Power Demand Forecasting Considering Actual Peak Load Periods Using Artificial Neural Network

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***Abstract*—Presently, electrical energy consumption continues to increase from year to year. Therefore, a short-term load forecasting is required that electricity providers can deliver continuous electrical energy to electricity consumers. By considering the estimation of the electrical load, the scheduling plan for operation and allocation of reserves can be managed well by the supply side. This study is focused on a forecasting of electrical loads using Artificial Neural Network (ANN) method considering a backpropagation algorithm model. The advantage of this method is to forecast the electrical load in accordance with patterns of past loads that have been taught. The data used for the learning is Actual Peak Load Period (APLP) data on the 150 kV system during 2017. Results show that the best network architecture is structured for the APLP Day and Night. Moreover, the momentum setting and understanding rate are 0.85 and 0.1 for the APLP Day. In contrast, 0.9 and 0.15 belong to the APLP Night. Based on the best network architecture, the APLP day testing process generates Mean Squared Error (MSE) around 0.04 and Mean Absolute Percentage Error (MAPE) around 4.66%, while the APLP Night generates MSE in 0.16 and MAPE in 16.83%.**

Keywords—Artificial Neural Network, Electricity Load, Load Forecasting.

I. INTRODUCTION

Electrical energy usages continue to increase from year to year. Number of customers Indonesia State Electricity Company (ISEC) from 2011 to 2015 has increased more than 33 percent. Based on the increasing number of customers, ISEC is required to meet all the demand for electrical energy continuously. Continuous distribution of electrical energy is the right of ISEC customers to be prioritized by ISEC as the main provider of electrical energy in Indonesia [1]–[6]. To be able to meet the needs of electrical energy continuously, it is a necessity to balance supply and demand sides. Thus, the power generated must always be equal to the power consumed by the electric power consumer [7]–[15]. Therefore, it is also necessary to estimate short-term electrical loads that can predict the need for the electrical usage. The short-term electrical load forecast (SELF) aims to predict electricity requirements in minutes, hours, days, and weekly hours [2], [8], [10], [16]–[18]. The SELF-brings out to forecast load requirements at a load center switchyard (LCS) and play an important role in the real-time control and security functions of the energy management. An accurate estimation of the electrical load can save operational costs and safe conditions, both can be done by the supply and demand side management[19]–[22]. The SELF can also be used as a reference to the ISEC's Operational Plan.

In general, the load forecasting is categorized into causal models and time-dependent models. The causal model is based on the relationship between the variables involved, whereas the forecasted model of the forecasting time is based on historical data of variables predicted unaffected by other variables [23]–[27]. Time series electrical load forecast can be applied because load characteristics have the same pattern trend in each period. The time-based electrical load forecast can be applied using several methods. A complicated method does not guarantee a high degree of accuracy of forecasts. One method that can be applied to the SELF is the Artificial Neural Network (ANN) algorithm [16], [23], [25], [28], [29]. These works are concerned in the exploration of ANN backpropagation for defining an effective algorithm as a forecasting method.

II. PROBLEM STATEMENT

In general, electric consumers are divided into 6 sectors, namely household, industry, business, social, government office building, and street public lighting [2], [30]–[33]. Each consumer of electric energy has different load characteristics based on electric energy consumption patterns in each sector [34]. Determination of electrical load characteristics is very important for evaluation and planning which are needed in distribution substations [35]. In addition, the load studies are crucial in the planning future system development. The description of load characteristics is expressed using a load assessment factors (LAF). This LAF can illustrate load characteristics in terms of quantity and quality. The LAF is also useful for estimating future electrical loads [7], [36], [37]. For the needs of daily electrical load estimation, the LAF covers the based demand, maximum demand, and peak load.

Furthermore, many intelligent methods have been developed to find out the optimal solution for various technical problems [19], [20], [40]–[46]. One of them is the ANN considered the backpropagation. The architecture of the ANN consists of the input layer, hidden layer, and output layer, where each layer consists of one or more neurons [47]–[51]. The backpropagation method uses three steps to perform the training presented in feedforward of the training input pattern, backpropagation of connected error, and weight adjustment [28], [52]. In details, the ANN-Backpropagation architecture is shown in Figure 1. The training procedures of this algorithm are reported in many investigated fields [53]–[56].

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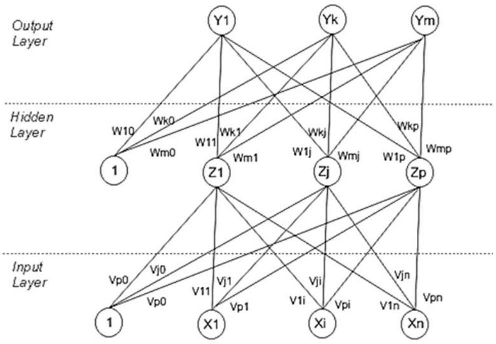

Fig. 1. ANN backpropagation architecture

III. APPLIED PROCEDURES

As many works, the algorithm is presented in many types of the structures for illustrating steps to get out the solution. This study is also given in a hierarchy to complete the works. This section is used to explain the whole steps of studies which are covered in quantitative processes of the secondary data analysis and all working sequences. Technically, required information is the historical data of daily electrical load on an effective day. The data used for the learning is actual peak load period (APLP) data on the 150 kV system of Buduran Area during 2017. Vulnerable time spent on the APLP Day and Night is also presented. The daily data load power information is obtained from the ISEC for the East Java Area Distribution. Moreover, the data of electrical load usage is covered for the historical data of the electrical load on the 150 kV of the LCS in Buduran, Sidoarjo District. In detail, Figure 2 presents hierarchies of the studies.

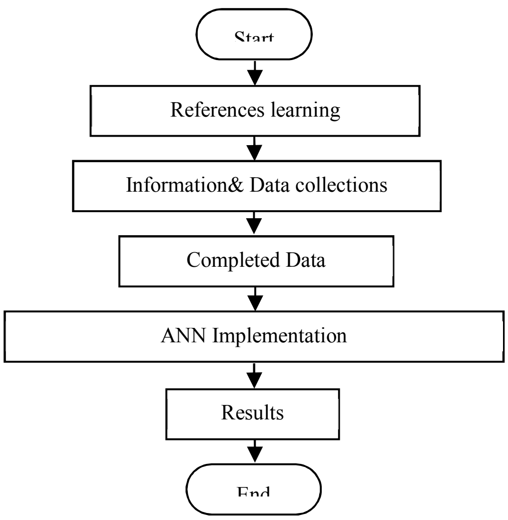

Fig. 2. Block diagram of the whole study

The formation of the best network architecture is structured using a quantitative model which is the most adaptable to every possibility. Moreover, the level of accuracy is tested on two types covered in Mean Squared Error (MSE) and Mean Absolute Percentage Error (MAPE). The MSE is used to test the error rate of a network architecture in the forecasting, whereas the MAPE is used to test the accuracy of the forecasting results. In this study, the ANN-Backpropagation model is presented in Figure 3 and Figure 4. Figure 3 shows the procedure for the forecasting and Figure 4 shows the ANN network architecture while Table I also shows the composition of this network architecture. In particular, Table II provides the parameter definitions and the MAPE is required as listed in Table III.

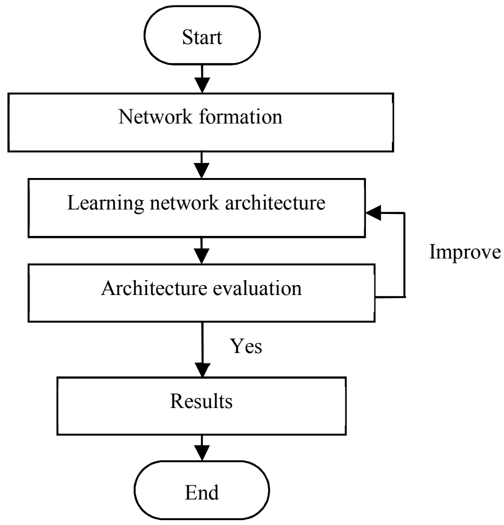

Fig. 3. Load forecasting steps

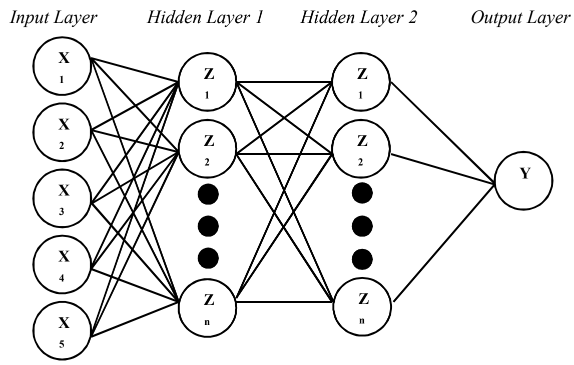

Fig. 4. ANN network architecture

TABLE I. ANN BACKPROPAGATION PARAMETERS

Parameter	Numer	Description
Input Layer	5 neuron	Daily load
Hidden Layer	HL 1-2	Testing data
Output Layer	1 neuron	Prediction
Epoch	10.000 epoch	Maximum setting
Training function	Traingdx	Function
Activation function	Sigmoid Biner	Function

TABLE II. INPUT AND TARGET ALGORITHM

Map	Data Masukan	Target
1.	X_1-X_5 is a daily load on Monday for 5 weeks, ranged in the 1st week to the 5th week	Load on Monday on the 6th week
2	X_1-X_5 is a daily load on Tuesday for 5 weeks, ranged in the 1st week to the 5th week	Load on Tuesday on the 6th week
3	X_1-X_5 is a daily load on Monday for 5 weeks, ranged in week 6th to week 10th	Load on Monday on the 11th week
4	X_1-X_5 is a daily load on Friday for 5 weeks, ranged in week 16th to week 20th	Load on Friday on the 21st week

TABLE III. MAPE PERCENTAGES

MAPE	Prediction
MAPE ≤ 10%	High
10 < MAPE ≤ 20	Good
20 < MAPE ≤ 50	Reasonable
> 50	Low

Based on Table I, Table II, and Table III, the training results are obtained in the form of network weights that will be used in the testing phase. Training results are applied to the test data pattern while weights and biases can be used to show results for data outside of training input data.

IV. RESULTS AND DISCUSSIONS

Based on the preparation of input and target matrices as detailed in Table I, Table II, and Table III, the ANN is processed as the given hierarchies in Figure 2, Figure 3, and Figure 4. The architecture composition of the training and test results are performed in the APLP Day and Night. The momentum setting and rate of understanding are 0.85 and 0.1 for the APLP Day, as well as 0.9 and 0.15 for the APLP Night.

In details, the results are given in following tables and figures. Table 4 shows the results of the training on APLP Day, Table 5 shows the results of the training on APLP Night. Figure 4 shows a graph of error in training.

TABLE IV. TRAINING RESULT OF THE APLP DAY

X1	X2	X3	X4	X5	T	JST
114.90	110.85	109.47	120.48	115.77	120.03	119.243
120.76	120.59	106.59	119.37	119.17	137.07	136.342
110.75	121.24	113.73	121.87	118.47	123.91	123.128
118.82	112.69	114.87	116.32	122.39	119.58	118.816
118.99	115.98	140.75	110.96	120.72	123.84	123.075
120.03	128.24	121.07	120.93	119.93	118.37	118.214
137.07	119.58	122.91	111.51	122.63	126.09	125.33
123.91	122.04	128.86	124.43	136.17	122.49	121.694
119.58	120.83	119.13	121.80	118.75	93.81	93.0896
123.84	126.27	119.58	120.48	121.45	118.37	117.307
118.37	127.69	120.62	119.23	108.32	115.70	114.994
126.09	130.67	123.18	118.30	114.80	122.87	121.99
122.49	130.80	122.91	124.74	115.77	119.30	118.489
93.81	129.56	124.36	124.74	114.32	117.57	116.807
118.37	125.82	122.56	121.35	119.62	118.33	117.127
115.70	113.31	117.54	125.33	122.04	122.73	121.963
122.87	121.76	120.03	121.07	123.29	125.82	125.071
119.30	123.74	128.17	120.38	124.29	128.97	128.276
117.57	123.74	121.00	118.65	122.80	124.33	123.598
118.33	119.17	121.76	118.33	118.33	122.39	121.587

TABLE V. TRAINING RESULT OF THE APLP NIGHT

X1	X2	X3	X4	X5	T	JST
148.71	136.49	135.48	121.66	142.27	135.48	135.241
151.73	140.89	140.54	135.55	129.94	129.97	129.446
150.48	140.30	141.06	144.21	144.73	88.13	88.078
142.65	134.48	141.61	141.20	143.31	135.62	135.982
145.35	144.00	136.73	138.77	143.31	138.25	138.022
135.48	129.35	130.74	133.75	130.63	115.91	115.631
129.97	138.91	141.96	124.92	146.15	147.33	146.945
88.13	135.00	140.82	145.25	140.95	131.15	130.830
135.62	134.96	148.02	145.98	139.29	139.74	139.768
138.25	139.46	137.70	128.31	142.89	134.68	134.498
115.91	138.25	134.86	147.85	139.08	145.80	145.648
147.33	146.64	148.37	151.24	151.03	142.03	141.771
131.15	144.14	148.99	152.11	151.97	146.77	146.254
139.74	136.94	148.75	155.05	148.51	148.26	147.908
134.68	130.94	140.23	163.40	147.50	149.61	149.244
145.80	139.22	137.04	144.18	136.62	142.58	141.867
142.03	111.47	145.53	131.43	142.06	144.70	144.341
146.77	139.19	143.17	139.64	112.90	153.43	152.994
148.26	137.84	145.28	138.91	145.91	149.30	148.084
149.61	145.35	139.33	139.64	126.51	148.30	148.304

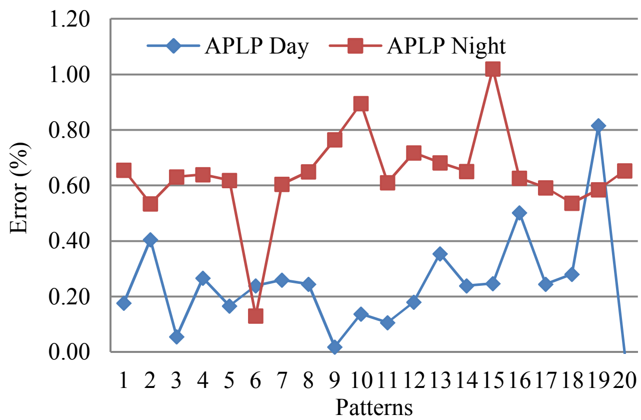

Fig. 5. Training error comparison

In particular, the testing process is conducted to see whether the training pattern can be applied to other patterns outside the training pattern. The best network architecture of the training process is given in Figure 5 for the error. This architecture can be adapted to test the other pattern as shown in Table VI for the APLP Day and Table VII for the APLP Night. Figure 6 shows the graph of the test results and Figure 7 shows the error graph of the test results.

TABLE VI. MAPE CONDITION OF THE APLP DAY

X1	X2	X3	X4	X5	T	JTS	Error
133.33	120.86	134.48	131.25	147.16	143.73	151.395	5.34
143.62	141.09	140.05	112.20	119.68	141.37	158.128	11.85
137.91	135.86	134.75	140.92	148.85	148.58	147.554	0.69
142.06	136.73	136.83	144.18	145.73	146.88	149.72	1.93
142.62	131.71	136.38	136.76	147.16	146.29	146.212	0.05
143.73	138.25	152.28	154.98	143.62	125.09	124.396	0.55
141.37	149.27	151.66	150.13	116.05	147.19	123.993	15.76
148.58	144.66	153.91	146.95	150.72	149.34	146.609	1.83
146.88	151.94	122.73	142.82	141.34	144.97	142.887	1.44
146.29	149.55	153.70	112.86	115.80	150.76	139.941	7.17
JUMLAH							46.62
MAPE							4.66%

TABLE VII. MAPE CONDITION OF THE APLP NIGHT

X1	X2	X3	X4	X5	T	JST	Error
120.03	115.49	120.79	138.11	139.98	136.62	101.141	25.9715
117.05	118.02	119.48	134.72	129.59	130.84	102.451	21.697
120.34	119.41	122.32	137.28	139.29	125.85	99.7304	20.755
116.15	117.02	122.18	139.29	131.81	127.65	104.28	18.3091
121.76	115.74	118.61	135.65	130.53	129.18	103.92	19.5518
136.62	128.14	120.93	119.93	118.37	124.95	117.534	5.93564
130.84	128.45	111.51	122.63	126.09	129.04	112.236	13.0205
125.85	126.06	124.43	136.17	122.49	127.41	95.0507	25.3975
127.65	131.50	121.80	118.75	93.81	130.87	138.304	5.6774
129.18	123.81	120.48	121.45	118.37	123.08	108.359	11.9602
JUMLAH							168.27
MAPE							16.82%

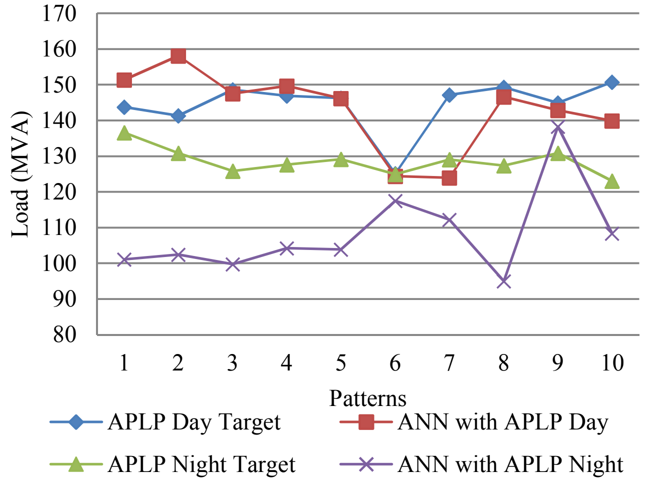

Fig. 6. Testing load results

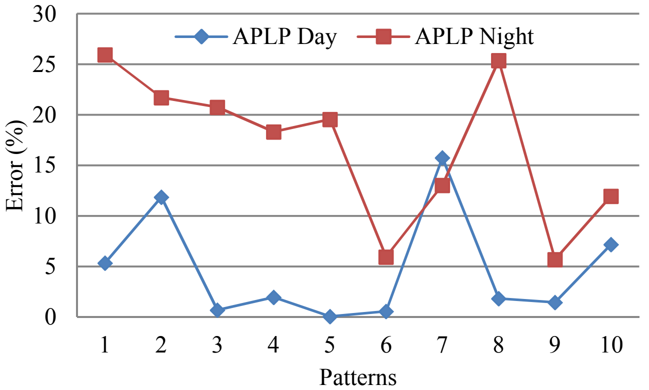

Fig. 7. Error testing results

Based on the results, the best network architecture has the MSE in 0.036084 and MAPE in 4.66% for APLP Day. In contrast, 0.15772 of the MSE and 16.83% of the MAPE belong in the APLP Night. In addition, the networks can adapt well and can produce fairly the accurate forecasting. These results are also shown that the APLP affordability forecasting has a high degree of accuracy, and for the APLP Night accuracy is good. The accuracy rate at the APLP Day is higher than the APLP Night. It can be understood that the 150 kV Buduran Switchyard is mostly for the industrial sector. The pattern of load characteristics in the industrial sector has a similar tendency of loading profiles, and the industrial sector is dominated by daytime activities, therefore, the load pattern used as input on ANN has the same pattern tendency, so the network is easier to learn patterns. Furthermore, the outcome of the forecasting has a high degree of accuracy.

In contrast, the accuracy of the APLP Night results is lower than that of APLP Day, because the night load is dominated by the household sector. The pattern of load characteristics in the household sector has considerable fluctuations because of the consumption of electrical energy is influenced by behavioral patterns of society which are depended on external factors. The forecasting accuracy on the APLP Night can be improved by adding external factors as input variables, so the network can be better.

V. CONCLUSION

Based on the results of the studies, the estimation of the electric load for the APLP Day and Night in the 150 kV Buduran Switchyard can be done by using Artificial Neural Network method with backpropagation algorithm model. Based on the best network architecture of the forecasting for the APLP Day and Night, a momentum setting and an understanding rate of 0.85 and 0.1 are produced by the APLP Day, as well as 0.9 and 0.15 for the APLP Night. The APLP Day testing process generates MSE in 0.036084 and MAPE in 4.66%, while for the APLP Night generates MSE in 0.15772 and MAPE in 16.83%. The MSE results indicate that the forecasting on the APLP Day has a high degree of accuracy and the forecasting on the APLP Night has a good level of accuracy. The addition of variables with external factors may increase the accuracy of the forecasting, especially for areas dominated by the household sector. For the future works, additional factor improvements are recommended.

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