

Transformer's Load Forecasting to Find the Transformer Usage Capacity with Adaptive Neuro-Fuzzy Inference System Method

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To cite this article:

I. Gde Made Yoga Semadhi Artha, Ida Bagus Gede Manuaba. Transformer's Load Forecasting to Find the Transformer Usage Capacity with Adaptive Neuro-Fuzzy Inference System Method. *Journal of Electrical and Electronic Engineering*. Vol. 7, No. 1, 2019, pp. 1-7.
doi: 10.11648/j.jee.20190701.11

Received: October 31, 2018; **Accepted:** November 27, 2018; **Published:** January 24, 2019

Abstract: The development of the tourist destinations of Bali Island, especially Nusa Dua area, should be included with the development of electricity supply in the region. To facilitate a process of electrical energy planning in the region, it is necessary to forecast the electrical load in the area. Forecasting is a process to estimate future events / things to come. In this research, the forecasting of the long-term electrical load for five years and this forecasting method using ANFIS method and use ANN method as a comparison. From the simulation conducted by MAPE which resulted from forecasting the weekly electrical load using ANFIS method is 0.028% while MAPE forecasting using ANN method is 51.57%. From the comparison result, it can be said that the annual electricity load forecasting using the ANFIS method has a better forecasting accuracy than using the ANN method. The forecasting results of this transformer load is used as a reference in planning the electricity system on the Bali Island.

Keywords: ANFIS, MAPE, Electrical Load

1. Introduction

Bali is a world tourist destination; Nusa Dua area located in badung regency is a tourism area. The development of the number of tourism in badung district is growing rapidly seen from the number of tourists in 2017 which increased about 23.5% from the previous year.

The development of tourism is very significant must be supported with the electrical system in the area of Nusa Dua. Certainty of electricity supply is one of the factors that must be fulfilled to maintain the tourism in the area, because the electricity needs are increasing every year. If large electricity consumption can be determined, then we can do the planning to always maintain the reliability of the power supply by following the development of electrical loads.

Forecasting is a process to estimate future events / things to come. Forecasting is an essential instrument in science research, and received much attention during the past three decades [1-4]. Forecasting is usually classified based on the future time it encloses, making accurate predictions is not

easy, there are several factors to consider [5]. Nowadays short term forecasting is used popularly in many fields such as electric load, traffic flow, stock exchange, disaster and wheather [6-9]. In the field of electric power, forecasting usually in the form of load forecasting (including forecasting of peak load (MW), load capacity usage (Ampere). Forecasting based on time span can be categorized into three: Short term, medium term and long term [10, 11].

Long-term forecasting starts from a matter of years to decades. Forecasting has an important role in the context of generation, transmission and distribution network planning in power systems. The ultimate goal of power system planning is to determine the economic expansion of equipment and facilities to meet future electricity needs of customers with acceptable levels of reliability and power quality [12].

The Adaptive Neuro-Fuzzy Inference System (ANFIS) is a method that uses artificial neural networks to implement fuzzy inference systems. This method is chosen because

ANFIS method has all the advantages possessed by fuzzy inference system and artificial neural network system. With the use of ANFIS method it is expected that the time required to forecast the electrical load can be shorter. For rapid and exact results neural computing techniques are majorly used, which works by training basis. ANFIS is a better approach in improving of Neuro-fuzzy in case of modeling nonlinear functions. The ANFIS sets the system parameters by error norms and learns the system by example data set [13].

In this research, ANFIS method will be used to predict the power load. Forecasting is done to calculate the amount of current on transformers 1, 2 and 3 in Nusa Dua Substation, in the working area of PT PLN (Persero) APB Bali.

2. Methodology

2.1. Adaptive Neuro-Fuzzy Inference System (ANFIS)

ANFIS is a kind of adaptive neuro-fuzzy inference system which connects fuzzy logic system with neural network and constructs a hybrid intelligent system and benefits from the advantages of both fuzzy logic and neural networks, and its efficiency in very accurate models has

Rule 1: IF x_1 is A_1 AND x_2 is B_1 premise

then

$Y_1 = p_1x_1 + q_1x_2 + r_1$ consequent

Rule 2: IF x_1 is A_2 AND x_2 is B_2 premise

then

$Y_2 = p_2x_1 + q_2x_2 + r_2$ consequent

Input: x_1 and x_2

The consequent is an Y . so this healing model is:

$$\frac{w_1 y_1 + w_2 y_2}{w_1 + w_2} = \bar{w}_1 + \bar{w}_2 \quad (1)$$

Next, ANFIS architecture for the case of two inputs, x_1 and x_2 , and one output denoted Y is illustrated by the following figure:

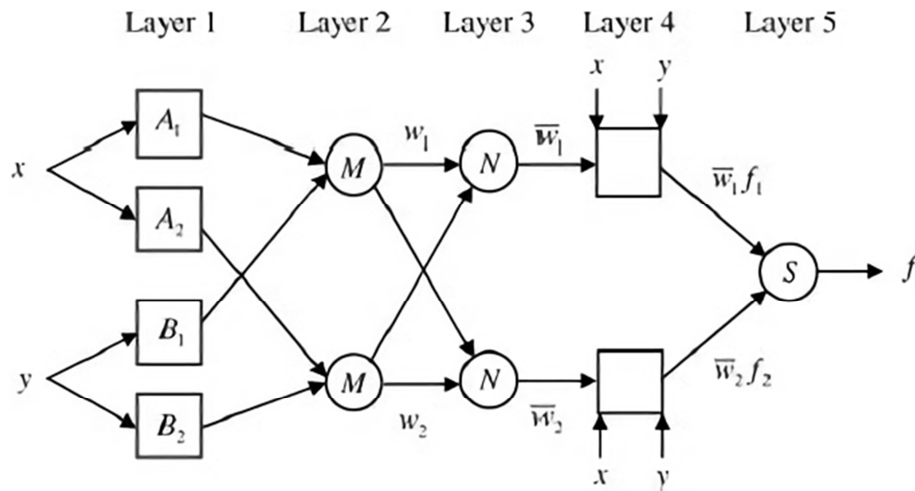


Figure 1. Architecture of ANFIS.

There are five layers, that is:

$$O_{1,i} = \mu_{B_i}(x_2), i = 3,4 \quad (3)$$

2.2.1. Layer 1

Each node i in this layer is an adaptive node with a function node:

$$O_{1,i} = \mu_{A_i}(x_1), i = 1,2 \quad (2)$$

2.2.2. Layer 2

Each node in this layer is labeled Π with the output multiplication of all incoming signals, namely:

$$O_{2,1} = w_1 = \mu_{A_i}(x_1) \Delta \mu_{B_i}(x_2), i = 1,2 \quad (4)$$

So:

$$w_1 = \mu_{A1}(x_1) \text{ AND } \mu_{A1}(x_2) \quad (5)$$

$$w_2 = \mu_{A2}(x_1) \text{ AND } \mu_{B2}(x_2) \quad (6)$$

Each node output expresses the weight of a rule. Generally the AND operation is used as a function node on this layer

2.2.3. Layer 3

Each node in this layer is given N notation. The node to - i calculates the ratio of the weight of i^{th} to the sum of all weights:

$$O_{3,i} = \bar{w}_i = \frac{w_i}{w_1 + w_2}, i = 1, 2 \quad (7)$$

2.2.4. Layer 4

Each node i in this layer is an adaptive node with a function node:

$$O_{4,i} = \bar{w}_i Y_i = \bar{w}_i (p_i x_1 + q_i x_2 + r_i) \quad (8)$$

2.2.5. Layer 5

A single node depicted on this layer serves to aggregate all output from layer 4 (which is defined as the sum of all incoming signals):

$$O_{5,i} = \sum_i \bar{w}_i Y_i = \frac{\sum_i w_i + Y_i}{\sum_i w_i} \quad (9)$$

Evaluation of Forecasting Accuracy Adaptive Neuro Fuzzy Inference System (ANFIS)

To measure the extent of the accuracy of ANFIS network output, required a quantization device. To calculate the output difference of ANFIS with the target data in the training process used MSE (Mean Square Error) based on the following equation:

$$MSE = \sum_{i=1}^P \frac{|actual - estimates|^2}{p} \quad (10)$$

where P is the number of data pairs. The accuracy of the Adaptive Neuro Fuzzy Inference System (ANFIS) forecasting in this study was calculated using the Absolute Percentage Error (MAPE) Meaning criteria that can be formulated as follows [4]:

$$MAPE (\%) = \frac{1}{N} \sum_{i=1}^N \frac{|p_h - p_h|}{p_h} \times 100\% \quad (11)$$

Explanation:

\bar{p}_h = Actual Load

(Ph) = Actual Load

N = Number of Data

If the MAPE value is less than 25% then the forecasting result can be received satisfactory

3. Result and Discussion

Power load forecasting that discussed in this study is the forecasting of annual electrical load using ANFIS method which then the result will be compared with forecasting result using ANN method. The data used is the data load in

transformer 1, transformer 2, and transformer 3 in Nusa Dua Substation. With the following data:

3.1. Transformer 1 Data in Nusa Dua Substation

Table 1. Load data Transformer 1.

Transformator 1	2015 (MW)	2016 (MW)	2017 (MW)
January	563.00	693.40	715.60
February	525.00	642.20	756.30
March	531.00	765.60	778.10
April	531.10	803.40	815.60
May	625.00	797.50	834.40
June	562.50	730.90	796.90
July	593.80	758.80	690.60
August	687.50	834.40	715.60
September	707.95	868.80	728.10
October	728.40	769.90	830.23
November	748.40	740.60	773.68
December	790.00	750.00	768.42
MAX (MW)	790.00	868.80	834.40
Used Capacity (%)	45.61	50.16	48.18

From the table 1, it is seen that the achievement of transformer 1 in Nusa Dua substation has reached 50.16%

3.2. Transformer 2 Data in Nusa Dua Substation

Table 2. Load data Transformer 2.

Transformator 2	2015 (MW)	2016 (MW)	2017 (MW)
January	806.00	804.10	718.80
February	669.00	754.10	781.30
March	913.00	819.70	768.80
April	881.30	792.20	818.80
May	771.60	689.40	806.30
June	685.50	780.00	775.00
July	705.30	775.90	778.10
August	958.40	809.40	790.60
September	866.25	837.50	818.80
October	774.10	762.50	741.94
November	792.50	775.00	762.21
December	890.30	865.60	858.67
MAX (MW)	958.40	865.60	858.67
Used Capacity (%)	55.33	49.98	49.58

From the table 2, it seen that the achievement of the transformer 2 in Nusa Dua substation has reached 55.33%

3.3. Transformer 3 Data in Nusa Dua Substation

Table 3. Load data Transformer 3.

Transformator 3	2015 (MW)	2016 (MW)	2017 (MW)
January	625.00	725.90	712.50
February	522.00	709.70	812.50
March	750.00	800.30	750.00
April	718.80	830.00	781.30
May	718.80	771.30	775.00
June	625.00	752.50	690.60
July	656.30	738.40	756.30
August	843.80	771.90	712.50
September	791.90	809.40	771.90
October	740.00	825.00	860.46
November	783.40	778.10	774.67
December	854.70	778.10	883.20
MAX (MW)	854.70	830.00	883.20
Used Capacity (%)	49.35	47.92	50.99

FROM the table 3, it seen that the achievement of the transformer 2 in Nusa Dua substation has reached 50.99%.

For the training phase, use the sample on load data from 2015 - 2017 Transformer 1 – 3

Next, using the same input data, the result of the ANFIS

forecasting will be compared with the forecast result using ANN method. For sample calculation using data on Transformer 2, so that the comparison of forecasting result as in table 4, and in Figure 2 explains how the structure in ANFIS for data processing.

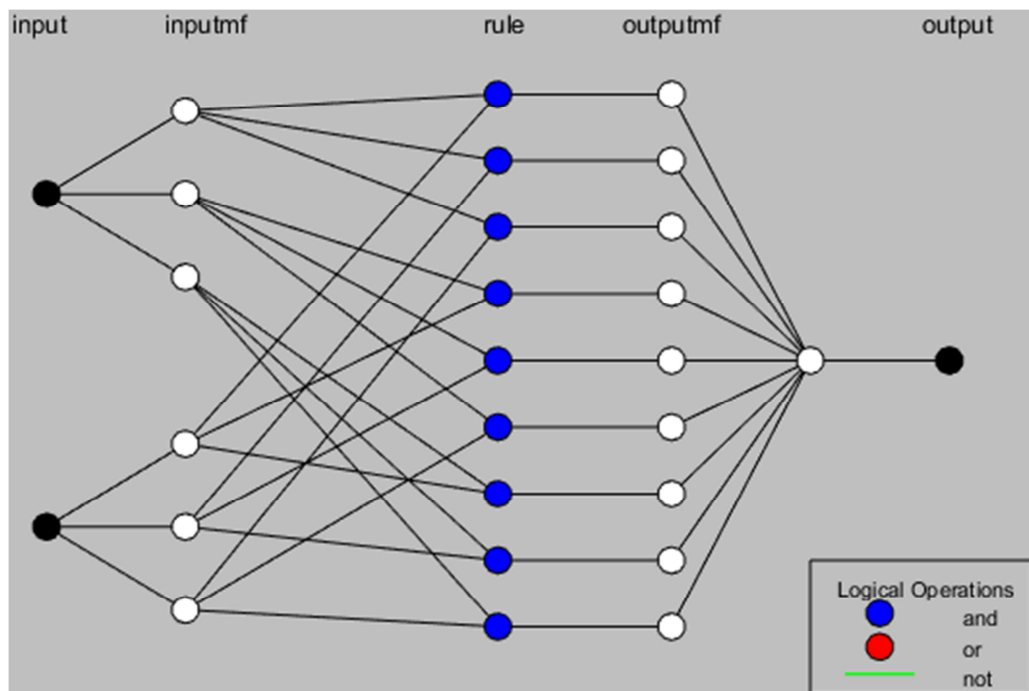


Figure 2. ANFIS Forecasting Structure.

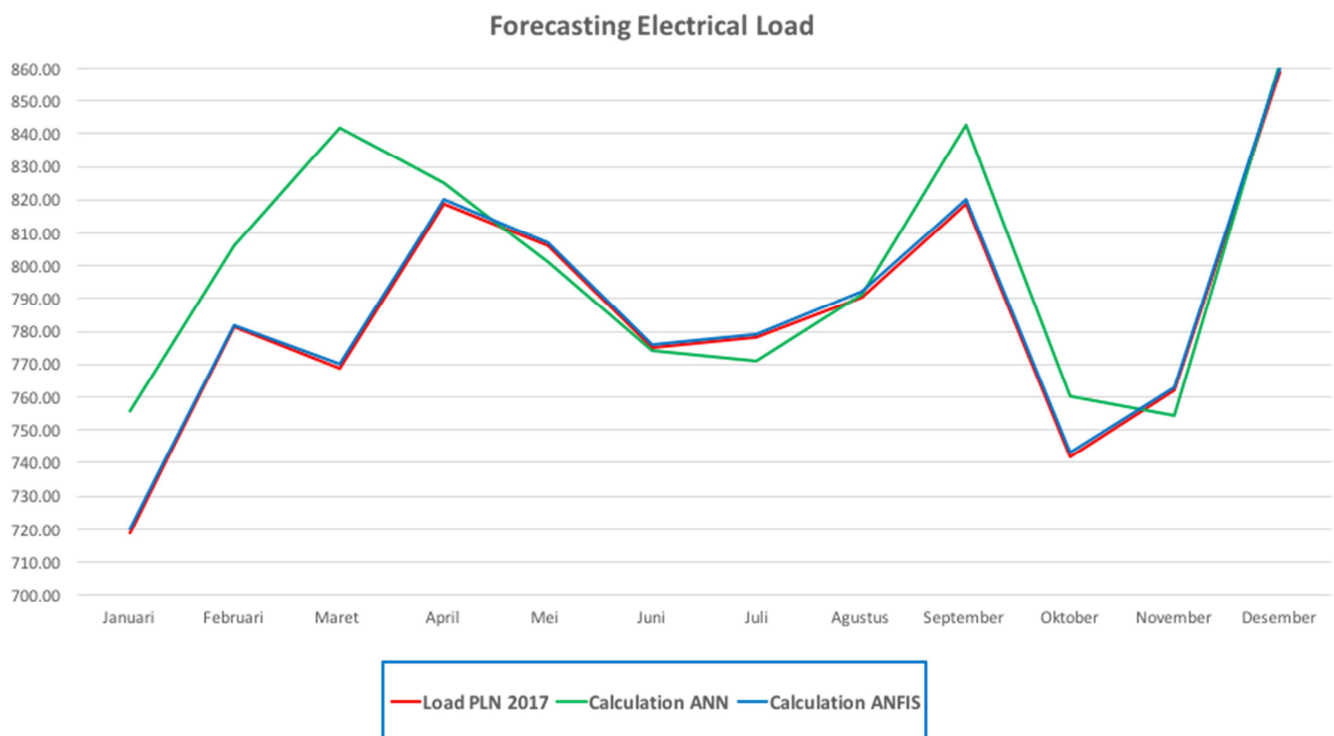


Figure 3. Comparison graph of ANN and ANFIS.

Table 4. ANN and ANFIS comparison table.

MONTH	LOAD PLN 2017	Calculation ANN	Calculation ANFIS	MAPE ANN	MAPE ANFIS
January	718.80	755.87	720	5.157	0.167
February	781.30	806.04	782	3.167	0.090
March	768.80	841.62	770	9.472	0.156
April	818.80	825.09	820	0.768	0.147
May	806.30	801.03	807	0.654	0.087
June	775.00	773.97	776	0.133	0.129
July	778.10	771.17	779	0.891	0.116
August	790.60	791.4	792	0.101	0.177
September	818.80	842.67	820	2.915	0.147
October	741.94	760.32	743	2.477	0.143
November	762.21	754.52	763	1.009	0.103
Desember	858.67	861.43	860	0.321	0.155

From the table 4 and the figure 3 above shows that the accuracy of weekly electrical load forecasting in Bali electricity system using ANFIS method has a higher accuracy rate than forecasting electrical load using ANN method, it can be seen from the MAPE forecasting produced by each method.

Then the long-term forecast calculation is continued by ANFIS Method using data of transformer 1, transformer 2, and transformer 3. And the following results are obtained.

Forecasting the load and the use of transformer 1 capacity in Nusa Dua substation.

Table 5. Forecasting transformer 1 until 2020.

Transformator 1	2015 (MW)	2016 (MW)	2017 (MW)	2018 (MW)	2019 (MW)	2020 (MW)	2021 (MW)	2022 (MW)
January	563.00	693.40	715.60	745.56	775.65	811.96	851.38	893.46
February	525.00	642.20	756.30	771.32	827.97	859.60	907.55	950.06
March	531.00	765.60	778.10	849.79	875.47	925.45	967.28	1017.28
April	531.10	803.40	815.60	905.04	930.19	986.65	1030.30	1084.36
May	625.00	797.50	834.40	874.90	911.48	954.90	1001.36	1050.97
June	562.50	730.90	796.90	833.59	875.66	915.76	961.95	1009.02
July	593.80	758.80	690.60	746.30	758.42	802.18	836.57	880.24
August	687.50	834.40	715.60	774.35	782.27	828.52	863.08	908.51
September	707.95	868.80	728.10	795.21	801.04	850.30	885.07	932.14
October	728.40	769.90	830.23	832.42	879.20	912.85	960.98	1006.48
November	748.40	740.60	773.68	771.46	810.63	841.70	885.28	927.34
December	790.00	750.00	768.42	764.28	800.61	831.41	873.97	915.60
MAX (MW)	790.00	868.80	834.40	905.04	930.19	986.65	1030.30	1084.36
Used Capacity (%)	45.61	50.16	48.18	52.25	53.71	56.97	59.49	62.61

Forecasting the load and the use of transformer 2 capacity in Nusa Dua substation

Table 6. Forecasting transformer 2 until 2020.

Transformator 2	2015 (MW)	2016 (MW)	2017 (MW)	2018 (MW)	2019 (MW)	2020 (MW)	2021 (MW)	2022 (MW)
January	806.00	804.10	718.80	791.35	882.28	914.48	971.52	1014.41
February	669.00	754.10	781.30	767.51	812.94	848.17	891.43	933.39
March	913.00	819.70	768.80	871.99	929.46	975.63	1025.47	1074.79
April	881.30	792.20	818.80	856.36	881.22	916.57	959.14	1004.50
May	771.60	689.40	806.30	750.08	866.41	933.86	992.57	1043.11
June	685.50	780.00	775.00	773.00	803.80	830.48	871.54	911.36
July	705.30	775.90	778.10	763.96	805.33	841.25	883.23	925.15
August	958.40	809.40	790.60	902.35	929.90	983.13	1026.28	1078.17
September	866.25	837.50	818.80	831.68	871.55	899.54	945.42	988.21
October	774.10	762.50	741.94	746.31	786.62	809.95	852.47	890.51
November	792.50	775.00	762.21	761.71	797.09	820.87	862.86	901.58
December	890.30	865.60	858.67	853.68	892.29	918.40	965.28	1008.52
MAX (MW)	958.40	865.60	858.67	902.35	929.90	983.13	1026.28	1078.17
Used Capacity (%)	55.33	49.98	49.58	52.10	53.69	56.76	59.25	62.25

Forecasting the load and the use of transformer 3 capacity in Nusa Dua substation

Table 7. Forecasting transformer 3 until 2020.

Transformator 3	2015 (MW)	2016 (MW)	2017 (MW)	2018 (MW)	2019 (MW)	2020 (MW)	2021 (MW)	2022 (MW)
January	625.00	725.90	712.50	774.27	826.61	905.32	984.41	1076.14
February	522.00	709.70	812.50	879.51	962.86	1049.36	1146.63	1251.42
March	750.00	800.30	750.00	845.33	949.59	1037.71	1138.47	1242.25
April	718.80	830.00	781.30	889.50	939.25	1039.38	1126.44	1234.28
May	718.80	771.30	775.00	806.11	865.38	940.41	1024.77	1118.40
June	625.00	752.50	690.60	816.98	927.13	1020.79	1120.56	1224.13
July	656.30	738.40	756.30	795.33	858.54	933.63	1018.17	1111.19
August	843.80	771.90	712.50	872.71	980.99	1089.60	1192.31	1305.17
September	791.90	809.40	771.90	846.04	940.74	1024.78	1122.85	1224.82
October	740.00	825.00	860.46	900.19	975.30	1059.14	1156.00	1261.15
November	783.40	778.10	774.67	808.57	874.25	949.40	1035.89	1130.17
December	854.70	778.10	883.20	965.77	1053.71	1150.93	1256.43	1371.98
MAX (MW)	854.70	830.00	883.20	965.77	1053.71	1150.93	1256.43	1371.98
Used Capacity (%)	49.35	47.92	50.99	55.76	60.84	66.45	72.54	79.21

Forecasting results using ANFIS found that the condition of the transformer for the next 5 years is estimated to have reached more than 60%, where the condition is not optimal for the parallel load maneuver need transformer. for that step necessary steps by the government and PLN anticipating the capacity of the transformer is nearing the maximum.

4. Conclusion

Accuracy of electric load forecasting using Adaptive Neuro-Fuzzy Inference System (ANFIS) method is better than Artificial Neural Network (ANN) method, this is indicated by MAPE resulting from weekly electrical load forecasting using ANFIS method is 0.028% while MAPE forecasting using method ANN is 51.57%. ANFIS method accuracy better than ANN method is caused by membership function which is part of fuzzy inference system that can assist in the best decision making, by mapping the existing data input so that the result obtained by ANFIS method becomes more accurate than the use ANN method itself without any combination with other optimization methods.

Further researchers are expected to continue the study by involving other parameters such as weather, electrical load consumption level, and environmental temperature.

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