FIS in 2015 and 2016 is 1.11%, meanwhile, the use of IT-2 FIS obtained 0.71% of average forecasting error. It can be concluded from the results that a very short term load forecasting can be done using IT-2 FIS with a smaller error value compared to the use of IT-1 FIS. In future research, a deeper collection of antecedents' data by using a day adjacent to the predicted day hours can be done by using other Artificial Intelligent.

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