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Forecasting South Sulawesi Electrical Energy Consumption Using Artificial Neural Network

***Abstract**. Electrical Energy must be provided in an amount according to needs. Energy that exceeds consumption needs causes power loss. On the other hand, when electricity is scarce, it causes blackouts. To produce electrical energy that meets these needs, there must be a plan for the provision of electrical energy which is carried out by forecasting electricity consumption. Therefore, forecasting electricity consumption is very important to ensure electricity efficiency. This research was conducted in the province of South Sulawesi, Indonesia. The research method used is the Artificial Neural Network (ANN) method. The results of forecasting energy consumption show that the Artificial Neural Network method, Network Type back-propagation, and the TRAINGDX training function of 1480.133602 MW are closest to the target value of 1480.167515 MW or a difference of 0.033913 MW, Mean Square Error (MSE) value is 0.000002131. TRAINCGB is 1480.115899 MW or a difference of 0.051616 MW, the Mean Square Error (MSE) value is 0.000003226. This forecast shows that the results are accurate.*

Streszczenie.** Energia elektryczna musi być zapewniona w ilości dostosowanej do potrzeb. Energia przekraczająca zapotrzebowanie powoduje utratę mocy. Z drugiej strony, gdy brakuje prądu, powoduje to przerwy w dostawie prądu. Aby wyprodukować energię elektryczną zaspokajającą te potrzeby, musi istnieć plan dostarczania energii elektrycznej, który odbywa się poprzez prognozowanie zużycia energii elektrycznej. Dlatego prognozowanie zużycia energii elektrycznej jest bardzo ważne dla zapewnienia efektywności energetycznej. Badania przeprowadzono w prowincji Sulawesi Południowe w Indonezji. Zastosowaną metodą badawczą jest metoda sztucznej sieci neuronowej (ANN). Wyniki prognozowania zużycia energii pokazują, że metoda sztucznej sieci neuronowej, propagacja wsteczna typu sieci oraz funkcja ucząca TRAINGDX wynosząca 1480,133602 MW są najbliższe docelowej wartości 1480,167515 MW lub różnicy 0,033913 MW, średniego błędu kwadratowego (MSE). wartość wynosi 0,000002131. TRAINCGB wynosi 1480,115899 MW lub różnica 0,051616 MW, wartość błędu średniokwadratowego (MSE) wynosi 0,000003226. Prognoza ta pokazuje, że wyniki są trafne.* (Prognozowanie zużycia energii elektrycznej w Południowym Sulawesi przy użyciu sztucznej sieci neuronowej***)

Keywords: Electricity consumption, Artificial Neural Network, back-propagation
Słowa kluczowe: Zużycie energii elektrycznej, sztuczne sieci neuronowe, propagacja wsteczna

Introduction

Electricity or electrical energy has become very important today both to meet daily needs and to meet industrial needs. The need for electricity or electrical energy continues to increase both quantitatively and qualitatively in line with population growth and various types of activities.

Electricity consumption has special characteristics that are generally different from other "commodities". Until then the transmission or distribution of electric power must be carried out through a certain network, where the level of generation or power generated by the electricity producer must match the level of demand or service load [1] [2] [3]. The arrangement or adjustment between production and electricity consumption needs is very important considering the specific nature of electricity, namely it is impossible to store electricity in large quantities, so that electrical energy must be provided when it is needed. As a result, problems arise when facing the need for electrical energy that is not fixed or always changing, therefore the use of the electricity system must be scheduled, so that it can always meet the demand for electricity consumption at any time and with high quality. and efficiency [4].

If the power delivered by the power plant is much higher than the load power requirements, then there is a waste of energy at the power company. Conversely, if the power provided or generated by a power plant is less than the consumer's demand or load demand, then an overload will occur which will lead to power outages which of course must be avoided because it is detrimental to consumers [5] [6] [7]. Therefore, there is a need for control or regulation between generation power and power demand. To adjust between electricity production and electricity demand or consumption, electricity producers need to know the load or demand for electricity for some time to come.

In this study, the authors tried to make a prediction model for electricity consumption using an artificial neural network (ANN) with a back-propagation learning algorithm and a sigmoid activation function. The data used is integrated energy consumption data for Sulawesi Island [8] [9].

Artificial Neural Network

An artificial neural network (ANN) is a computer system whose architecture and operation are inspired by the knowledge of biological neurons in the human brain [3] [10] [11]. Another definition of an artificial neural network by Faucett (1994) is an information processing system with properties like biological neural networks [12].

Artificial neural networks are created as a generalization of a mathematical model of human thinking based on the following assumptions:

- Information processing takes place in simple elements called neurons, units, cells, or nodes.
- Signals travel between nerve cells/neurons through connections.
- Each connecting joint has a corresponding weight. This weight is used to multiply the signals sent through it.
- Each neuron applies an activation function to the weighted sum signal it receives to determine its output signal.

The characteristics of an artificial neural network are determined by:

a. model of connections between neurons (called network architecture);
b. the method of determining the connecting weights (which is called the training/learning/algorithm method);
c. activation function.

Like the human brain, a neural network is made up of many neurons and there are connections between them. Some neurons transform the information they receive through output connections from other neurons. In other words, a neuron is an information processing unit on which an artificial neural network operates. These neurons are modeled after simplified human neurons. The following image is an image of a neuron.

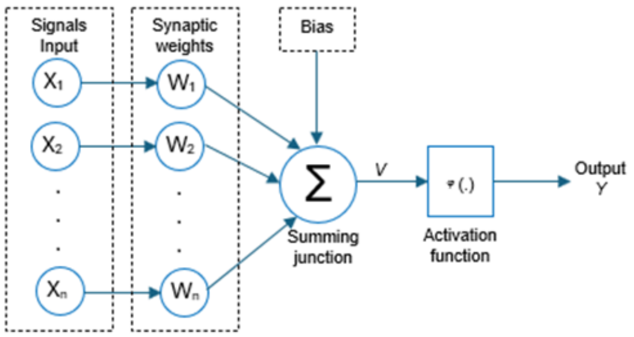


Fig. 1. The structure of the neural network unit

Architecture of Artificial Neural Network

Artificial neural networks are designed with general rules where all network models have the same basic concept. ANN architecture in relation to the arrangement of neurons, shows the pattern of connections between neurons and the number of layers spread across the network [3] [11]. Network architecture determines the success of the goals to be achieved, because not all problems can be solved with the same architecture. A multilayer network has one or more layers between the input layer and the output layer, as shown in the following figure.

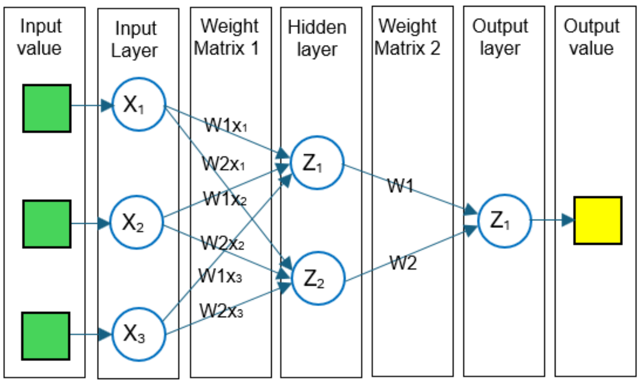


Fig. 2. Multilayer artificial neural network

Backpropagation network

Backpropagation network is one of the algorithms that is often used to solve complex problems. This is possible because the network equipped with this algorithm is trained using a supervised learning method. The network receives a pattern pair consisting of the input pattern and the desired pattern. When a pattern is supplied to the network, the weights are changed to minimize the difference between the source pattern and the desired pattern. This exercise is repeated so that all patterns provided by the network can fulfill the desired pattern.

The backpropagation neural network training algorithm consists of two steps, namely forward/propagation and back/propagation. During network training, forward and backward propagation steps are performed in the network for any given pattern. Backpropagation network consists of three or more layers. The difference is only in the number of hidden layers in it. Forward propagation begins by entering the input pattern in the input layer. This input pattern is the activation value of the input unit. During further progress, the activation value of the next layer unit is calculated. At each layer, each processing unit takes a weighted sum and uses the sigmoid function to calculate the output.

The formula used to calculate the total weight is as follows:

(1) $S_j = \sum_{i=0}^{n} X_i W_{ji}$

Where: *xi* - input from unit *i, wji* - weight from unit *i* to unit *j*.

After the value of *Sj* is calculated, *Sj* is applied to form the sigmoid function *f(Sj)*. This sigmoid function has the equation:

(2) $f(S_j) = \frac{1}{1+e^{-Sj}}$

The result of this *f(Sj)* calculation is the activation value of processing unit *j*. This value is sent to all outputs of unit *j*. After forwarding is complete, the network is ready for back-propagation.

If *j* is one unit of the output layer, the output layer error can be calculated by the following formula:

(3) $\delta_j = (t_j - y_j)\, f'(S_j)$

Where: *tj* - desired output in unit *j*, *yj* - output of unit *j*, *f'(Sj)* - first derivative of the sigmoid function, *Sj* - weighted sum.

If *j* is a hidden layer, the hidden layer error can be calculated using the following formula.

(4) $\delta_j = [\sum \delta_k W_{kj} \cdot f'](S_j)$

(5) $\Delta_{wij} = \alpha \,.\, \delta_j \,.\, x_i$

Where: *Δwji* - change in weight of unit *i* to unit j, α - learning rate, δ_j - hidden layer error, *xi* - input from unit *i*.

The variable α represents the value learning constant between 0.25 and 0.75. This value indicates the learning speed of the network. A value that is too high can make the network unstable, while a value that is too low can cause a long learning time. Therefore, the selection of α values must be as optimal as possible to achieve fast learning.

The complete backpropagation network training algorithm is as follows (Fausett 1994):

Stage 0 : Initialize the weights (set them to small random values).

Stage 1 : If the stop condition is false, do steps 2-9.

Stage 2 : Complete steps 3-8 for each exercise pair

Continue to enter:

Stage 3 : Each input unit (xi, i = 1,....,n) receives the input signal xi and forwards it to the hidden unit.

Stage 4 : Each hidden unit (zj, j = 1,...,p) sums the weighted input signals,

(6) $Z\_in_j = v_{oj} + \sum_{i=1}^{n} x_i v_j$

apply the activation function calculation:

(7) $Z_j = f\,(z - in_j)$

Stage 5 : Each output unit (yk, k = 1...., m) sums the weighted input signals,

(8) $y\_in_k = w_{ok} + \sum_{j=1}^{n} Z_j w_{jk}$

apply the activation function calculation:

(9) $y_k = f\,(y - in_k$

Reverse Error Propagation:

Stage 6 : Each output unit (yk, k = 1..., m) is assigned a target pattern associated with its input training pattern.

Calculate error data:

(10) $\delta_k = (t_k - y_k)\, f'(y\_in_k$

Calculate weight correction and preposition:

(11) $\Delta_{wjk} = \alpha \,.\, \delta_k \,.\, z_j$

(12) $\Delta_{wok} = \alpha \,.\, \delta_k$

Stage 7 : Each hidden unit (zj, j = 1,....,p) sums the input delta (upper layer unit).

(13) $\delta\_in_j = \sum_{k=1}^{m} \delta_k \; w_{jk}$

Calculate error data:

(14) $\delta_j \;\; = \delta\_in_j \, f' \, (z\_in_j$

Calculate weight correction and preposition:

(15) $\Delta \, v_{ij} = \alpha \, . \, \delta_j \, . x_i$

Update weights and positions:

Stage 8 : Each output device (yk, k=1..., m) updates its weight and position (j=0,1, ..., p).

(16) $w_{jk}(baru) = w_{jk}(lama) + \Delta w_{jk}$

Each hidden unit (zj, j=1..., p) updates the weights and prepositions (i = 0,1..., n);

(17) $v_{ij}(baru) = v_{ij}(lama) + \Delta \, v_{ij}$

Stage 9 : Test shutdown mode.

The weight updating procedure can be changed using momentum. By adding momentum to the weight reform formula, convergence is usually achieved more quickly. When updating the weight per pulse, the repetition weight (t + 1) is determined by the repetition weight t and t (t-1).

The weight reform formula is as follows:

(18) $\Delta w_{jk}(t+1) = w_{jk}(t) + \alpha \delta_k z_j + \mu \left[w_{jk}(t) - w_{jk}(t-1) \right]$

or

(19) $\Delta \, w_{ij}(t+1) = \alpha \delta_k z_j + \mu \, \Delta \, w_{ij} \, (t)$

and

(20) $v_{ij}(t+1) = v_{ij}(t) + \alpha \delta_j x_i + \mu \left[v_{ij}(t) - v_{ij}(t-1) \right]$

or

(21) $\Delta \, v_{ij}(t+1) = \alpha \delta_j x_i + \mu \, \Delta \, v_{ij} \, (t)$

Where: x1...xn – input, y1...yn – output, z1..zn - value of hidden layer, vij - weight between input and hidden layer, wjk - weight between hidden layer and output layer, - information error, α - speed or learning rate, μ - momentum

Mean Square Error (MSE)

The backpropagation neural network was trained using a supervised learning method. In this method, the network receives a set of pattern pairs consisting of the input pattern and the desired pattern. Training is done repeatedly to build a network that responds correctly to all inputs. The error count measures how well a network can learn to recognize easily compared to new patterns. Net output error is the difference between the actual output (current output) and the desired output or target [3] [13] [14]. The resulting difference between the two is usually determined by calculation using the following formula:

a. Sum Square Error (SSE) :

(22) $SSE = \sum_p \sum_j (T_{jp} - Y_{jp})^2$

b. Mean Square Error (MSE):

(23) $MSE = \dfrac{SEE}{n_P \, n_j}$

c. Root Mean Square Error (RMSE) :

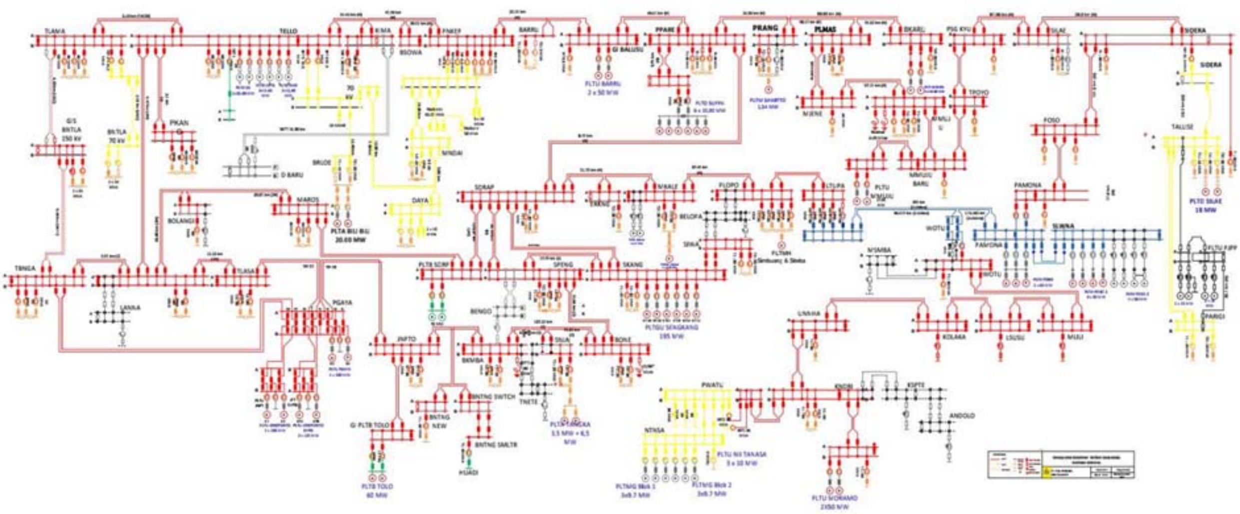
(24) $RMSE = \sqrt{MSE}$

Where: Tjp - desired output value or target neural network, YJP - neural network output value, np - total number of patterns nj - number of exits.

Data Transformation

Before using the data with the method or technique used, we must pre-process the data. This is done using machine learning or data mining techniques to get more accurate analysis results. In some cases, preprocessing can reduce the value of data without changing the information it contains. There are several ways to transform data before applying a method, including normalization or scaling, which is the process of transforming data to a certain scale (Santosa 2007). This scale can be between (0,1), (-1,1) or other desired scale. Suppose we change the electrical load data; the load data is converted into a scale or range of values from 0 to 1 [3]. In this case, the lower limit (LL) is 0 and the upper limit (UL) is 1. If the maximum value for each column is Xmax and the minimum value is Xmin, you can modify a new scale formula for each data:

(25) $X' = \dfrac{X - X_{min}}{X_{max} - X_{min}} (UL - LL) + LL$



Source: PT PLN (Persero) UIKL Sulawesi

Fig. 3. Single Line Diagram of the Sulbagsel System

Table 1. Data that has been transformed

Months	Years							
	2013	2015	2017	2018	2019	2020	2023	2024
	X	X	X	X	X	X	X	Y
1	3,38E-08	1,57E-01	3,24E-01	4,08E-01	4,93E-01	6,64E-01	8,36E-01	2,69E-08
2	7,07E-02	2,47E-01	4,32E-01	5,25E-01	6,20E-01	8,09E-01	1,00E+00	1,00E+00
3	1,29E-02	1,73E-01	3,41E-01	4,26E-01	5,11E-01	6,83E-01	8,55E-01	1,10E-01
4	3,97E-02	2,07E-01	3,81E-01	4,69E-01	5,58E-01	7,35E-01	9,13E-01	4,63E-01
5	2,57E-02	1,89E-01	3,58E-01	4,44E-01	5,29E-01	7,02E-01	8,74E-01	2,21E-01
6	5,30E-02	2,23E-01	3,99E-01	4,87E-01	5,76E-01	7,54E-01	9,33E-01	5,77E-01
7	3,86E-02	2,05E-01	3,81E-01	4,61E-01	5,48E-01	7,20E-01	8,93E-01	3,31E-01
8	6,63E-02	2,40E-01	4,17E-01	5,06E-01	5,95E-01	7,74E-01	9,53E-01	6,92E-01
9	5,15E-02	2,21E-01	3,93E-01	4,79E-01	5,66E-01	7,39E-01	9,12E-01	4,42E-01
10	7,96E-02	2,56E-01	4,35E-01	5,24E-01	6,24E-01	7,93E-01	9,72E-01	8,06E-01
11	6,43E-02	2,37E-01	4,10E-01	4,97E-01	5,84E-01	7,57E-01	9,31E-01	5,52E-01
12	9,29E-02	2,73E-01	4,52E-01	5,42E-01	6,32E-01	8,12E-01	9,92E-01	9,20E-01

Materials and Methods

Material

Sulbagsel's electricity system consists of 76 busbars and several generators connected by transmission systems with different voltage levels, namely 275 kV, 150 kV, 70 kV and 30 kV lines [2] [15] [7] [16]. Energy consumption data used to predict are as follows.

Data used in forecasting annual energy consumption in South Sulawesi is shown above. The data has been transformed with the Logsid method which is in the value 0 to 1. As for another single picture of the diagram, it can be seen as follows.

Method

The research method used is Artificial Neural Network (ANN), with the following research flow chart.

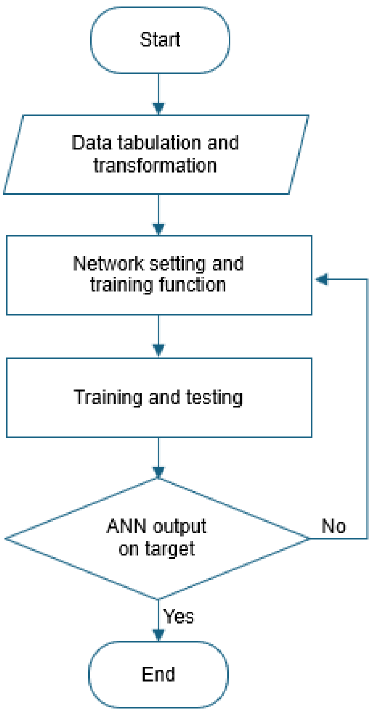


Fig. 2. Flow chart of energy consumption research

Results and Discussion

Research on forecasting electricity consumption in South Sulawesi uses six stages of the training function. The training function used can be seen in the following table.

Table 1. The training function on energy consumption forecasts

Training Function	MSE	Description
TRAINGD	0,019554692	Not yet converge
TRAINCGP	0,007474800	Not yet converge
TRAINGDM	0,002072808	Not yet converge
TRAINCGF	0,001119050	Not yet converge
TRAINCGB	0,000003226	convergent
TRAINGDX	0,000002131	convergent

The test results with the various types of training functions above show that Trainingdx produces the lowest Mean Square Error (MSE) value, namely 0.000002131, then Traincgb, which is 0.000003226. The two training functions produce convergent values. While the others have not converged.

The results of forecasting electricity consumption in South Sulawesi using an Artificial Neural Network (ANN) can be seen in the following table.

Table 2. Forecasting results of annual energy consumption

Real Data Target (MW)	ANN TRAINGDX (MW)	ANN TRAINCGB (MW)
1398,817204	1409,057638	1398,920364
1558,452381	1546,565963	1558,439629
1416,451613	1413,195223	1416,274905
1472,777778	1473,304581	1472,734683
1434,086022	1424,240702	1434,181186
1491,000000	1488,169810	1491,043244
1451,720430	1453,915289	1448,353599
1509,222222	1508,510528	1509,190574
1469,354839	1467,781203	1468,651215
1527,444444	1546,727195	1527,456033
1487,002688	1483,412682	1485,982808
1545,680556	1546,722406	1550,162544
Annual Average Prediction		
1480,167515	1480,133602	1480,115899

The results of forecasting energy consumption show that the Artificial Neural Network, Network Type back-propagation, and training function TRAINGDX methods are 1480.133602 MW closest to the target value, namely 1480.167515 MW or a difference of 0.033913 MW. TRAINCGB of 1480.115899 MW or a difference of 0.051616 MW.

The consumption of electrical energy in South Sulawesi has increased year after year. This is caused by an increase in infrastructure development and the community's economy. For more details about the growth of energy consumption can be seen in the following table.

Table 3. The growth of electricity consumption in South Sulawesi.

Years	Electrical energy consumption
2013	761,1901588
2015	917,7254518
2017	1078,889705
2018	1159,426641
2019	1241,478103
2021	1403,646316
2023	1567,041328
Forecast (2024)	1648,834181

The graph of energy consumption growth can be seen in the following figure.

The graph of energy consumption growth in South Sulawesi shows that the forecast results have the same pattern as the previous year. This growth pattern can be used as an indicator that forecasting results are accurate.

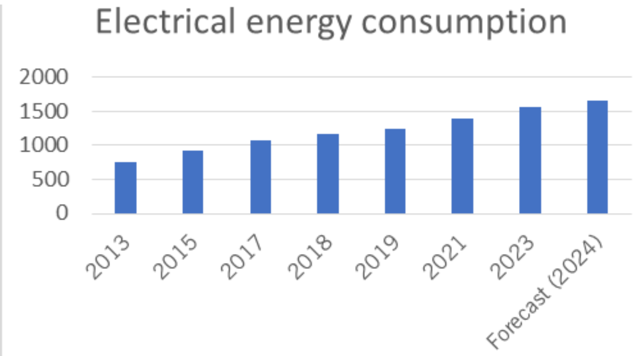


Fig. 3. Growth in electricity consumption in South Sulawesi

Conclusion

The results of energy consumption forecasting show that the Artificial Neural Network, Network Type back-propagation, and training function TRAINGDX methods of 1480.133602 MW are closest to the target value of 1480.167515 MW or a difference of 0.033913 MW, the Mean Square Error (MSE) value is 0.000002131. TRAINCGB of 1480.115899 MW or a difference of 0.051616 MW, the Mean Square Error (MSE) value is 0.000003226. This forecast shows that the prediction results are very accurate.

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