Very Short Term Load Forecasting Using Hybrid Regression and Interval Type-1 Fuzzy Inference

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To cite this article: J Jamaaluddin and I Robandi 2018 TOP Conf. Ser.: Mater. Sci. Eng. 434 012209

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Very Short Term Load Forecasting Using Hybrid Regression and Interval Type -1 Fuzzy Inference

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Abstract. The growth of electricity consumption in this world is getting higher. The operation of the electric power starts from the generation system, Transmission system, and distribution system up to the load. All systems must be well integrated. Power generation settings should be appropriate. Therefore, load forecasting is important to do in generation system so that it is not too high from the existing load. There are two kinds of load forecasting; Short Term and Very Short Term. The very short term load forecasting is to forecast the load amount in every 30 minutes on one day before the day of loading. This research aims to discuss very short term load forecasting which uses hybrid regression method in the primary data of its loading history forecasting with Interval Type - 1 Fuzzy Inference System (IT-1 FIS). The finding indicates that the forecasting in 2015 obtained error of 0,9558%, and 1,4226% in 2016.

1. Introduction

The growing use of electricity in the world is getting higher. The operation of this electric power starts from the generation system, distribution system, distribution system up to the load [1]. Electric power is used in various sectors, among others: the industrial sector, public services, hospitality, research centers, education and household [2, 3]. The Java Bali electrical system is one of the big provider's electricity in Indonesia. Java-Bali electricity system has its own loading characteristics, among others: Seasons and commuting patterns [4, 5]. This should be done for economic considerations so that will get the planning of power generation, which should operate and which are not. This problem is related to generating efficiency, maintenance implementation and labor management. In these 2 decades to do load forecasting, have used computing. In this computation has been using Fuzzy Logic for very short-term load forecasting [6-8].

All systems must be well integrated. Power generation settings should be appropriate. In the generation system so as not to be too high from the existing load, then do load forecasting. Forecasting this load there are 2, namely: Short Term Load Forecasting and Very Short Term Load Forecasting. This very short-term forecasting is to forecast the load amount every 30 minutes on the 1 day before the D-Day of loading. This research will discuss about very short term forecasting. This very short term forecasting exploit uses hybrid regression method in the primary data of its forecasting history with Interval Type - 1 Fuzzy Inference System. With this method is expected to get the better value of forecasting.

Previous researchers very short term load forecasting using Artificial Neural Network (ANN) obtained (MAPE) between 0,89% – 1,25% [9]. While if using Based on Autoregressive Integrated Moving Average Model (ARIMA) Model and Intelligent Systems have MAPE ARIMA between 2.62% - 5,27%, if using Adaptive Neuro-Fuzzy Inference System (ANFIS) have result 10,21% - 18,45% [10]. On further development conduct very short term load forecasting using Nonlinear Autoregressive Model with Exogenous Input (NARX-neural network), using this method get the result MAPE between 0,5189% - 0,7973% [11].

2. Experimental method

The stages of this study are divided into 3 parts: the stages of preparation, processing and advanced, with the explanation as follows:

2.1. Preparation

That is the preparation of load data at the time that will be forecast, which is the Fourth Friday of October at 21.00 pm, 20.00 pm and 19.00 pm, while the activities are as follows:

- Conducting short-term electrical load data collection for 5 years, then grouping for each hour.
- Identify the load on each time on the Third Friday, the second Friday, and the first Friday at the forecast hour.

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

Where $TD_{(i)}$ is the Time Load Defference which is average $TD_{(i)}$ (Time Load) First Friday, Second Friday and Third Friday.

Calculates the difference in electrical load at predicted time LD(i) with the equation as below:

$$LD_{(i)} = \frac{SD_{(i)} - TD_{(i)}}{TD_{(i)}} \times 100$$
 (2)

Where $SD_{(i)}$ The Time load at the time to be forecast.

- Looking for TLD_(i) (The Typical Time Load Defference) with the calculate Electrical load average LD_(i) at Friday on October to be forecast with the same time at Friday the 1 year before.
- Calculate VLD (Variation Load Difference at each time) will be forecast.

$$VLD_{(i)} = LD_{(i)} - TLD_{(i)}$$
(3)

2.2. Processing

At this stage a very short-term electrical load forecasting process is done using Type-1 Interval Fuzzy Inference system, with the following process sequence:

- Creating an input membership function of Type-1 Fuzzy Inference System for X and Y values, and output membership function Z for the time to be predicted with the following conditions [12]:
 - $X: VLD_{(i)}$ the same time in the year before the forecast year.
 - Y: VLD₀ the same time at Friday 4th; Friday 3rd; Friday 2nd and Friday 1st in The year which forecast.
 - Z: Forecast $VLD_{(i)}$ electrical load at the time (T) will forecast.

This is input variable (X,Y) dan variable output (Z) consist of 11 Fuzzy membership [6, 13, 14]:

- a) Negative Very Big (NVB) with the range value -6 to -4
- b) Negative Big (NB) range value -5 to -3
- c) Negative Medium (NM) range value -4 to -2
- d) Negative Small (NS) range value -3 to -1
- e) Negative Very Small (NVS) range value -2 to 0
- f) Zero (ZE) range value -1 to 1

- g) Positive Very Small (PVS) range value 0 to 2
- h) Positive Small (PS) range value 1 to 3
- i) Positive Medium (PM) range value 2 to 4
- j) Positive Big (PB) range value 3 to 5
- k) Faitive Very Big (PVB) range value 4 to 6
- Make fuzzy rules interval type 1 fuzzy inference system (IT1-FIS) as follows:

IF X is A_i AND Y is B_i THEN Z is C_i

- Applay AND operation at interval type-1 fuzzy inference system (IT1-FIS).
- Apply implication function MIN at fuzzy rules.
- Apply MAX Composition at result fuzzy rules implication.
- Calculate defuzification value with reducer type using Kernik Mendel algorithm and get VLD forecast value.

2.3. Post processing

At this stage, it searches the value of the electrical load at the time of the forecast and looks for forecasting errors from VLD, in the following order:

Calculate the difference forecasting at time forecast:

$$Forecast \, LD(i) = Forecast \, VLD(i) + TLD(i) \tag{4}$$

Calculate the difference load at the time forecast:

$$P_{(i)} = WD_{(i)} + \frac{LD \times WD_{(i)}}{100}$$
 (5)

Calculate the error forecast:

$$Error\% = \frac{P_{forecast} - P_{actul}}{P_{actual}} x \ 100$$

$$Error\% = \frac{P_{(i)} - SD_{(i)}}{SD_{(i)}} x \ 100$$
(6)

$$Error\% = \frac{P_{(i)} - SD_{(i)}}{SD_{(i)}} \times 100 \tag{7}$$

3. Results and discussion

This research using sample Java Bali system electrical load [15-17]. Where will the load be analyzed on Friday 4th; Friday 3rd; Friday 2nd and Friday 1st October of 2012 until 2016. In 2012, conducted a search value of TD and LD, as a basis for further process this can be seen in table 1 and table 2.

Table 1. Calculation of TD and LD for 2012.

TIME		in 2		TD	LD		
	F-3	F-2	F-1 F		ID	LD	
19.00	20.655,77	20.855,77	20.555,77	21.055,77	20.689,10	1,77	
20.00	20.359,19	20.659,19	20.459,19	20.059,19	20.492,52	(2,11)	
21.00	19.644,05	19.845,05	19.944,05	19.940,05	19.811,05	0,65	

Table 2. Calculation of *TD* and *LD* for 2013.

TIME		in 2		TD	LD	
	F-3	F-2	ID	LD		
19.00	22.068,45	21.818,45	21.768,45	21.568,45	21.885,12	(1,45)
20.00	21.807,14	21.407,14	21.307,14	21.007,14	21.507,14	(2,32)
21.00	21.266,36	21.469,36	20.863,36	20.061,36	21.199,69	(5,37)

After obtaining the value of TD and LD, it can be calculated TLD and VLD for 2014 with the result as shown in table 3.

Table 3. Calculate the TD, LD, TLD and VLD at 2014.

TIME		in 2	014		TD	ID	TID	VLD
	F-3	F-2	F-1	F	TD	LD	TLD	VLD
19.00	22.704,61	21.904,61	21.854,61	22.904,61	22.154,61	3,39	0,16	3,22
20.00	22.779,65	22.479,65	22.579,65	23.079,65	22.612,98	2,06	(2,22)	4,28
21.00	22.286,85	21.883,85	21.196,85	22.481,85	21.789,18	3,18	(2,36)	5,54

in the same way it will be able to forecast results for the years 2015 and 2016. The results obtained in table 3, are used to determine the values of X, Y and Z.

Tabel 4. X, Y, Z value for input the fuzzy logic.

TIME	2014	2015	Inp	out	Output		
	VLD	VLD	X	Y	Z		
19.00	3,2226	0,9205	3,2226	(6,5848)	0,9205		
20.00	4,2834	(6,5848)	4,2834	4,2737	(6,5848)		
21.00	5,5382	4,2737	5,5382	0,9205	4,2737		

After the X, Y and Z values are known, the basic rules of Input X, Y and Z for forecasting 2015 are performed. With the results as shown in tables 5,6 and 7. X, Y and Z value put in membership function, as example the value of X at 19.00: 3.226, entered into the degree of membership, on Positive Medium (PM) 0.7774 and Positive Big (PB) 0.2226 (The other is empty). The same is done for Y and Z.

Table 5. Establishment of basic rules for input X forecasting year 2015.

TIME	Value	1	1 Membership Function (μ)										Sets
	X	NVB	NB	NM	NS	NVS	ZE	PVS	PS	PM	PB	PVB	X
19.00	3 2 2 2 6									0.7774	0.2226		PM
20.00	42834										0.7166	0.2834	PB
21.00	5.5382											1	PVB

Tabel 6. Establishment of basic rules for input y forecasting year 2015.

	1 1 2 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1												
TIME	Value		Membership Function (μ)										
	1	NVB	NB	NM	NS	NVS	ZE	PVS	PS	PM	PB	PVB	Y
19.00	(6.5848)	1											NVB
20.00	4.2737										0.7263	0.2737	PB
21.00	0.9205						0.0795	0.9205					PVS

Tabel 7. Establishment of basic rules for input Z forecasting year 2015.

ПМЕ	Value		Membership Function (μ)										Sets
	Z	NVB	NB	NM	NS	NVS	ZE	PVS	PS	PM	PB	PVB	Z
19.00	0.9205						0.0795	0.9205					PVS
20.00	(6.5848)	1											NVB
21.00	4.2737										0.7263	0.2737	PB

From the table 5, 6, 7 we make an example Table 5 at 19.00 – Positive Medium (PM) 0.7774, Positive Big (PB) 0.2226, its mean have a membership function as Positive Medium (PM), in the same way then the results obtained as shown in table 8.

Table 8. Conversion of 2015 forecasting basic rules for matlab softw

No of	Antecendent		Consequen	Consequen		Antec	Antecendent	
rules	X	Y	Z		rules	X	Y	Z
1	PM	NVB	PVS		1	9	1	7
2	PB	PB	NVB		2	10	10	1
3	PVB	PVS	PB		3	11	7	10

From table 8, we get the Fuzzy Rules Forecasting as shown Table 9.

Table 9. Fuzzy rules forecasting 2015.

ХУ	NVB	NB	 PVS	PS	PM	PB	PVB
NVB							
NB							
PM	PVS						
PB						NVB	
PVB			PB				

With the table rules as shown in Table 9, then get Convert Basic Forecasting Rule Year 2015 for Software Code Matlab. While forecasting output is the result of Matlab process, as shown in Figure 1.

Mengo	gunkan Type	-1 Fuzzy	Inferen	ce System
τ	Universitas	Muhamma	diyah Si	doarjo
Aktual	Forcast	ing Er	ror	
(VLD)	(VLD)	(V	LD)	
ns =				
0.9205	0	0.9205		
-6.5848	-4.9987	-1.5862		
4 2727	4.0017	0.2720		

Figure 1. Output calculation forecasting 2015 using Matlab.

From the result of the equation done by Matlab is inserted into the forecast output column as shown in table 10, so it will generate Error value in 2015, and table 11 in know 2016. From the error value at 19.00, 20.00, 21.00, then in the obtained MAPE value as can be seen in the table 12.

Table 10. Error very short term load forecasting 2015.

TIME	in 2015		TD	TD LD	TLD	VLD	Output	Forecast	Peramalan	Actual	Error		
	F-3	F-2	F-1	F	ID	LD	ILD	VLD	Forecast	LD	$P^*(MW)$	(MW)	(%)
19.00	23.136,51	22.038,51	22.932,51	23.131,51	22.702,51	1,89	0,97	0,92	-	0,97	22.922,54	23.131,51	(0,90)
20.00	22.936,65	22.737,65	22.631,65	21.239,65	22.768,65	(6,72)	(0,13)	(6,58)	(4,9987)	(5,13)	21.600,79	21.239,65	1,70
21.00	22.082,91	21.989,91	21.588,91	22.582,91	21.887,24	3,18	(1,10)	4,27	4,0017	2,91	22.523,37	22.582,91	(0,26)

Table 11. Error very short term load forecasting 2016.

TIME	in 2016			TD	LD	TLD	VLD	Output	Forecast	Peramalan	Actual	Error	
	F-3	F-2	F-1	F	ID	LD	TLD	VLD	Forecast	LD	$P^+(MW)$	(MW)	(%)
19.00	23.838,27	23.333,27	23.235,27	24.047,27	23.468,94	2,46	2,64	(0,17)	-	2,64	24.087,93	24.047,27	0,17
20.00	23.628,02	23.322,02	23.629,02	23.723,02	23.526,35	0,84	(2,33)	3,16	-	(2,33)	22.979,17	23.723,02	(3,14)
21.00	22.641,35	22.349,35	22.141,35	22.645,35	22.377,35	1,20	3,18	(1,98)	(1,0063)	2,17	22.863,47	22.645,35	0,96

T-11. 12	3.4.			
Table 12	. Maximum	average	percetage	error.

TIME	2015	2016
19.00	0,9034	0,1691
20.00	1,7003	3,1356
21.00	0,2636	0,9632
Amount	2,8674	4,2678
Avg	0,9558	1,4226

With the graph mode as shown in Figure 2.

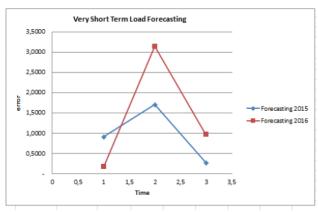


Figure 2. Error of forecasting year 2015 and 2016.

4. Conclusions

From the data and explanation above, it can be concluded that by using regression method and interval Type-1 Fuzzy Inference System, then got error result for forecasting year 2015 equal to 0,9558%, while for forecasting year 2016 got result of error equal to 1,4226%. It shows that in the process of Short Term Load Forecasting, the combination of regression and IT-1-FIS methods is sufficient to be used as a method for forecasting.

Acknowledgements

We acknowledged Universitas Muhamma-Diyah Sidoarjo (UMSIDA) and Institut Teknologi Sepuluh Nopember, Surabaya.

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