Peak Load Forecasting Using Long-Short Term Memory : Case Study of Jawa-Madura-Bali System

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***Abstract* — The process demand forecast at PLN uses many assumptions of projections originating from external PLN, such as economic growth assumptions, population growth, population, inflation, electrification ratio targets, and new and renewable energy development targets. This paper provides an alternative method of calculating annual peak load forecasts using the Long Short-term Memory (LSTM) approach as a part of the Deep Neural Network in Artificial Intelligence (AI). This method aims to improve the accuracy of expense forecasts on the realization of expenses that have occurred by studying patterns that happened in the past. The calculation of the load forecast shows that the Root Mean Square Error (RMSE) of the peak load forecast with the Recurrent Neural Network (RNN)-LSTM maximum is 2,167. The Mean Absolute Percentage Error (MAPE) value of the RNN-LSTM obtained a maximum of 8.6% or fell within the range <10% (very accurate category)**

Keywords—artificial intelligence, demand forecasting, neural network, long-short term memory

I. INTRODUCTION

An electricity company aims to supply electrical energy to customers, both large, medium, and small, with reliability and quality. An electricity company's responsibilities are to recognize electricity demand and fulfill them. Environmental factors and limited energy sources and costs require more efficient use of electrical power and the fulfillment of electricity needs that are more precise and optimal. The completion of electricity needs is closely related to the load forecasting process. Load forecasting is generally divided into short-term forecasts, medium forecasts, and long-term forecasts[1]. The long-term forecast is used for power system planning. It is also related to future investment plans and considers the historical load, the number of customers in different categories, and other factors. Many long-term forecast techniques have been proposed for resource planning and utility expansion in the last 30 years.

The long-term forecast methods can be categorized into two main parts: parametric methods and artificial intelligence methods. The artificial intelligence methods are further classified into neural networks, genetic algorithms, wavelet networks, fuzzy logic, ANFIS, expert systems, and other methods[2]. The parametric methods are based on connections load demand to its affecting factors like population and income by a mathematical model. The model parameters are estimated using statistical techniques on electrical load, economic and demographic data. Parametric load forecasting methods can be generally categorized by regression and time series prediction methods [3].

Recurrent Neural Networks (RNNs) are a very popular type of model[4]. However, they suffer from an inherent problem of vanishing gradient descent. RNN-LSTM-(Recurrent Neural Network-Long Short-Term Memory) is used to solve this problem and formulate long-term dependencies between training samples, which significantly increases the precision of the proposed model[5].

Indonesia has several extensive systems, and the biggest one is Jawa-Madura-Bali System. Based on 10-year development planning (RUPTL 2019-2028) prepared by the state-owned utility company, PT Perusahaan Listrik Negara (PT PLN) [6]. Peak load forecasting for the Jawa-Madura-Bali System, in the RUPTL 2006-2015 to RUPTL 2019-2028, the average peak load increase is 2,250 MW compared to the average realization of the growth per year is 1,076 MW. It will result in a capacity increase of nearly double what is necessary for peak load realization. As can be seen from this explanation, peak load forecasting accuracy is essential since it significantly impacts the subsequent phase of the system planning process in PT PLN (Persero).

This paper will provide an alternative solution method with a Long-Short-Term-Memory based Recurrent Neural Network (RNN-LSTM) model for forecasting electricity demand for a period of ten years. The technique calculates the estimated peak load, aiming to increase the realization accuracy with the study case in Jawa-Madura-Bali System. With higher accuracy, it is hoped that the addition of generating capacity and excessive investment in power system planning will be avoided and avoid the power shortages caused by higher load forecasting.

The rest of the paper is structured as follows: Section II explains basic theory about the Recurrent Neural Network (RNN) and Long Short-Term Memory (LSTM) and model in mathematical terms. The research methodology is depicted in Section III, and Section IV describes the simulation and results. The paper has been recapitulated in Section V, and potential future works have also been discussed.

II. Basic Theory

A. Demand Forecast

Power system planning is a series of activities to get an investment activity in the electric power system. System planning begins with an estimate of electricity demand to obtain electrical energy in the future. In the load forecast itself, there is no standard regarding the time horizon. However, load forecasts are generally divided into short-term, medium-term, and long-term forecasts [7].

- Long-term load forecasting (LTLF)

  This load forecast has a time range of 1 to 20 years—this load forecast is input for strategic plans, new power plants, and other electrical systems.

- Medium-term load forecasting (MTLF)

  Load forecasting with a time horizon of one week to a year for planning operations.

- Short-term load forecasting (STLF)

  Load forecasting with a time range of one hour to one week is essential for day-day operations and scheduling plant operations in more detail

In long-term planning, load forecasting begins the following process such as generation, transmission, and substations. Accurate long-term demand forecasting plays an essential role in electric power system planning. It corresponds to load demand forecasting with lead times to develop a new generation, transmission, and distribution. The electricity demand is drive by several primary factors: economic growth, population growth, electricity tariffs, electrification, and government programs, including building industrial regions and national tourism strategic areas.

The demand forecast in the RUPTL itself is divided into three as follows: 1) energy demand forecast (GWh), 2) peak load forecast (MW), and 3) substation forecast [6]. Energy demand forecast (GWh) is related to electricity needs closely associated with supporting economic growth. Therefore, the projection assumptions follow from sources other than PLN and the targets set by the government.

The peak load forecast is obtained after the energy demand forecast (GWh) results in peak load (MW) with a load factor. The load factor is the ratio between the average load and the peak load measured over a certain period [8]. The results of the peak load forecast are input for the process of generation expansion and substations planning the relationship between load factor and peak load as in the equation. Load factor equation is in Eq.(1) [1].

$$Load\ Factor = \frac{Energy\ Demand\ (in\ kWh)}{Peak\ demand\ (in\ kW) * 8760\ hrs/year} \tag{1}$$

Load forecast in substation planning is done by dividing the peak system load obtained into each substation by considering the diversity factor at each substation. The diversity factor is defined as the ratio between the individual maximum demand in each substation to the maximum peak load of the whole system [8]. After getting the load per substation, it is continued to calculate the need for a transformer to meet the energy supply needs of customers.

B. Recurrent Neural Networks (RNN)

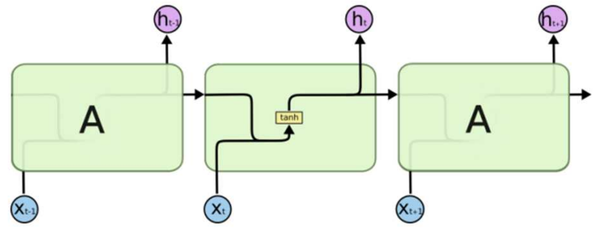

Fig. 1. Process of Recurrent Neural Network (RNN) [9]

Recurrent Neural Networks (RNN) is one of the architectural forms of Artificial Neural Networks (ANN) specially designed to process continuous and sequential data. In the process, RNN does not just throw away information from the past in the learning process (training) but functions as input for making current forecasts. It distinguishes the RNN from the usual ANN because RNN can store memory (feedback loop), allowing it to recognize data patterns well and then use them to make accurate predictions. The basic structure of the process of the recurrent neural network is shown in Fig. 1.

The basic calculation of RNN is in Eq.(1).

$$\boldsymbol{h_t} = tanh\ (\boldsymbol{W_h} * \boldsymbol{x_t} + \boldsymbol{b_h});\ \boldsymbol{y_t} = \boldsymbol{W_y} * \boldsymbol{h_t} + \boldsymbol{b_y}; \boldsymbol{p_t^{(i)}} = \frac{e^{y_t^{(i)}}}{\sum_j e^{y_t^{(j)}}} \tag{1}$$

Given input $\boldsymbol{x_t}$, which for example, maybe the last ten observations, it will forecast the following observation based on the model's output $\boldsymbol{y_t}$. Through the training, to minimize the negative log-likelihood is using stochastic gradient descent concerning parameters $\boldsymbol{W_h}$, $\boldsymbol{W_y}$, $\boldsymbol{b_h}$ and $\boldsymbol{b_y}$. If this were a classification task, $\boldsymbol{p_t^{(i)}}$ would be the probability of class *i*, and our goal would be to maximize $\boldsymbol{p_t^{(k)}}$ **.** Where *k* is the correct class for the observation at time *t* [9].

C. Long Short Term Memory (LSTM)

LSTM (Long Short-Term Memory) is another type of processing module in RNN. LSTM was created by Hochreiter and Schmidhuber in 1997. There are modifications to the LSTM by adding a memory cell that can store information for an extended period. LSTM is proposed as a solution to overcome the vanishing gradient in RNN when processing long sequential data. This vanishing gradient problem causes the RNN to fail to capture long-term dependencies, reducing the accuracy of a prediction on the RNN. The process of LSTM is shown in Fig. 2.

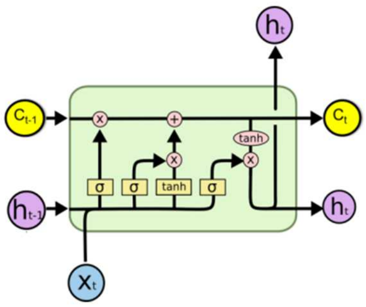

Fig. 2. Process of Long Short Term Memory (LSTM)

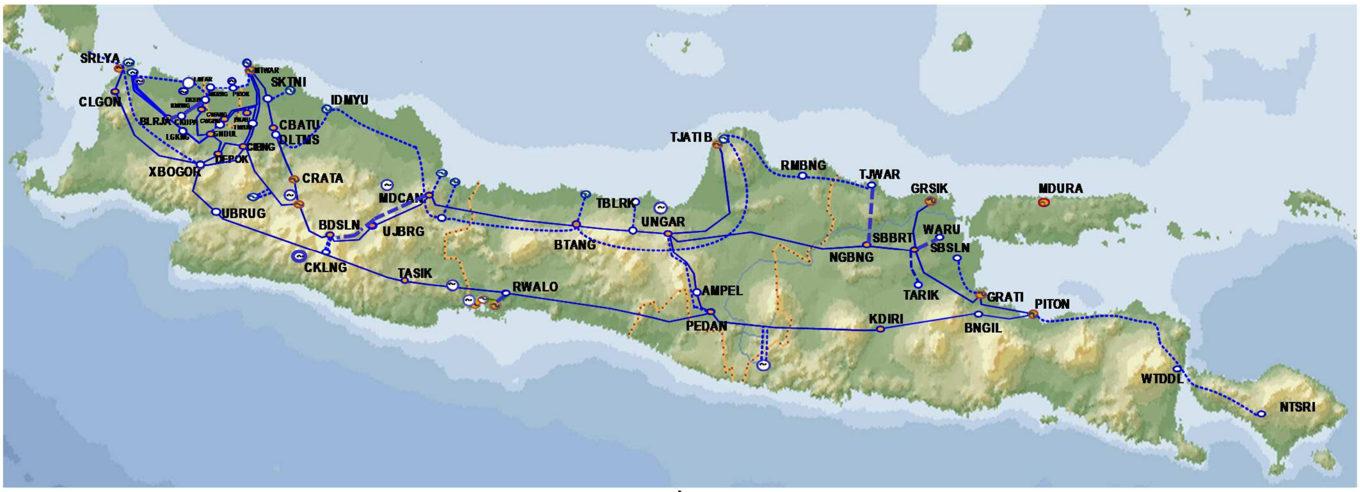

Fig. 3. Jawa-Madura-Bali 500 kV single line diagram [6]

In addition to the recurrent component $\boldsymbol{h_t}$, the model also includes a long-term memory component $\boldsymbol{C_t}$ Which is manipulated at each time step through various 'gates.'
The basic calculation of RNN is in Eq.(2)-(4).

$$\boldsymbol{f}_t = \sigma\left(\boldsymbol{W_f} * [\boldsymbol{h_{t-1}}, \boldsymbol{x_t}] + \boldsymbol{b_f}\right);\ \boldsymbol{i_t} = \sigma\left(\boldsymbol{W_f} * [\boldsymbol{h_{t-1}}, \boldsymbol{x_t}] + \boldsymbol{b_i}\right) \tag{2}$$

$$\widetilde{\boldsymbol{C}}_{\boldsymbol{t}} = \tanh\left(\boldsymbol{W_f} * [\boldsymbol{h_{t-1}}, \boldsymbol{x_t}] + \boldsymbol{b_C}\right);\ \boldsymbol{C_t} = \boldsymbol{f_t} * \boldsymbol{C_{t-1}} + \boldsymbol{i_t} * \widetilde{\boldsymbol{C}}_{\boldsymbol{t}} \tag{3}$$

$$\boldsymbol{o_t} = \boldsymbol{\sigma}(\boldsymbol{W_o} * [\boldsymbol{h_{t-1}}, \boldsymbol{x_t}] + \boldsymbol{b_o});\ \boldsymbol{h_t} = \boldsymbol{o_t} * \tanh(\boldsymbol{C_t});\ \boldsymbol{y_t} = \boldsymbol{W_y} * \boldsymbol{h_t} + \boldsymbol{b_y};\ \boldsymbol{p}_{\boldsymbol{t}}^{(i)} = \frac{e^{y_t^{(i)}}}{\sum_j e^{y_t^{(j)}}} \tag{4}$$

Given input $\boldsymbol{x_t}$, forecast the following observation based on the model's output $\boldsymbol{y_t}$. The training algorithm is identical to that of RNNs except that an LSTM has more parameters involved. Although it looks complicated, the LSTM method is like a neural network and its training process. The LSTM method can learn what needs to be understood, remember what needs to be recognized, and remember what needs to be placed without special training or optimization [10]. There are three gates, namely the input gate and the forget gate, which regulate the state of the cell, which is long-term memory. An output gate produces an output vector or hidden state that is the focus of memory for use [11].

III. Methodology

A. Jawa-Madura-Bali System

The Jawa-Madura-Bali system is Indonesia's most extensive electricity system, with a peak load in 2019 of 27,973 MW, an increase of 3.34% (903 MW) against peak loads in 2018, and total energy production in 2019 was 194.55 TWh[12]. The peak load Jawa-Madura-Bali System from 2004 until 2019 is shown in Fig. 4.

The net power capacity of the installed generators in the Java-Bali system until the end of 2019 has amounted to 36,993 MW. So that the power supply of the Jawa-Madura-Bali System in 2019 is relatively sufficient to serve consumer needs with an average reserve margin currently of 41% [12]. The Jawa-Madura-Bali System has Extra High Voltage (EHV, 500 kV) for transmission backbone and HV (150 kV and 66 kV) as meshed transmission. The distribution system consists of Medium Voltage (MV, 20 kV) and Low Voltage (LV, 380 V).

The total electricity sales in Jawa-Madura-Bali System in 2019 amounted to 179.2 TWh. Industrial customers had the most significant contribution to sales in the Java-Bali System, or around 37.6% of total electricity sales in the Jawa-Madura-Bali System, household customers at 37.5%, business customers at 18.7%, and public customers at 6.2% [13]. The electricity sales (GWh) in the Jawa-Madura-Bali System from 2004-2019 is shown in Fig. 5. The total number of customers in the Jawa-Madura-Bali System is around 47.6 million customers [13]. The household customers have the most significant number of customers, about 92% of the total number of customers, followed by business customers at 5%, public customers at 2.9%, and industrial customers at 0.2%.

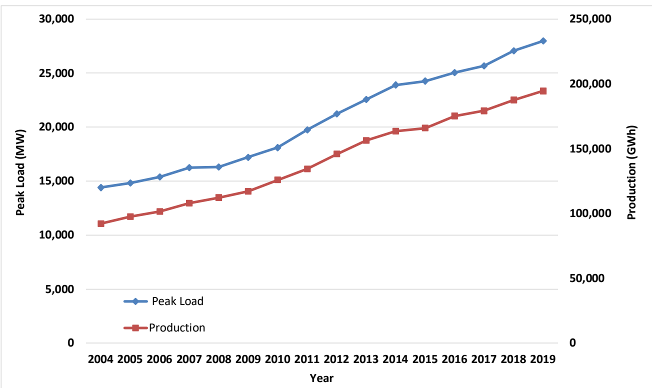

Fig. 4. Peak load (MW) and production (GWh) in Jawa-Madura-Bali System from 2004-2019

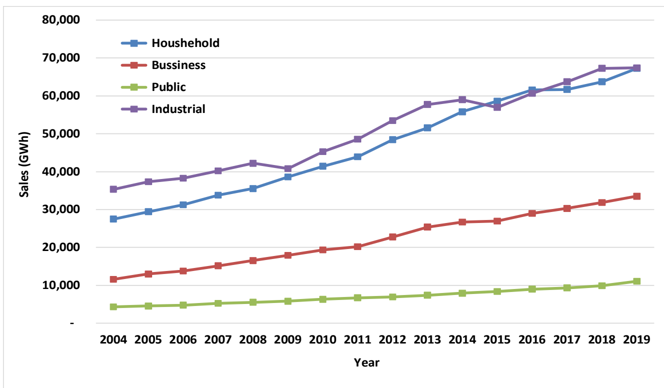

Fig. 5. The electricity sales (GWh) in the Jawa-Madura-Bali System from 2004-2019

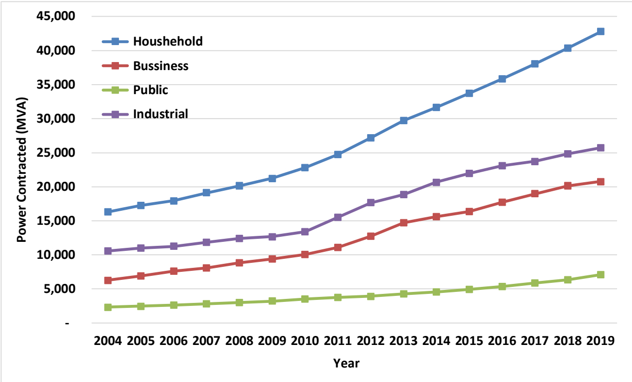

Fig. 6. The power contracted (MVA) in the Jawa-Madura-Bali System from 2004-2019

Meanwhile, household customers accounted for 44.4% of the power contracted (MVA), followed by industrial customers at 26.7%. So even though industrial customers are the least in number, they contribute more to the power contracted (MVA). The power contracted (MVA) in the Jawa-Madura-Bali System from 2004-2019 is shown in Fig. 6.

B. Flowchart

In this paper, the calculation of peak load forecasts for the Jawa-Madura-Bali System from 2020-2029 with RNN-LSTM will be an alternative to calculating peak loads from the existing method. The flowchart for RNN-LSTM describes the process and stages of research in general, starting with data collection and then grouping the data according to the type of customer at PLN, then proceeding with modeling and forecasting the load and continuing with evaluation.

The data used follows the data in the preparation of the load forecast in the RUPTL document. All historical data was collected from 2004 to 2019 includes Gross Regional Domestic Product (GRDP), total population, number of households, electrification ratio, energy sales (TWh), power contracted (MVA), number of customers, tariff, peak load (MW), energy production (TWh), and losses. The research flowchart is shown in Fig. 7.

The next step is data splitting, namely grouping the available data into two groups; training data as data used for input in making models of load forecasts and test data used to see the quality of the load forecast results produced. The data starts from 2004 to 2019. The simulation will predict the peak load forecast from 2012-2021 with data from 2004-2012 as data training and test data from 2012-2021. The simulation process conducts year by year until 2018-2027.

Next, where the input data has many variations and range, it is necessary to process data normalization. Data normalization converts a numeric column value into a set with a scale without changing the difference in the range of values after that is to start modeling the load forecast using the RNN-LSTM method. The simulations results were evaluated with RMSE (Root Mean Square Error) and MAPE (Mean Absolute Percentage Error).

- RMSE (Root Mean Square Error)
  RMSE is calculated by squaring the error, then dividing by the data number, and then rooted. A low RMSE value indicates that the variation in the value produced by a

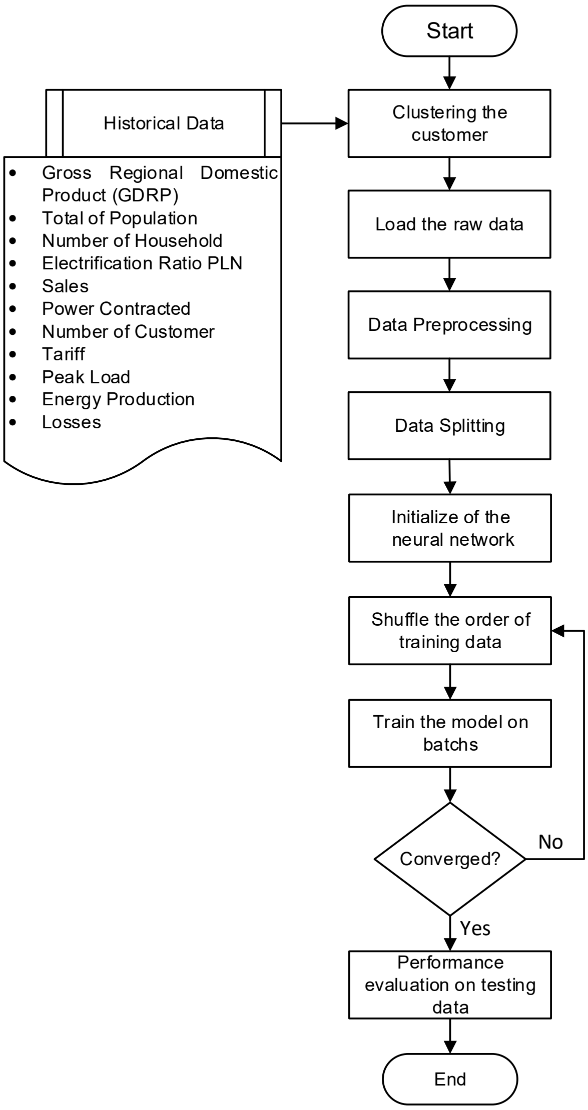

Fig. 7. Peak Load Forecast Flowchart With RNN-LSTM

forecast model is close to the variation in the observed value. The smaller the RMSE value, the closer the predicted and observed values are. The RMSE calculation equation is as in Eq.(5).

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(P_i - O_i)^2}{n}} \quad (5)$$

Where:

P = estimated value
O = realized value
n = amount of data

- MAPE (Mean Absolute Percentage Error)
  It is a measure of relative error that states the percentage of error in the estimation or forecast against the realization results during a specific period, which will provide information on whether the error rate is too high or too low. In other words, MAPE is the average absolute error during a specific period multiplied by 100% to get the results as a percentage. MAPE values can be interpreted

into 4 categories, namely <10%: very accurate, 10-20%: good, 20-50%: reasonable, >50%: inaccurate [14]. The smaller the MAPE value, the smaller the forecast error. On the contrary, the larger the MAPE value, the greater the forecast error. The equation for MAPE calculation as in Eq.(6).

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{P_i - O_i}{O_i}\right| \text{x } 100\% \tag{6}$$

Where :

P = estimated value
O = realized value
n = amount of data

All the processes that have been run previously using the KERAS module. This module is an open-source module specifically for Neural Networks, including RNN-LSTM. The KERAS module also serves as an interface to other related library modules. The license for KERAS is held by the Massachusetts Institute of Technology (MIT). Meanwhile, TensorFlow is used for data computing and developing datasets in the data training process. Google acquired the TensorFlow module, and both modules are in the Python programming language.

IV. Simulation

The main idea of the RNN-LSTM method is to connect the path between the old context C_{t-1} to the new context C_t at the top of the RNN-LSTM module. Context is called C_t, also cell state, or it can also be called memory cell. With this path, a value in the old context will be quickly passed to the new context with minor modifications if needed. Context is a vector value whose number of elements is determined by the RNN-LSTM network maker. Before starting, it is necessary to decide on several parameters for the load forecast modeling operation, including the epoch value, batch size, and iterations in shown Table I.

Epoch itself is when the entire dataset has gone through the training process until it is returned to the beginning for one round. Because the epoch is too large, it needs to be divided into small units (batches). As the epoch increases, more weight changes in the neuron and will affect the shape of the curve representing the optimum condition or the overfitting curve. The batch size is the number of data samples distributed to neurons because they cannot pass the entire dataset into the neural net at once.

TABLE I. Epoch, Batch, And Layer Value

Assumptions	Number
epoch	250
Batch Size	5
LSTM layer	12

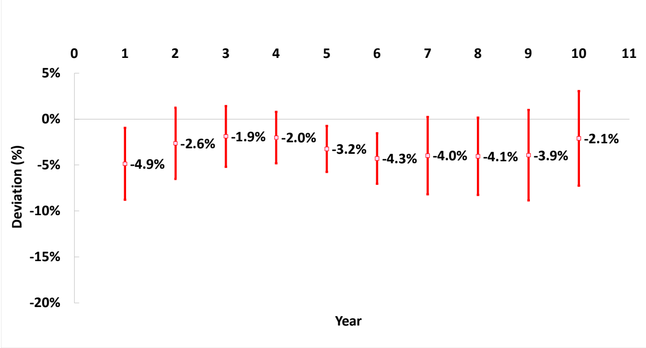

Fig. 8. Deviation of the RNN-LSTM peak load on the realization of the Jawa-Madura-Bali system

Furthermore, the need to divide the dataset aims to make the data set into several parts to be processed. Meanwhile, change the calculation period according to the needs of the load forecast by changing the time step parameter. The training process also displays plot accuracy and plot loss, which serves to see whether there is underfit, overfit, or optimal from the load forecasting model in each load forecast period. The results of the load forecast for each period are shown in Fig. 9.

The deviation calculation from the results of the load forecast with the RNN-LSTM is related to the realization per year. The average deviation in the first year from 2009-2018 to 2018-2027 was obtained at 4.9%, followed 2.6% decrease in the second year. The load forecast deviation varied in subsequent years maximum of 4.3%. The result of the deviation calculation is shown in Fig. 8.

The evaluation process of the load forecast is by calculating the value of RMSE and MAPE, which is to see how accurate the model of the load forecast. The RMSE value ranges from 522-2167, while the MAPE value is obtained from 1.7-8.6%. The largest RMSE and MAPE values were obtained in the 2009-2018 load forecasts due to the short-range between training and test data, where for 2009-2018 load forecasts using data from 2004-2008, the data patterns are not fit enough to make models. The results of the RMSE and MAPE calculations are shown in Table II.

The smaller the RMSE value, the closer the predicted and observed values are. As for the MAPE interpretation, where everything is still in the range <10%, the results from the modeling into the very accurate category.

TABLE II. Result Of RMSE And MAPE

Year	RMSE	MAPE (%)
2009-2018	2167	8.6
2010-2019	1008	3.4
2011-2020	870	3.0
2012-2021	522	1.7
2013-2022	549	1.7
2015-2024	662	2.4
2016-2025	1158	4.2
2017-2026	1068	3.7
2018-2027	444	1.6

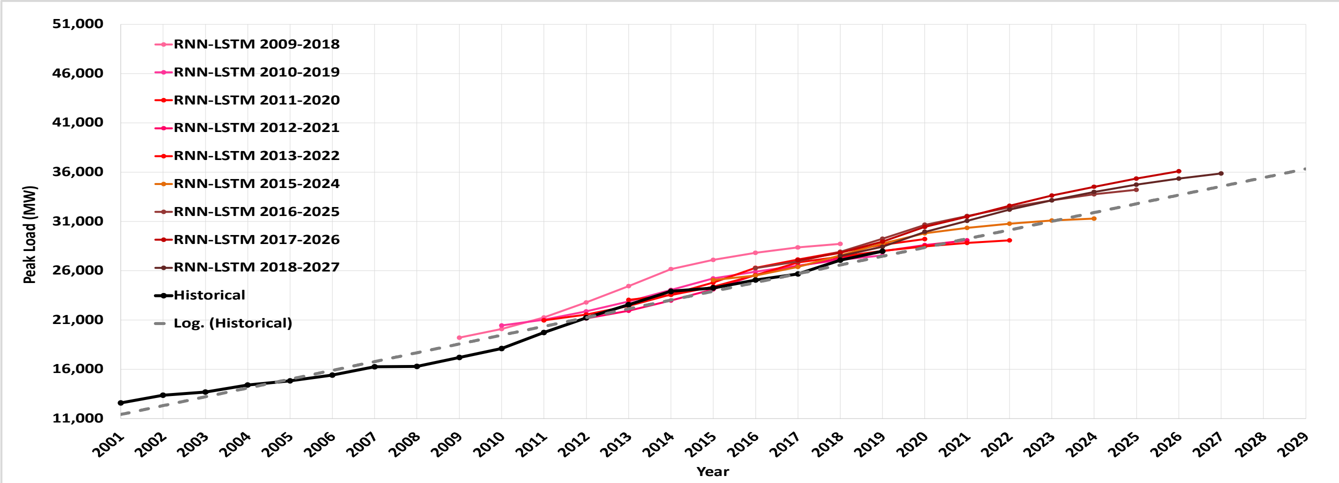

Fig. 9. Peak Load Forecast Flowchart With RNN-LSTM

V. Conclusion

This paper presents an alternative method for forecasting peak loads, using the RNN-LSTM method, which aims to increase the accuracy between forecast and realization. From simulations results were evaluated with RMSE (Root Mean Square Error) and MAPE (Mean Absolute Percentage Error). The result of RMSE value ranges from 522-2167, while the MAPE value is obtained from 1.7-8.6% or is in the <10% range. From this result shows that the peak load forecast using the RNN-LSTM is very accurate. Next, development of modeling by considering other external factors such as environmental factors. Provide other cases in the modeling of peak load forecasts, such as energy conservation or by giving the influence of electric vehicles in peak load forecasting. The research is expanded by looking at the impact that occurs if the load forecast is wrong or inaccurate.

References

[1] G. E. Oamek, B. C. English, H. Hall, and B. C. English, “A Review of Load Forecasting Methodologies,” *CARD Work. Pap.*, p. 20, 1984.

[2] N. Cetinkaya, “Long-term electrical load forecasting based on economic and demographic data for Turkey,” *CINTI 2013 - 14th IEEE Int. Symp. Comput. Intell. Informatics, Proc.*, pp. 219–223, 2013.

[3] V. Ş. Ediger and H. Tatlidil, “Forecasting the primary energy demand in Turkey and analysis of cyclic patterns,” *Energy Convers. Manag.*, vol. 43, no. 4, pp. 473–487, 2002.

[4] L. R. Medsker, *RECURRENT NEURAL Design and Applications*. CRC Press, 2001.

[5] S. Hochreiter and J. Schmidhuber, “Long Short-Term Memory,” *Neural Comput.*, vol. 1780, pp. 1735–1780, 1997.

[6] PT PLN (Persero), *Rencana Usaha Penyediaan Tenaga Listrik PT PLN (Persero) 2019-2028*. Jakarta, Indonesia, 2019.

[7] M. A. Hammad, B. Jereb, B. Rosi, and D. Dragan, “Methods and Models for Electric Load Forecasting : A Comprehensive Review,” vol. 11, no. 1, pp. 51–76, 2020.

[8] T. Hong and M. Shahidehpour, “Load Forecasting Case Study,” p. 171, 2015.

[9] J. Hyuk Han, “Comparing Models for Time Series Analysis,” vol. 162, 2018.

[10] X. Zhang, J. Wang, and K. Zhang, “Short-term electric load forecasting based on singular spectrum analysis and support vector machine optimized by Cuckoo search algorithm,” *Electr. Power Syst. Res.*, vol. 146, pp. 270–285, 2017.

[11] D. P. Short-term, “An Ensemble Model Based on Machine Learning Electric Load Forecasting,” 2017.

[12] PT. PLN (Persero) Pusat Pengatur Beban (Load Dispatching Center), *Evaluasi Operasi Sistem Jawa Bali 2019*. Jakarta: PT PLN (Persero) Unit Induk Pusat Pengatur Beban, 2020.

[13] PT.PLN (Persero), *Statistik PT PLN 2019*. 2019.

[14] R. J. C. Chen and P. Bloomfield, “An Evaluation of Alternative Forecasting Methods to Recreation Visitation,” vol. 35, no. 4, pp. 441–454, 2003.