Implementation of Artificial Neural Network Method for Estimating Connected Power and Electric Energy Consumption

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Abstract

Abstract—Electricity is vital for modern society's welfare. Daily electricity usage depended on the customers' type. Hence, there was a difference between the connected power with consumption. Therefore, there needed an estimation method for long-term connected power and energy consumption to improve the safety of energy management and operation plan for the generator. This research used the Artificial Neural Network method with a backpropagation algorithm model to estimate the connected power and electricity consumption. This method has the advantage of following past patterns after the training process. This research used data such as total population, Gross Regional Domestic Product, total customers, produced energy, remaining energy, distribution loss, total transformer, peak load, and load factor as the independent data. The energy consumption and connected power served as the dependent data. The data was taken from Srengat Network Service Unit, East Java, for ten years, which started in 2008. This research used literature study, information and data collection, information and data process, data estimation and analysis, and conclusion as the procedures. Based on the results, the best network structure was 9-9-2 with the 10^{-6} goal, 0.9 momentum value, and 0.15 learning rate to produce the smallest Mean Squared Error of 0.00442 in 2015, Mean Absolute Percentage Error of 7.88% for the connected power, and 11.27% on electricity consumption target.

Keywords
transformer age, linear trend, load growth, ambient temperature

1. Introduction

Electricity is a vital factor in society's welfare. The welfare level is the main factor in daily electricity usage [1]–[5]. The utilization depends on the customers' type; hence, there was a difference in the connected power with electricity consumption. Electric supplier should consider the maximum consumption demand correctly until a defined period. The connected power to meet 2016 electricity consumption was 67 MW while in 2017 was 72 MW. This occurrence shows that consumption increases every year. To fulfill the increasing demand, there needs a balance from the production and consumption to equalize the consumption with production level [6]. Therefore, there needs an estimation in long-term connected power and electricity consumption.

This estimation was performed to know the target level of connected power and electricity consumption accurately to improve the security of energy management, save the operational cost, and safety for production and consumption, and as a reference for the Operational Plan [7]–[11]. Based on the reference study, it can be concluded that the connected power and electricity consumption have complex factors and non-linear characteristics. A good estimation can be obtained using traditional methods. However, the Artificial Neural Network (ANN) with feed-forward and feed-backward functions and backpropagation algorithm is a high accuracy method with a small error level to find the non-linear connection, economic factor variations, and other factors, and adjusting itself on changes that occur [12]–[16].

2. Network Architecture Formation

The network architecture formation was modeled based on the obtained data. Figure 1 illustrates the network architecture, while Table I shows the network architecture structure.

Fig. 1. Network Architecture

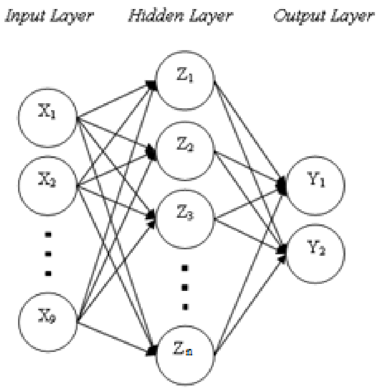

TABLE I
NETWORK ARCHITECTURE COMPOSITION

Parameter	Amount	Description
Input Layer	9 neurons	Research Data
Hidden Layer	9 neurons	Research Results
Output Layer	2 neurons	Estimation of power and energy consumption
Epoch	10,000	Maximum epoch
Training Function	Traingdx	-
Activation Function	Binary Sigmoidal	-

After the error value in training was smaller than the targeted error, the final update load during training was used in the testing stage to observe whether the load and bias could be used and obtained a good result. Table II presents the input and target organization in this research.

TABLE II

INPUT AND TARGET PATTERNS

Pattern	Input Data	Target
1	X_1-X_5 were the independent data from 2008	2008 dependent data
2	X_1-X_5 were the independent data from 2009	2009 dependent data
.	.	.
.	.	.
10	X_1-X_5 were the independent data from 2017	2017 dependent data

3) Testing Evaluation

Optimizing the network architecture was conducted by trial and error in the targeted Mean Squared Error (MSE) during the training. The Mean Absolute Percentage Error (MAPE) was used o see the precision and accuracy of the estimation results on the real data [17]–[19]. Equation 1 shows the MAPE equation.

$$MAPE = \frac{\sum \frac{|yi-fi|}{yi} x100}{n} \quad (1)$$

The *yi* value is the real data, *fi* is the estimation results, and *n* is the total data. Table III presents the MAPE accuracy level in the estimation.

TABLE III

MAPE ACCURACY LEVEL IN THE ESTIMATION

MAPE Value	**Accuracy Level**
$\leq$10%	High
10% < $x \leq$ 20%	Good
20% < $x \leq$ 50%	Reasonable
> 50%	Low

3. Method

. *Research Framework*

This research is quantitative with secondary data analysis. Figure 1 displays a flowchart of the research framework.

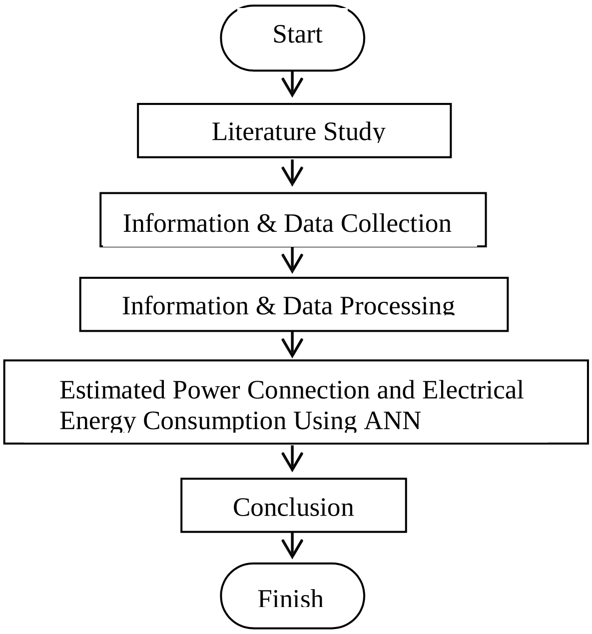

Fig. 2. Research Framework Chart

B. Research Data

The information and data in this research consisted of independent and dependent variables. Independent variables covered total population, Gross Regional Domestic Product in the regency, total customers, produced energy (kWh), remaining energy (kWh), distribution loss %, total transformer, peak load, and load factor (%). Meanwhile, the dependent variables covered the consumed energy (kWh) and connected power (VA) that also acted as the targeted data. The data was obtained from Srengat Network Service Unit, East Java and Blitar Regency Statistics. The data contained yearly data for the last ten years.

C. Initial Data Processing

The transformed data were processed using the ANN-backpropagation method in the initial data training to adjust the output range into (0.1) using the binary sigmoidal function. If the error were smaller than the targeted error, the training would stop. This study used the gradient descent with momentum backpropagation.

D. Data Analysis

Figure 2 presents the steps in estimating the connected power and electricity consumption.

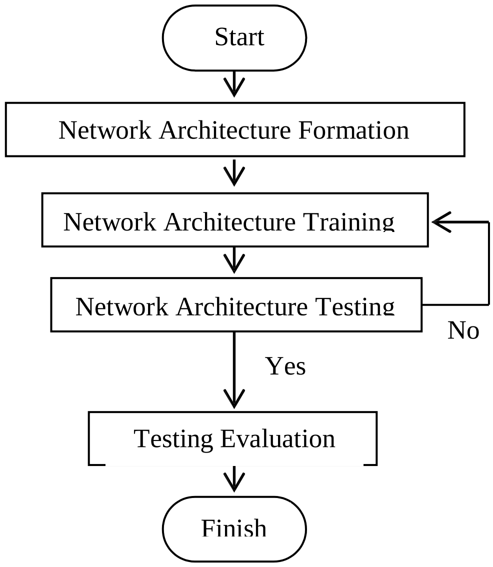

Fig. 3. Estimation Steps of Connected Power and Energy Consumption

4. Result

Based on the network architecture composition in Table I and the input and target patterns in Table II, this study obtained the best network architecture composition from the training and testing that was 9-9-2 with the goal of 10^{-6}, momentum value of 0.9, and 0.15 learning ratio. Below are the results of this research:

TABLE IV. COMPARISON OF ESTIMATION TRAINING

Year	Target Value (VA)	JST Value (VA)	Error (%)
2008	32,526,775	32,615,611	0.273
2009	36,492,585	36,296,363	0.538
2010	40,458,395	40,667,869	0.518
2011	44,424,205	44,245,877	0.401
2012	48,390,015	48,478,252	0.182
2013	56,558,565	56,552,204	0.011
2014	60,241,515	60,236,464	0.008

TABLE IV. COMPARISON OF ENERGY CONSUMPTION DATA

Year	Target Value(kWh)	JST Value (kWh)	Error (%)
2008	45,137,523	45,140,241	0.006
2009	50,547,295	50,531,405	0.031
2010	55,957,068	56,002,945	0.082
2011	61,366,841	61,305,066	0.101
2012	66,776,613	66,810,018	0.050
2013	76,358869	76,357,060	0.002
2014	83,905,547	83,903,324	0.003

TABLE V. COMPARISON OF ESTIMATION TESTING RESULTS WITH THE ACTUAL CONNECTED POWER

Year	Target Value (VA)	JST Value (VA)	Error (%)
2015	64,047,015	68,727,089	7.31
2016	67,821,615	61,234,043	9.71
2017	72,597,565	67,791,728	6.62
MAPE			7.88

TABLE VI. COMPARISON OF ESTIMATION RESULTS WITH THE ACTUAL ELECTRICAL ENERGY CONSUMPTION DATA

Year	Target Value(kWh)	JST Value (kWh)	Error (%)
2015	88,842,658	84,414,009	4.98
2016	95,221,877	97,342,762	2.23
2017	97,749,567	123,743,804	26.59
MAPE			11.27

Based on the research results, the best result was in 2015 with 0.004422 MSE and 7.88% MAPE for the connected power and 11.27% MAPE for the electricity consumption target. The network architecture composition recognized the patterns well and accurately delivered the estimation following the MAPE value. The estimated connected power had high accuracy, while the estimated electricity consumption had good accuracy. Higher accuracy in electricity consumption compared to the connected power was due to the various types of customers. Thus, consumption experienced large fluctuations. The changing patterns of the community's behavior followed the external factors (technology, climate, economy, others). Otherwise, the low accuracy in the connected power was due to the small demands of new installations each year. A small number of industries and low migration levels also influenced the electrical installation. Housing customers with middle-lower economical levels dominated the electricity installation in Srengat. Hence, the new installations only increased a little. The accuracy level on the consumption target each year could be improved by adding external factors and macroeconomic value as the input variables so that the network could adjust better.

5. Conclusion

Based on the research, the estimated connected power and electricity consumption in PT. PLN (Persero) UPJ Srengat, East Java, could be conducted using the Artificial Neural Network (ANN) method with feed-forward and feed-backward functions from the backpropagation algorithm. The 0.9 momentum value and learning speed of 0.15 and network architecture of 9-9-2 was the best network. The smallest MSE proved a reasonable error adjustment in this research in 2015 that was 0.04422 and 7.88% MAPE value for the connected power, and 11.27% MAPE value for the electricity consumption target. The MSE was the indication that the network could adjust well or not. The value below one showed that the network could be used as the estimation method and adjust well. The external factors and macroeconomic value were correlated and influence the estimation and could be used as the input variables to improve the estimation accuracy.

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