Analysis of Artificial Neural Network in Predicting the Fuel Consumption by Type of Power Plant

Widodo Saputra¹, P Poningsih¹, Muhammad Ridwan Lubis¹, Sundari Retno Andani¹, Irfan Sudahri Damanik², Anjar Wanto²

¹ AMIK Tunas Bangsa, Sudirman Street Pematangsiantar, Medan - Indonesia
² STIKOM Tunas Bangsa, Sudirman Street Pematangsiantar, Medan - Indonesia

Abstract. The electric is one of the needs for human, the growth of the electric power in Indonesia is very increased. There are 13 types of power plants in Indonesia, including to require the fuel in its operational. Fuel consumption needs to be recorded at regular intervals so that the needs of fuel for the power plant remain fulfilled. This research discusses about the predictions fuel consumption based on the type of power plants. The method used is the Artificial Neural Network with the back propagation algorithm. This method is good enough to use in predicting the data. The data used is fuel consumption data based on the type of power plant of the year 2014-2016. The best architecture is 8-23-1 that gets results accuracy of 88%, epoch 6016 iteration and MSE 0.0005509801. From these results then predict using the 8-23-1 architecture is the best architecture.

1. Introduction

The growth of electricity demand in Indonesia is increasing. This is due to the increasing the growth of buildings needs the electricity on every operation. Indonesia has 13 types of power plants. The Power plants are part of industrial equipment used to produced and generate electricity from various sources of energy, include the need for fuel to produce electricity. The fuel is the one important factor in supporting the performance of power plants. Indonesia is one of the countries that has a natural resources incude the fuel, but currently the Director of corporate planning of PLN said the use of fuel for electricity activities keep on descreasing [1]. Therefore the reason that data collection on fuel is use a barometre to saee the future needs. And one of the method that can be used to see the future needs is Artificial Neural Network (ANN) [2]–[4].

The Artificial Neural Network (ANN) are a very popular way to predict in a number of fields incude the finances, the power of generation, medicine, water resources and the science environment [5]. ANN learn to problem solving by the develop memory capable to corelate the large numbers of input patterns with a set will be producted [6]. ANN is processing information systems that have specific performance characteristics as the neural network of the human brain, with the learning process at the change of weights [7].

This research will discuss about the use of fuel based on the type of generator to see the needs of the type of power plant of the year. Based on the data that has been obtained from PT.PLN (Persero) and Directorate general of electricity, while other supporting data regarding Energy comes from the Directorate general of Oil and Gas, and the Directorate general of Mineral and Coal, and Directorate general of Renewable Energy and Energy Conservation, which are processed by using material data.
fuel per type of plant from 2014-2016. This research will used the backpropagation algorithm and look for the best architecture. Many research have shown that artificial neural networks outperform the traditional method in time series Forecasting [5]. Back propagation neural network devided three-layered feed forward architecture. There are input layer, hidden layer and output layer [8]. To get a best architecture in back propagation will be used as the output value for the prediction in the next year.

2. Methodology

2.1. Data Used
The data used in this research is Fuel Consumption by Type of Power Plant since 2014-2016 (table 1). The data been has obtained from Electricity data sources were gathered from the Directorate General of Electricity and PT. PLN (Persero), while supporting data regarding to other primary/secondary energy were gathered from the Directorate General of Oil and Gas, Directorate General Mineral and Coal, and also Directorate General of New and Renewable Energy, and Energy Conservation in Indonesia.

| Fuel                  | Unit                | 2014        | 2015        | 2016        |
|-----------------------|---------------------|-------------|-------------|-------------|
| Steam Oil             | (kilo liters)       | 316931      | 182204,8    | 324131,5    |
| Steam Coal            | (tons)              | 43862412    | 48995169    | 50556446    |
| Steam Natural Gas     | (mmScf)             | 51347       | 52166,27    | 48502,37    |
| Oil Gas Turbine       | (kilo liters)       | 590588      | 456626,6    | 386117,5    |
| Natural Gas Turbine   | (mmScf)             | 82073       | 57088,04    | 65059,19    |
| Oil Combined Cycle    | (kilo liters)       | 1034466     | 237960,5    | 67788,94    |
| Gas combined cycle    | (mmScf)             | 293011      | 316505,1    | 347951,4    |
| Oil diesel            | (kilo liters)       | 5463831     | 4602071     | 3888994     |

Source: Directorate General of Electricity and PT. PLN (Persero)

2.2. Flowchart Research
Here's a flowchart that was used in this study, can be seen in the figure below:

The figure above shows that flow diagram started from a group of data. In the normalization data used normalization formula [9]–[13]:

\[
x' = \frac{0.8(x-a)}{b-a} + 0.1
\]  

Explanation:
x': Transformed data, x : The data will be normalized, a : Minimum data, b : Maximum data

after normalization data will be divided in 2 part there are training data and testing data. The training data will be trained by using back propagation algorithm and the testing data will be tested by using back propagation algorithm to get result of the best architecture. The best architecture is used to analyze the result of prediction.

3. Results and Discussion
The data can be seen at table 1 will be normalization. There is the result of the normalization data

| Year | Steam Oil | Steam Coal | Steam Oil | Natural Gas Turbine | Oil Gas Turbine | Natural Gas Turbine | Oil Combined Cycle | Gas Combined Cycle | Oil Diesel |
|------|-----------|------------|-----------|--------------------|----------------|---------------------|--------------------|-------------------|-----------|
| 2014 | 0.10425   | 0.79397    | 0.10005   | 0.10859            | 0.10053        | 0.11562             | 0.10387            | 0.18577           |
| 2015 | 0.10212   | 0.87527    | 0.10006   | 0.10646            | 0.10014        | 0.10300             | 0.10424            | 0.17212           |
| 2016 | 0.10437   | 0.90000    | 0.10000   | 0.10535            | 0.10026        | 0.10031             | 0.10474            | 0.16083           |

This research used matlab for get the best architecture. To look for the best architecture it has been several attempt of experiments there are 8-20-1, 8-22-1, 8-23-1, 8-24-1, 8-25-1 and 8-30-1. From 6 experiments obtained 1 the best architecture is 8-23-1 with 88% accuracy. The process of training data and testing data can be seen below :

![Figure 2. Training, Performance and Regression with architecture 8-23-1](image)

It can be seen from figure above, that used architecture 8-23-1 to get the maximum epoch 6016 iteration with 23 second duration.
Table 3. Best Architecture Results with Architecture 8-23-1

| Pattern | Data Training | Data Testing |
|---------|---------------|--------------|
|         | Pattern       | Target       | Output       | Error         | SSE           | Pattern | Target       | Output       | Error         | SSE           |
| 1       | 0.10212       | 0.0767327    | 0.02539      | 0.0006443989 | 0.01394       | 0.0001944334 |
| 2       | 0.87527       | 0.8615399    | 0.01373      | 0.0001885385 | 0.00947       | 0.0000895945 |
| 3       | 0.10006       | 0.0742835    | 0.02577      | 0.000643270  | 0.02175       | 0.0004729697 |
| 4       | 0.10646       | 0.0763089    | 0.03016      | 0.0009093499 | 0.02516       | 0.0006328262 |
| 5       | 0.10014       | 0.1263301    | -0.02619     | 0.0006861340 | -0.03160      | 0.0009984851 |
| 6       | 0.10300       | 0.0396762    | 0.06332      | 0.0040100120 | 0.06367       | 0.0040536066 |
| 7       | 0.10424       | 0.1244474    | -0.02020     | 0.0004081387 | -0.01770      | 0.0003132428 |
| 8       | 0.17212       | 0.1942323    | -0.02211     | 0.0004887600 | -0.02019      | 0.0004075825 |
|         | Sum           | 0.0079996589 | Sum          | 0.006153584  | MSE           | 0.0006153584 |
|         | MSE           | 0.0006153584 | MSE          | 0.0005509801 |              |          |

Table 4. Architectural Results In Backpropagation

| Architecture | MSE       | Epoch       | Accuracy (%) |
|--------------|-----------|-------------|--------------|
| 8-20-1       | 0.0007651948 | 13448 Iteration | 75           |
| 8-22-1       | 0.0007149371 | 4374 Iteration | 75           |
| 8-23-1       | 0.0005509801 | 6016 Iteration | 88           |
| 8-24-1       | 0.00111811473 | 18156 Iteration | 75           |
| 8-25-1       | 0.0006157852 | 10869 Iteration | 88           |
| 8-30-1       | 0.0012280491 | 8583 Iteration | 63           |

Figure 3. Graph results in Back propagation

From the chart above that from 6 experiments the best architecture is 8-23-1 with 88% accuracy, epoch 6016 iteration and MSE 0.0005509801.
4. Conclusion
The conclusion that can be taken from the discussions above with the title Artificial Neural Network to predict the fuel consumption by type of power plant is:

a. Architecture 8-23-1 is the best architect used, resulting accuracy in prediction is 88%.

b. Fuel consumption by type of plants can be predict used Artificial Neural Network with back propagation algorithm.

c. This research can helps Directorate General of Electricity and PT. PLN (Persero) to get the needs of the fuel consumption by type power plant.

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