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Electricity load forecasting using long short-term memory: Case study from Central Java and DIY

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Electricity Load Forecasting using Long Short-Term Memory: Case Study from Central Java and DIY

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Abstract. Forecasting power system loads refers to the study or use of a mathematical method for methodically processing historical and future loads, while taking capacity expansion into consideration to meet accuracy criteria. Improving load forecasting technology enables planned power management, which enables rational grid operation and unit maintenance planning, as well as the formulation of suitable power supply construction plans and facilitation of power improvement. Now, there are numerous approaches for electricity load forecasting. We present an electrical load forecasting model in this article that uses long short-term memory (LSTM) for case studies of electrical data in Central Java and DIY. The proposed implementation of LSTM is extremely well matched to the time series dataset, which can improve the training process's accuracy of convergence. We experiment with different time steps to accelerate the training process's convergence. It is discovered that by forecasting the different timesteps, all scenarios attain significantly varying forecasting accuracy. We present several variations on epochs and the number of hidden layers to identify the best model for the basic RNN and LSTM models.

INTRODUCTION

With increasing load requirements and the sophistication of power plants, knowing the electrical load in advance is critical for a variety of benefits, including significant technical and economic consequences. For decades, traditional time series approaches such as ARMA, SARIMA, and ARMAX have been used. In recent years, the discipline of time series analysis has seen the emergence of artificial intelligence (AI) approaches like as neural networks and deep learning [1- 4]. Artificial neural networks (ANN) and recurrent neural networks (RNN) are being investigated, as they have showed promise in forecasting significantly better than traditional methods. The most recent techniques primarily use neural networks, time series analysis, regression analysis, support vector machines, and fuzzy prediction. However, most of them do not apply to long-term time series projections, and hence the prediction accuracy for long-term power grids is low. Predicting the load is critical for a dynamic electrical network. A forecasting algorithm that is improved significantly reduces the cost of the load [2]. Long short-term memory (LSTM) networks are a subset of RNNs that can learn long-term dependencies. We collected data on short-term electrical loads at half-hour intervals in this work. The training data is utilized to fine-tune the LSTM network. To ensure a fair comparison, the data is also used to model the load time series using standard approaches. The LSTM forecasts are compared to the outcomes of older approaches using some time series forecast error metrics. Numerous experiments demonstrate that the LSTM-based prediction is superior to other methods and has the potential to further increase forecast accuracy [5]. Sadaei et al. [6-7] use several models to evaluate and compare short-term projections, including fuzzy time series, seasonality, and long memory. The results indicate that the method outperforms in terms of accuracy, implying that it is an efficient solution for load forecasting problems.

Proper planning and effective applications of electric load forecasting necessitate specific forecasting intervals, also known as lead time. Load forecasting is classified into four types based on lead time: very short-term load forecasting, short-term load forecasting, medium-term load forecasting, and long-term load forecasting [8-10]. RNNs

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are a subclass of artificial neural networks that have been shown to be effective at solving a variety of forecasting issues in a variety of applications. Additionally, researchers discovered that RNNs are an effective model for forecasting electric load [57]. However, RNN appears to have difficulty learning "long-term dependencies", as Bengio et al. [11] demonstrated in 1994. Long Short-Term Memory (LSTM) is a type of RNN proposed by Hochreiter and Schmidhuber in 1997 that addresses the problem of learning long-term dependencies [12]. LSTM has a wide range of applications. Kwon et al. (2020) demonstrated that LSTM outperforms for precise electricity load forecasting [13]. Bouktif et al. investigated short to medium term aggregate load forecasting and discovered that an LSTM-based model outperformed a machine learning model refined by hyperparameter tuning [14]. Tian et al [15] perform a deep neural network model for short-term load forecast based on long short-term memory network and convolutional neural network.

In this paper, we present electricity consumption modeling using long short-term memory for case studies of data in Central Java and DIY (Special Region of Yogyakarta). We provide a description as an overview of the data characteristics for modeling. We conduct experiments to find the model that has the best accuracy with minimal errors. We use several error measures for comparison.

Electricity Load Data

Descriptive statistical analysis aims to exploit the information contained in the data without making inferences. Through the display of time series plots, we can visually identify seasonal patterns, trends, and data stationarity in terms of mean and variance. In addition, the time series plot displays every half hour and based on active days and working holidays can be used to explore the electricity consumption patterns of the area Central Java and DIY in the period January 1, 2019, to August 31, 2019. The electricity load data per half hour is shown in Fig. 1. The pattern of short electrical load data shows that there is a multiple seasonal pattern (Fig. 2).

There is a downward pattern in June due to the influence of the Eid al-Fitr holiday. It should be noted that Eid al-Fitr falls on June 5, 2019, the phenomenon of a decrease in the burden of electricity consumption occurs about 7 days before until 7 days after Eid al-Fitr 2019. About one week before to one week after Eid is a day of collective leave so that some industries do not operate, as a result the load of electricity consumption reaches a low peak point.

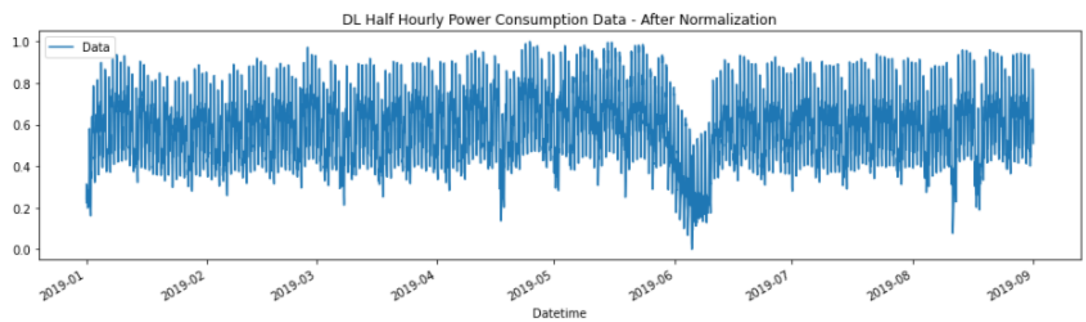

FIGURE 1. Half-hourly normalized power consumption data

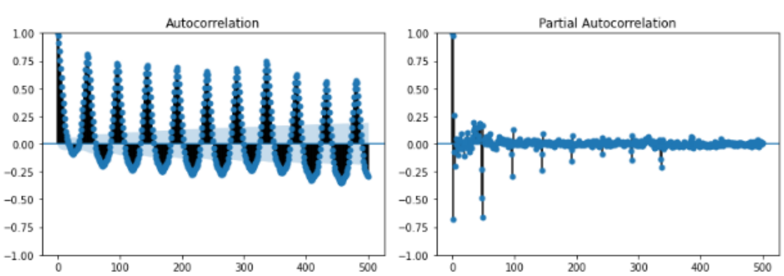

FIGURE 2. ACF and PACF of normalized data

Electricity load has a high fluctuation starting at 08.00 in the morning as community activities begin until 18.00 in line with the end of work activities for most of the community. The fluctuation of electricity load during the day is dominated by the industrial sector, which mostly operates during the day. Meanwhile at night there is no such high fluctuation because at night the consumption of electricity is dominated by the household sector.

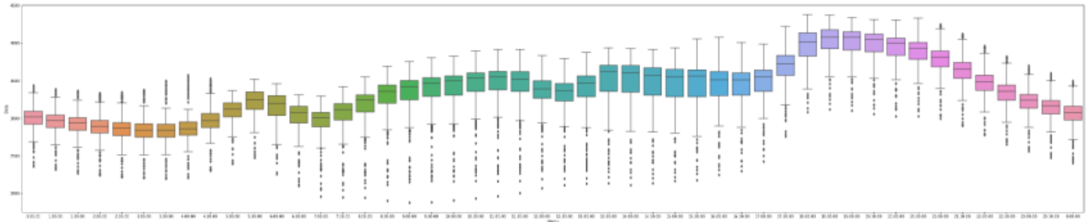

FIGURE 3. Boxplot of daily electricity load every half hour

Fig. 3 shows that the load data of electricity consumption per half hour has many outliers. Outliers that are worth less than the confidence interval are more than outliers that are worth more than the confidence interval. This indicates that the public's electricity consumption load more often experiences the lowest peak load than the highest peak load. In general, time series plots of electricity consumption loads recorded per half hour show a seasonal and non-stationary pattern. It can be observed that the lowest average load of electricity consumption occurs on Sunday. The industrial sector which accounts for the largest consumption of electrical energy stopped operating on Sunday. Meanwhile, on active working days, the average consumption of electrical energy rose again as the industrial sector, public facilities, as well as various government offices and agencies resumed operation. The lowest variance of electricity consumption load occurs on Saturday and Sunday. On working holidays, the pattern of electrical energy consumption is dominated by the household sector where the pattern of energy consumption tends to be stable according to the lifestyle of each family. Meanwhile, on active working days, the pattern of energy consumption is also contributed by the industrial sector and agencies that only operate on active working days so that the pattern of energy consumption is quite varied.

RESULT AND DISCUSSION

Hochreiter and Schmidhuber initially proposed LSTM neural network, which is commonly used to analyze sequence information that has its benefits in detecting long-term dependencies. Consequently, an LSTM neural network model for high-frequency financial time series data may be theoretically established. Fig. 1 shows the structure of each neuron at LSTM and consists of a cell and three doors. Cell records the neuronal status and receives, outputs, and changes the parameters of the input and output gate function. Forget Gate controls the forgotten extent of the preceding neuronal state, i.e., the information to be deleted from the cell. The choosing of the activation function is an important aspect of the neural network training process which enables the neural network to discover nonlinear data variables. This study uses the standard sigmoid activation function and tanh activation function. It comprises basically the following phases.

The objective for developing LSTM was to address the issue of disappearing gradients that occurs when using RNN to evaluate long-term dependencies. The Standard RNN is composed of a series of repeated neural network modules, each of which is composed of a structure. These module structures are discovered to be quite simple. Although LSTMs and RNNs both have a chain of repeating modules, the LSTM module structure is significantly more sophisticated. Each module has four layers rather than the single layer seen in an RNN module. There are modules or memory blocks are made up of an input gate, a forget gate, an output gate, and the state of the cell.

Gates are an optional way to let information through. The gate consists of layers of sigmoid neural net and pointwise multiplication operations. The sigmoid layer outputs a number between zero and one, explaining how much of each component must be skipped. A value of zero means “don't let anything pass”, while a value of one means “let it all pass!”. The LSTM has three gates to protect and control the cell state. The first step in the LSTM is to decide what information to remove from the cell state. This decision is made by a sigmoid layer called the “Forget gate layer”.

In this study, we experimented to find the best LSTM and basic RNN model by comparing several variations in the input epoch and hidden layer. Of the 11,664 data records, they are divided into 2, namely 10,223 for training data and 1,421 for testing data. The grid is set to values of 10, 50, 100, and 200. Hidden layer is set to values of 50, 100, 150, and 200. For each experiment, it is checked with several error sizes, namely mean squared error (MSE), mean absolute error (MAE), root mean squared error (RMSE), mean absolute percentage error (MAPE). Table 1 and Table

2 show the results of comparative experiments for the LSTM and RNN models. We also use the TBATS (Trigonometric regressors to model multiple seasonality) model to apply to the multi-seasonal model. TBATS is a forecasting method for time series data. The main goal is to forecast time series with complex seasonal patterns using exponential smoothing. The TBATS model can deal with complex seasonality (e.g., non-integer seasonality, non-nested seasonality, and large-period seasonality) with no seasonality constraints, allowing for detailed, long-term forecasts. Modeling using TBATS requires a long processing time, because the modeling process is carried out by comparing several basic stationary and seasonal models.

TABLE 1. Comparison of RNN experimental results of several epoch values, hidden layer, and error values.

Epoch	Hidden Layer	MSE	MAE	RMSE	MAPE	Average Error
10	50	0.0108	0.0882	0.1037	0.1766	0.0948
	100	0.0078	0.0749	0.0885	0.1498	0.0803
	150	0.0091	0.0796	0.0953	0.1546	0.0847
	200	0.0093	0.0858	0.0963	0.1741	0.0914
50	50	0.0022	0.0381	0.0471	0.0743	0.0404
	100	0.0015	0.0297	0.0386	0.0560	0.0314
	150	0.0016	0.0315	0.0406	0.0607	0.0336
	200	0.0026	0.0431	0.0512	0.0844	0.0453
100	50	0.0010	0.0223	0.0318	0.0392	0.0236
	100	**0.0009**	0.0214	0.0306	0.0379	0.0227
	150	**0.0009**	0.0213	0.0307	0.0381	0.0228
	200	0.0012	0.0253	0.0351	0.0443	0.0265
200	50	**0.0009**	**0.0208**	**0.0302**	**0.0370**	**0.0222**
	100	**0.0009**	**0.0208**	0.0304	**0.0370**	0.0223
	150	0.0010	0.0231	0.0321	0.0421	0.0246
	200	0.0010	0.0215	0.0314	0.0376	0.0229
Min		**0.0009**	**0.0208**	**0.0302**	**0.0370**	**0.0222**

TABLE 2. Comparison of LSTM experimental results of several epoch values, hidden layer, and error values.

Epoch	Hidden Layer	MSE	MAE	RMSE	MAPE	Average Error
10	50	0.0174	0.1088	0.1320	0.2148	0.1183
	100	0.0138	0.0914	0.1177	0.1822	0.1013
	150	0.0098	0.0751	0.0992	0.1450	0.0823
	200	0.0121	0.0853	0.1101	0.1721	0.0949
50	50	0.0014	0.0269	0.0380	0.0518	0.0295
	100	0.0012	0.0231	0.0348	0.0412	0.0251
	150	0.0013	0.0240	0.0359	0.0417	0.0257
	200	0.0012	0.0234	0.0353	0.0410	0.0252
100	50	0.0008	0.0194	0.0291	0.0349	0.0210
	100	0.0009	0.0205	0.0297	0.0370	0.0220
	150	0.0009	0.0199	0.0300	0.0356	0.0216
	200	0.0009	0.0204	0.0306	0.0363	0.0220
200	50	0.0007	0.0174	0.0259	0.0324	0.0191
	100	**0.0006**	0.0172	0.0251	0.0320	0.0187
	150	**0.0006**	**0.0164**	0.0246	**0.0303**	**0.0180**
	200	**0.0006**	0.0165	**0.0244**	0.0309	0.0181
Min		**0.0006**	**0.0164**	**0.0244**	**0.0303**	**0.0180**

The results of the analysis show that modeling with LSTM can achieve very good accuracy with a percentage of 92% to 99% in the range of grids performed. The RNN model also shows a fairly good level of accuracy, which is in the range of 90% to 98%. From the experiment, we find that the epoch increases from 10 to 200 can reduce the average error of about 90%. We also find that R^2 values ranged from 92% to 99%, with an average R^2 of 95% and an average error of about 2.5%. Analysis using TBATS on multi-seasonal data requires a longer processing time with lower accuracy than the RNN and LSTM models. Plots of prediction results and actual data for 1421 (about 30 days) testing data are presented in Fig. 4.

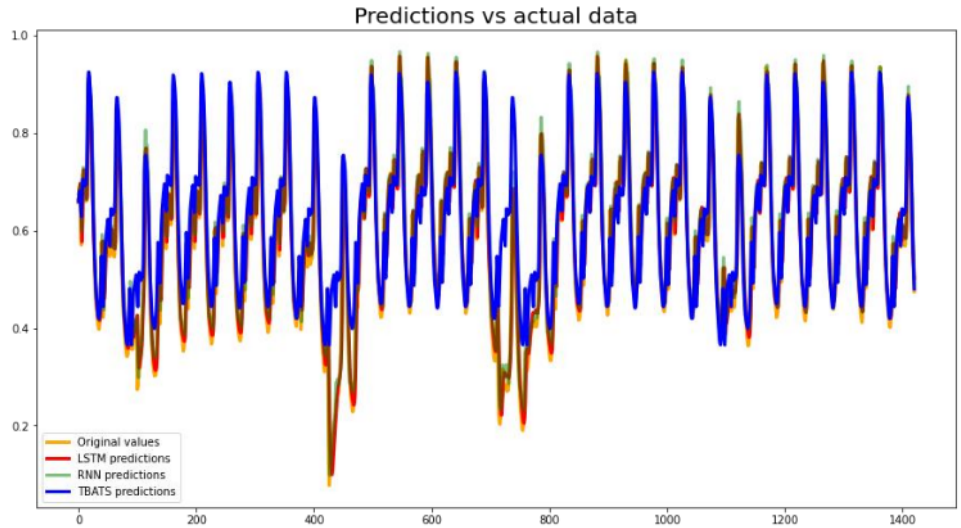

FIGURE 4. Prediction versus actual data modeling of electricity load data

Based on the comparison of forecasting plots on real data and the model developed, it is possible to conclude that the LSTM model outperforms the basic RNN and TBATS models in terms of accuracy. The LSTM model is good enough to predict data with multi-seasonal characteristics.

CONCLUSION

Experiments to get the best model for basic RNN and LSTM is done by developing a model based on batch and epoch variations. For each model generated, calculated the value error evaluation using MSE, MAE, RMSE, and MAPE. Based on the results of the analysis, it was found that the best model was obtained with the LSTM model. Some things that can be obtained from the results of the analysis are as follows. The results with TBAT are less accurate than the RNN and LSTM models. Model setup time is longer than using LSTM or RNN. The accuracy of using LSTM and RNN is generally better than TBATS. Based on the experimental results, both the LSTM and RNN methods can obtain a convergent and accurate solution with relatively the same results. We also find that R^2 values ranged from 92% to 99%, with an average R^2 of 95% and an average error of about 2.5%. From the experiment, we find that the epoch increases from 10 to 200 can reduce the average error of about 90%.

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