Spatial neural network for forecasting energy consumption of Palembang area

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Abstract. Spatial Neural Network proposed as a new approach to determine the level of energy consumption in the future in the Palembang region, South Sumatra. Back-propagation is used to train Artificial Neural Networks. Population size, Gross Regional Domestic Product (GRDP), economic growth, Household Energy Consumption spatially per sub-district is used for this estimate. Data for 2008-2012 is used to train Spatial Neural Networks (ANN) and Data for 2013-2017 is used to validate this new approach to electricity demand prediction. The proposed Spatial ANN approach provides relatively good predictions about energy demand in acceptable errors and high accuracy for electricity demand predictions.

1. Introduction
Energy has a special and important position in the development and competitiveness of the nation. Growth in energy used were a supporting requirement for economic growth. In other words, economic development depends on the level of energy supply including electricity. As the economy increases, the demand for electricity in the industry, trade and public housing use also increases significantly.

Palembang is seventh largest city in Indonesia and the second largest city in Sumatra Island. During 2014-2018, Palembang City had economic growth above the South Sumatra and National average. Based on BPS data, Palembang's economic growth in 2018 is 6.0 percent or the highest in the last 5 years. Electricity demand also increased very dramatically, which was originally in the amount of 1959GWh in 2015 rose to 2218GWh in 2017. However, the increase in these needs was less anticipated by electricity companies. This is evidenced by frequent power outages in the city of Palembang and the most severe is the power outages after the opening of the ASIAN GAMES 2018. To anticipate this, electricity forecasting plays an important role so that power companies have good decisions and plans for electricity supply.

The most important challenge for the electrical energy industry is ensuring the availability and usefulness of electricity for all electricity users. The availability and reliability of electrical energy is a major problem in the policy making of electricity supply. Therefore, accurate electricity load forecasting is needed as a reference in the effective production of electrical energy.

Load estimates can be classified into four types. Very short-term load forecasting involves forecasting one minute ahead, important for real-time operations. Estimates of short-term expenses are one to three months ahead, important for unit commitment and operation. Estimates of medium-term expenses are for three months to the next three years, important for planning fuel reserves and unit commitments. Finally, long-term load forecasting has a three-year forecast horizon of no more than fifteen years [1].
Long-term load forecasting can be divided into two main categories: static spatial and dynamic time [2,3]. Spatial static prediction methods use certain characteristic factor objects and are measured first. Based on the equation formed, predictive values are obtained by certain time characteristic factors in the future. For the dynamic time method, it does not prioritize certain characteristic factors but uses historical data on load usage.

Neural network (NN) has been used as a prediction of the load forecasting time series with accurate and reliable results in recent times [4-9]. NN has the advantage of learning independently based on sample data (learning process) and after completion, NN can know non-linear dependence. The advantages of artificial neural networks (ANN) compared to regression-based models for 20-year forecasting based on monthly data training [10]. The use of Recurrent Neural Networks (RNN) in forecasting the burden of Long-term Memory (LTM) without using external variables on the input and shows the ability to study seasonal variants very well [11,12]. These all method has been using the historical load data to perform the load forecasting.

This paper proposes a model with a combination of spatial and Neural Network (NN) for Long-Term Memory (LTM) electricity forecasting. The main feature in this proposed model is forecasting by dividing it into spatial areas to minimize the loss of forecasting. The forecasting results derived from this proposed method are compared with the original LTM.

2. Method

2.1. Neural network

NN was the standard type of artificial neural network [13]. The network structure in NN as shown in Figure 1 usually has one or more hidden layer and using the sigmoid activation function. The number of neurons in the input and output layer is given based on the number of input and output variables in the related cases [14].

In this study, the number of input neurons used was four, each representing electricity consumption, population, Gross Regional Domestic Product (GRDP), and economic growth. The number of output neurons is one which is the estimated value of electricity consumption for the future. Inside the hidden layer, for each neuron there is a main NN process. The process in NN in each step is added the bias with the weighted input and activate it with the activation function.

The training process in the neural network is the process of adjusting the weights and biases of a network for minimizing the loss function on the network outputs (predicted and ground-truth), which is in this research is the case of supervised learning (given the set of input and the ground-truth output).

2.2. Spatial Palembang area

Palembang is the capital of South Sumatra province in Indonesia. The city proper covers 369.22 square kilometer (142.56 square miles) of land on both banks of the lower Musi River on the eastern lowland of southern Sumatra, with an estimated population of 1,633,161 in 2017. Palembang consists of sixteen sub-districts.
2.3. Methodology
The purpose of the methodology in this study is to estimate electricity consumption in the Palembang area. Based on historical time series data on electricity consumption, population, GRDP, and economic growth in each sub-district presented in Figure 2. We estimate electricity consumption for several time steps in the future using the method we propose. In this case, we need to estimate electricity consumption in the next five years based on data from the previous five years. For training data, we use data from 2008-2012. As for the trial data we use data from 2013-2017.

In this study, for the proposed model we combined the Spatial Palembang area in 16 NN components of each sub-district to forecast electricity consumption per sub-district shown in Figure 3. Experiments have been carried out using the shared data.

![The Factors Affecting Electricity Consumption](image1)

| The Factors Affecting Electricity Consumption | Neural Network | Forecasting Energy Consumption |
|---------------------------------------------|----------------|--------------------------------|
| POPULATION                                  |                |                                |
| ELECTRIC CONSUMPTION                        |                |                                |
| GROSS REGIONAL DOMESTIC INCOME              |                |                                |
| ECONOMIC GROWTH                             |                |                                |

![Figure 2. Forecasting with neural network for one sub-district.](image2)

3. Results and discussion
First, using population, GDP, economic growth, and energy consumption data between 2008-2012 training on artificial neural networks is done with Matlab™. Each sub-district has an artificial neural network, each training result based on regional data. Training of artificial neural networks using the BP algorithm. The Learning Level is set to 0.01 and the accuracy of errors is set as 0.0000001. Learning outcomes are presented in table 1.
From table 1 we can see that Artificial Neural Networks are able to make predictive models with very small MSE, namely 1.0065x10^{-15} to 6.3084x10^{-30}. This shows that the input data is highly correlated with the data output from the model.

To prove the accuracy of the model, a comparison test with actual electricity consumption data for 2013-2017 was also carried out. The results of this trial are presented in figure 4.

| Sub-District       | Mean Square Error | Epoch | Gradient   |
|--------------------|-------------------|-------|------------|
| Ilir Barat II      | 2.8109 e^{-18}    | 66    | 8.0528 e^{-08} |
| Gandus             | 4.1872 e^{-25}    | 10    | 4.2978 e^{-10}    |
| Seberang Ulu I     | 4.213 e^{-30}     | 8     | 7.6992 e^{-10}    |
| Kertapati          | 1.0041 e^{-25}    | 31    | 8.5666 e^{-09}    |
| Seberang Ulu II    | 1.0065 e^{-15}    | 215   | 9.8085 e^{-08}    |
| Plaju              | 3.6624 e^{-18}    | 15    | 3.2708 e^{-08}    |
| Ilir Barat I       | 6.3084 e^{-30}    | 94    | 1.0755 e^{-08}    |
| Bukit Kecil        | 9.1348 e^{-20}    | 16    | 6.9952 e^{-08}    |
| Ilir Timur I       | 8.0628 e^{-16}    | 59    | 9.9842 e^{-08}    |
| Kemuning           | 1.0753 e^{-29}    | 431   | 2.4847 e^{-09}    |
| Ilir Timur II      | 6.8387 e^{-20}    | 27    | 6.51 e^{-09}      |
| Kalidoni           | 1.3143 e^{-18}    | 23    | 3.7363 e^{-09}    |
| Sako               | 1.5699 e^{-24}    | 19    | 7.0965 e^{-11}    |
| Sematang Borang    | 1.4345 e^{-26}    | 15    | 1.1071 e^{-09}    |
| Sukarami           | 1.779 e^{-17}     | 26    | 8.7598 e^{-08}    |
| Alang-alang Lebar  | 1.5051 e^{-22}    | 22    | 3.1938 e^{-09}    |

From figure 4 the predictions of the spatial neural network results for 2013 to 2017 are very closely related to the electrical energy needs of Palembang in the same year. Compared to the prediction data from State Electricity Company (PLN), Spatial Neural Network is closer to the actual electricity needs. The error rate is only 0.01% and this shows that the prediction of electrical power requirements using the proposed method is very accurate.
Based on the results of the 2013-2017 prediction, we make predictions for the years 2018-2022 with the results as shown in figure 6 and comparisons with the prediction data held by the electricity providers (PLN) are also presented.

Based on Figure 5, it can be stated that the prediction from PLN is higher if compared with the results of predictions using spatial artificial neural networks. The biggest difference is around 9%, namely in 2022.

4. Conclusion
In this paper, based on historical data on load, population, economic growth, and GRDP in Palembang, predictions of load requirements are carried out with spatial neural networks using MATLAB. The validity and application of neural network spatial algorithms is proven through the learning process with 2008-2012 data and simulation test processes with 2013-2017 data, as well as predicting electricity loads for 2018-2022. The proposed Spatial ANN approach provides relatively good predictions about energy demand in acceptable errors and high accuracy for electricity demand predictions.

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