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Indonesian load prediction estimation using long short term memory

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ABSTRACT

Prediction of electrical load is important because it relates to the source of power generation, cost-effective generation, system security, and policy on continuity of service to consumers. This paper uses Indonesian primary data compiled based on data log sheet per hour of transmission operators. In preprocessing data, detrending technique is used to eliminate outlier data in the time series dataset. The prediction used in this research is a long-short-term memory algorithm with stacking and time-step techniques. In order to get the optimal one-day forecasting results, the inputs are arranged in the previous three periods with 1, 2, 3 layers, 512 and 1024 nodes. Forecasting results obtained long short-term memory (LSTM) with three layers and 1024 nodes got mean average percentage error (MAPE) of 8.63 better than other models.

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1. INTRODUCTION

Electrical load forecasting in the electric power industry is important because it relates to the management of generating sources, cost-effective power system planning, system security, customer service and policy making [1], [2]. Electrical load forecasting research is based on past load patterns [3] which may reappear in the future. Load forecasting can be classified based on the length of the horizon and the method used. Load forecasting can be classified based on the length of the horizon and the method used [4]. Based on the length of the forecasting horizon [5], [6] long-term forecasts of 1 year or more, medium-term 1 week to 1 year, and short-term 1 hour to 1 week. Based on the load forecasting method, the statistical method is used with a mathematical approach based on correlation regression, while the machine learning and deep learning methods are built based on the training and testing process to train and test the performance of the model. The advantage of the deep learning model is that it is more efficient to train complex neural networks, with generalization capabilities that increase accuracy around 20-45% [7]. Among the three learning methods, deep learning techniques are the most successful methods in the field of image, text and data mining [8].

Several studies using deep learning methods for load forecasting include using the convolutional neural network (CNN) neural network method, where the CNN layer is used to extract features from historical loads in homogeneous residential load clustering [9], [10]. Recurrent neural network (RNN) architecture in load forecasting supports non-stationary discrete time input signals, making RNNs more suitable for sequential or sequential data [11]–[13]. Long-short term memory (LSTM) by combining short-term memory with long-term memory, through gate control prevents signal loss during the prediction process, so as to a better accuracy [14]–[16]. Gate recurrent unit (GRU) is applied in the demand side energy forecasting which is still limited [17], predict electrical power load [18], shows the prediction performance of GRU is still lower than LSTM, but better than traditional models.

Modeling in particular with time-series data sets using the LSTM technique is quite popular for solving complex sequence models such as electrical loads, by studying long-term dependencies and tracing patterns that occurred far in the past. Several studies using the LSTM algorithm have been developed for short-term electrical load forecasting and become the best algorithm for prediction for time series data [5], [16], [19]–[22]. According to [16], [21] the vital problem in forecasting models using the LSTM structure is to choose the right sequence of lag times along with the right hyperparameter model for certain time series data. Electric load prediction based on one day ahead [19] using supervised learning k-Means technique for the classification of consumer features based on the time sequence, namely adjacent times; adjacent day; and the same day of the adjacent week. The experimental result [19], [23] shows that the hyperparameter tuning of variations in the number of nodes in the parallel layer LSTM shows good accuracy performance, and overall LSTM performance can find energy consumption patterns from consumers. Kwon *et al.* [5] applying the short-term forecasting method by extracting features from historical data, with the separation of features, namely the day of the week, the average load of the last two days, the hourly load and the hourly temperature so as to get good accuracy for forecasting the electricity load one day ahead in Korea. The recent research [20] uses a half-hour period data set from 2008-2016 from metropolitan France for one-day forecasting. Bouktif *et al.* [20] discusses the optimal configuration of the LSTM model by tuning the hyperparameter of the number of layers, the number of neurons in each layer, lag time, batch size, and type of activation so as to reduce the complexity of the dataset used. Abdel-Nasser and Mahmoud [22] comparing the basic LSTM architecture, LSTM with sliding windows technique, LSTM with time steps and stacked LSTMs with other benchmark models in modeling temporal changes in photo voltaic (PV) output power per hour in Egypt. The architecture of all LSTMs outperforms benchmark models for one-hour predictions ahead, and LSTM architectures with time steps get the lowest error compared to all other LSTM architectures.

The research in this paper proposes to predict the short-term load one day ahead with the stacking technique and the LSTM time step which is used for planning operations at the load control center one day ahead. This study uses a primary load dataset of Indonesia's electrical energy consumption, which until now is still limited. The dataset is compiled from PT PLN's daily logsheet based on the records of the transmission system operator every hour, for five years, 2013-2017. In preliminary research [24] our validation shows that LSTM-based forecasting models outperform other alternative approaches. Based on this preliminary research, we developed an LSTM algorithm by setting the optimal lag time and time step which is integrated with 3 layers LSTM stacking. To get the predictive performance of the electrical load, it is measured using the mean absolute error (MAE) and the mean absolute percentage error (MAPE). The rest of this article is structured: Part 2 of the research methodology, provides an overview of building prediction techniques that we propose. Section 3 describes the experimental results, validation and comparing with other LSTM models and deep learning models. Section 4 draws conclusions from the research that has been done.

2. RESEARCH METHOD

In this section, a short-term forecasting methodology for the next one day will be explained using the LSTM algorithm. We propose a three-step framework, namely, dataset preparation and preprocessing, LSTM algorithm construction and comparison machine learning (ML) algorithm, LSTM algorithm training and validation. In the following, we present an overview of the methodology, and an explanation for each component of the methodology in detail from the Indonesian electricity consumption dataset in this case study.

2.1. Data preparation and preprocessing

Forecasting this electrical load uses sequential data, which is related to past values. Past data on the use of electrical energy represents trends and load patterns as well as anomalies that occur. An exploratory analysis of the electrical load time series can be useful for identifying trends, patterns, and anomalies. Consumption patterns are grouped into daily, monthly and yearly electrical load consumption so that a graphical correlation can be seen between time and electricity usage.

2.1.1. Dataset

To find out the pattern of electricity consumption contained in this dataset, it is shown in Figures 1-3, the graph depicts the electricity load per day, per month and per year. Due to it is sequentially every hour, the total data in each year consists of 365 days or 8670 data. The daily load profile for 24 hours is shown in Figure 1, load consumption has an upward trend starting from 08.00 hours to its peak at

11.00-15.00 hours and decreases again along with reduced population activity. The peak load occurred at 18.00-20.00 with an increase in the load in housing and industry consisting of lighting and electronic equipment (65% of the load was housing load). Load consumption was reduced until the next following morning. From Figure 2, the hourly electricity consumption for one month obtained a lot of load outlier data in a few hours, this anomaly causes weather or humam errors, and will be overcome by preprocessing the load before being used as input for the maching learning model. In addition, Figure 3 illustrate the electrical consumption for one year. It infers that in the beginning of year, the electrical load slightly fluctuates. However, in the next following segment (middle to end of year) the electrical consumption relatively steady.

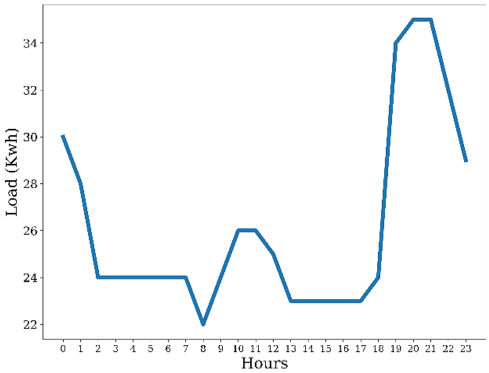


Figure 1. Twenty-four-hour electrical load

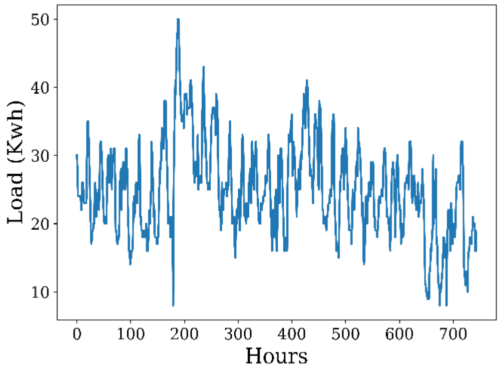


Figure 2. Monthly daily electrical load

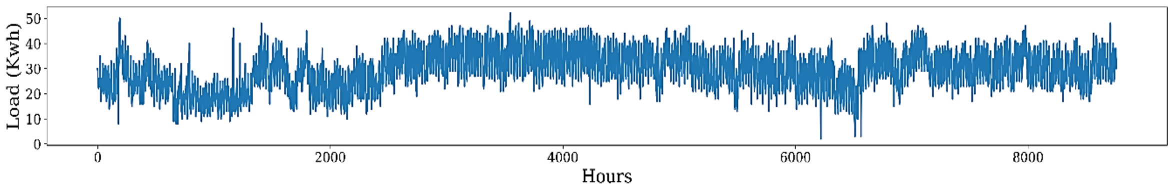


Figure 3. Yearly electrical load

Forecasting electrical load data in this study is a short-term forecast. The data used is the electrical load per hour on the same day. For example, to predict the electrical load on Monday, the model reference data from the previous Monday. In order to compose the input data using historical value, the previous three periods was used. The use of too much historical data can cause multicollinearity problems so that the prediction results of the model become less sensitive. Figure 4 shows the process of data reshaping as input for the LSTM model.

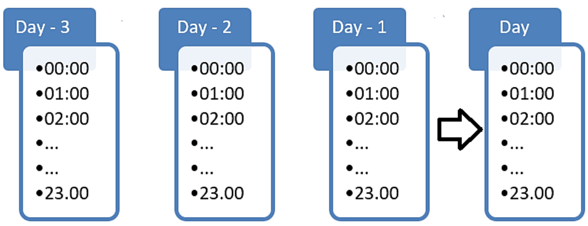
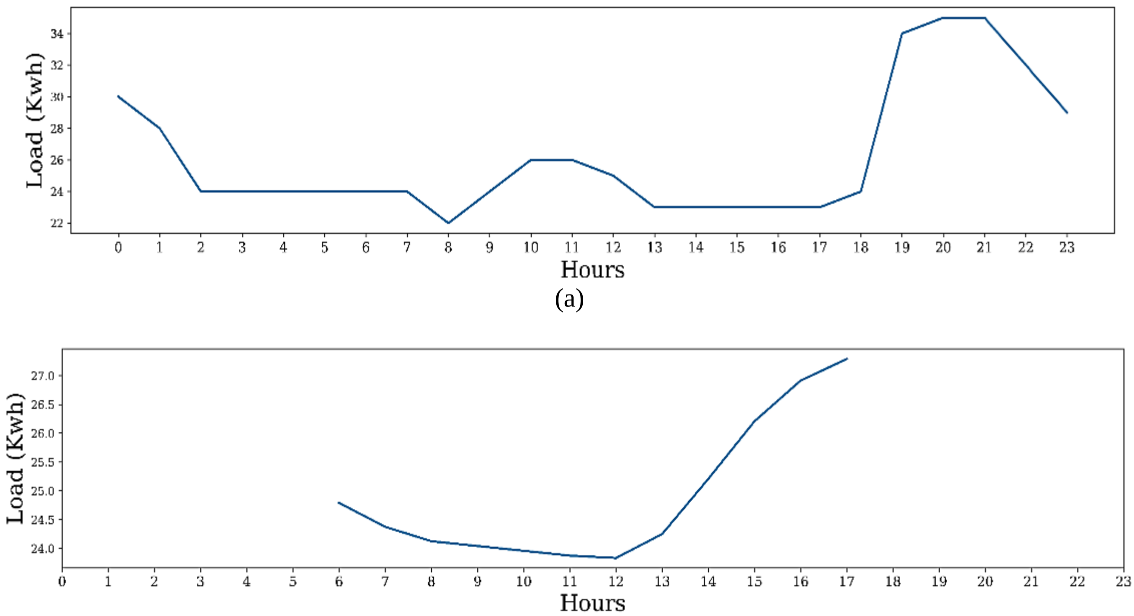


Figure 4. The used of three historical data period to forcast one next period

2.1.2. Data pre-processing

The dataset used in this study comes from Indonesian data from 2013-2017, from operator data recording of the high-voltage overhead line transmission system. In research using univariant datasets, we only use active power (MW) i.e. power usage or electricity consumption and reduce other data in the transmission operator's records. Furthermore, data pre-processing is consists of imputing missing value, detrending to remove distortion in the form of an increase or decrease from normalized time series data. Detrending is a process that aims to remove trends from the time series. The trend usually refers to the average change over time. When performing the detrending process, aspects that may distort the data will be removed. Distortion in time series data can be seen as fluctuations in time-series graphs. By eliminating the distortion, the graph of the increase or decrease of the time series data can be seen. Figure 5(a) illustrate the raw data which contain an extreme fluctuation and may distor the training process. Thus, a detendring process was performed which illustrated in Figure 5(b). In this study normalization changes the feature range into the range [-1, 1] because this range is suitable for use on data that has outliers. The results of the normalization stage are carried out in a pre-processing stage, which is followed by data management, which includes data transformation and data splitting into training and testing data. Training and testing data are separated using an 80/20 ratio for training and testing respectively [25].



(a)

(b)

Figure 5. Illustrate (a) observed data (b) detendring result

2.2. Research methodology

In this study, the electrical load forecasting process was carried out using the deep learning method. The deep learning method used is RNN with LSTM architecture. The LSTM network is a development of the RNN architecture. RNN architecture is a network that works for sequence or time series data by considering the output (information) of the previous process and storing the information for a short time (short-term memory).

The LSTM architecture accepts input in the form of an Xt feature, where this feature is the value of the electrical load. This feature is then entered into the LSTM block for processing. The LSTM block receives input ht-1 (hidden state from the previous LSTM block), Ct-1 (Cell state from the previous LSTM block), and Xt (feature input). The LSTM block also has outputs in the form of h¬t and Ct, namely the current hidden state and the current cell state (memory). In addition, in the LSTM block there are sigmoid and tanh activation functions, which act as input gates, forget gates and output gates. Several parameters are used to tune the LSTM model, such as the number of nodes and hidden layers. Figure 6 shows the research methodology of this research.

2.3. Evaluation metrics

To measure the model's performance, an error rate was calculated using the MAPE. The lower the error rate, the higher the data accuracy. MAPE provides results in the form of absolute percentage averages with forecast errors compared to actual data.

$$MAPE = \frac{1}{N}\sum_{i=1}^{N}\frac{Y_i - \check{Y}_i}{Y_i}x100$$

Where, N is number of samples, Y_i is actual value, and $\check{Y}i$ is prediction value.

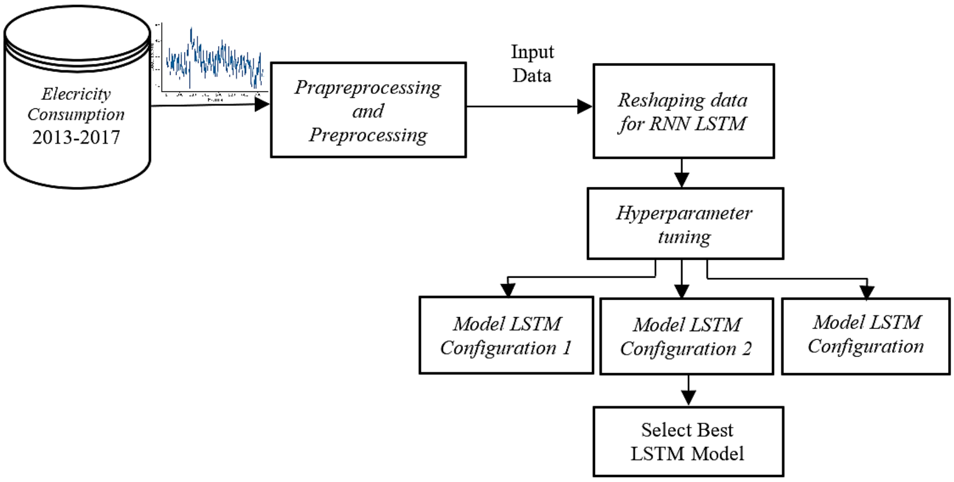


Figure 6. Research methodology

3. RESULTS AND DISCUSSIONS

In this study, testing was carried out with the distribution of the dataset of 80:20 for training data and validation data. Each dataset is trained using the LSTM model. The parameters used in this study include the number of hidden layers, the number of hidden nodes, the batch size of 4, epoch 100 and using the ADAM optimizer optimization method.

3.1. LSTM 1 layer

In LSTM architecture, layer 1 has 512 and 1024 hidden units, with Adam optimizer, and loss function mean squared error (MSE). The number of epochs for this layer is 100 with a batch size of 4. Units in the input and output layers are 1 unit. While the number of parameters generated in the LSTM 1 layer architecture is 1,053,185 and 4,207,617 parameters for 512 and 1024 respectively. The results of the single layer LSTM test are shown in Table 1.

3.2. LSTM 2 layers

In building 2 layers LSTM architecture, two LSTM blocks are stacked into one, thus forming a stack of LSTM blocks. The 2-layer LSTM architecture does not have much difference in the 1-layer LSTM architecture. Consists of 512 and 1024 hidden units, with Adam optimizer, and loss function MSE. The number of epochs and batch size for this layer is still the same, namely 100 and 4. Then the units in the input and output layers are 1 unit. However, because the number of layers is more, the parameters generated in the LSTM 2 layers architecture are also increased to 3,156.481 parameters for 512 nodes and 12,604,417 for 1024 nodes. The results of the two-layer LSTM test are shown in Table 2.

Table 1. LSTM one layer evaluation result

Node	MAPE	Parameters
512	9.37	1,053,185
1024	9.29	4,207,617

Table 2. LSTM two layers evaluation result

Node	MAPE	Parameters
512	9.28	3,156.481
1024	9.04	12,604,417

3.3. LSTM 3 layers

The 3 layers LSTM architecture is the same as the 2 layers LSTM architecture, but the number of stacks of LSTM blocks is 3 stacks. This architecture consists of 512 and 1024 hidden units, with the Adam optimizer, and the loss function MSE. The number of epochs and batch size for this layer is still the same, namely 100 and 4. Then the units in the input and output layers are 1 unit. However, because the number of layers is more, the parameters generated in this 3 layers LSTM architecture also increase to 5,257,729 parameters. The results of the three-layer LSTM test are shown in Table 3. In order to evaluate the model's ability to predict the forecasting pattern that has been carried out, we compared it with other models from the state of the art research [7] and [19], in the MAPE evaluation metrics which is summarized in Figure 7.

Table 3. LSTM three layers evaluation result

Node	MAPE	Parameters
512	9.13	5,257,729
1024	8.63	21,001,217

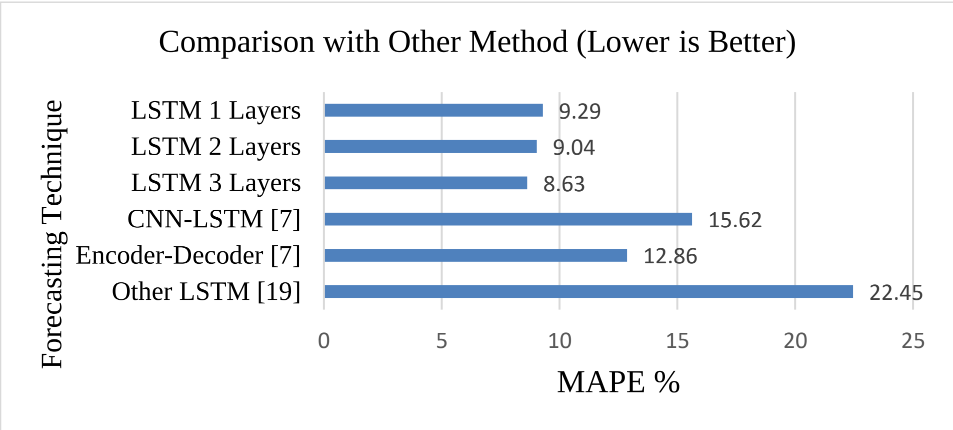


Figure 7. Comparison of MAPE value with other forecasting techniques (lower is better)

4. CONCLUSION

This study applies LSTM to predict the electrical load energy. Based on the experimental result the best architecture was LSTM three layers with 1024 nodes. It reaches 8.63 of MAPE value. The historical features used in this study was three previous period.

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