Comparison of Short-Term Electrical Load Forecasting Models using Datasets from The Building Automation System in The Department of Electrical Engineering ITN

by F. Yudi Limpraptono

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2023 IEEE International Conference on Communication, Networks and Satellite (COMNETSAT) | 979-8-3503-4110-2/23/$31.00 ©2023 IEEE | DOI: 10.1109/COMNETSAT59769.2023.10420633

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***Abstract*—Overloading in electrical systems can cause hazards such as damaging electrical devices, melting cable lines, and potentially even a fire. Monitoring the use of electric load alone is less effective in preventing overload. The short-term forecasting process is needed for the use of the load. In this paper, we describe a comparison of electrical load forecasting methods consisting of the Kalman Filter, Autoregressive Integrated Moving Average (ARIMA), and Long Short-Term Memory (LSTM) Network. The dataset was used in the form of a reading history of power sensors installed in the Building Automation System (BAS) of Institut Teknologi Nasional (ITN) Malang. The experiment was carried out by comparing the loss rate in each forecasting model with the Root Mean Square Error (RMSE) calculation method. The results obtained include an average loss value of 29.474 for forecasting electrical load using Kalman Filter, another average loss value of 29.136 for forecasting electrical load using ARIMA, another average loss value of 27.931 for forecasting electrical load using LSTM with three input variables, and another average loss value of 28.049 for forecasting electrical loads using LSTM with six input variables. These results indicate that the LSTM model with three input variables has the smallest average loss level compared to other models.**

***Keywords*—ARIMA, forecasting, kalman filter, LSTM, overloading, short-term forecasting**

I. Introduction

Overload can occur when the electric power used exceeds the capacity that can be provided by the electrical network system. This can be caused by high power consumption of electronic devices or too many devices connected to the electrical system. Overloads can cause abnormal heating of cables, electrical devices, and other components in the electrical system. This may result in damage to electrical devices and melting of wiring[1]. In addition, improper heating can also trigger a fire. Therefore, it is important to understand the utilization of electric power based on the capacity provided by the electricity grid system. However, manual monitoring still allows for more burdens to occur[2].

Institut Teknologi Nasional Malang (ITN) has developed a smart building system, or it can be called the Building Automation System (BAS). The system is installed in the Electrical Engineering Laboratory building. The concept of an intelligent building system can provide more effective power monitoring compared to manual systems. This system can read the electricity consumption using a special sensor. The system can also turn off electrical devices without direct human intervention. The sensor reading process can be combined with the ability to adjust the on/off of electronic devices to minimize the occurrence of overload. However, there will be a problem if there is a spike in the load at any time because the system only reads the current electricity usage.

Electrical load data is time series data that can be predicted with several forecasting methods. There are three methods commonly used in short-term forecasting of time series data, including Kalman Filter, Autoregressive Integrated Moving Average (ARIMA), and Long Short-Term Memory (LSTM) Network[3]–[10]. The electric load forecasting process can be combined with a smart room system to avoid overloads more effectively because the system also predicts the usage of the load later.

In this research, a comparative process of the three short-term forecasting methods is carried out in predicting the use of electric power. The results of the comparison will determine the method to be used in future projects to realize the process of monitoring and securing electricity usage in real-time.

II. Methods

A. Kalman Filter

This method is a technique commonly used in the process of predicting time series data by observing measurements from time to time[11]. The prediction process is carried out based on a dynamic linear system[12]. The Kalman Filter model defines state evolution from $k-1$ to k time, which is represented in (1).

$$x_k = \boldsymbol{H}x_{k-1} + \boldsymbol{I}u_{k-1} + v_{k-1} \quad (1)$$

Where $\boldsymbol{H}$ is the state transition matrix applied to the state vector x_{k-1}, $\boldsymbol{I}$ is the input control matrix applied to the control vector u_{k-1}, and v_{k-1} is the process noise vector assumed to be zero-mean Gaussian with covariance.

B. ARIMA

This method was developed by George Box and Gwilym Jenkins in 1970. ARIMA is used to process short-term forecasting from time series data. It uses past and recent values of the dependent variable to produce accurate short-term forecasts[13]. This method is not suitable for long-term forecasting because the value will tend to be constant[14]. The purpose of ARIMA is to determine a good statistical relationship between the variables being forecasted and the historical values of these variables so that forecasting can be carried out[15].

The ARIMA model consists of three processes, namely autoregressive, integrates, and moving averages with orders **(p, d, q)** or denoted by **ARIMA (p, d, p)**. This model uses a differencing process so that the data becomes stationary. The number of differencing processes is denoted by **d**. The general form of the autoregressive model is denoted by (2).

$$X_k = \varphi_0 + \varphi_1 X_{k-1} + \varphi_2 X_{k-2} + \cdots + \varphi_p X_{k-p} + e_k \quad (2)$$

Where X_k is the variable value at time k, φ_0 is a constant, $\varphi_1 \dots \varphi_p$ is the autoregressive coefficient, and e_k is the residual value at time k. The order or degree of autoregressive is denoted by p. The order value is determined by the number of periods of the dependent variable entered the model. The number of past values used determines the level of the model.

The Moving Average order **q** model is generally represented by (3).

$$X_k = \phi_0 - \phi_1 e_{k-1} - \phi_2 e_{k-2} - \cdots - \phi_q e_{k-q} + e_k \quad (3)$$

Where X_k is the variable value at time k, ϕ_0 is a constant, $\phi_1 \dots \phi_q$ is the moving average coefficient, and e_k is the residual value at time k. The ARIMA model is a combination of all the processes that have been described.

C. LSTM

This Network is one of the developments of Recurrent Neural Networks (RNNs) by adding several types of gates, namely input gates, forget gates, and output gates[16]–[18]. RNN is an Artificial Neural Network (ANN) that is used to process sequence data. RNNs can remember information from previous times and use that information to produce output at the current time.

Long sequential data produces explosive gradients which can cause the RNNs training process to be unstable. RNNs also have limited memory capacity. These limitations cause RNNs to be less good at handling tasks that require long-term context understanding. LSTM is designed to overcome these limitations by adding input gates, forget gates, and output gates. These gates can control the gradient flow better to provide a more stable training process. LSTM also have long-term memory units that enable them to store more

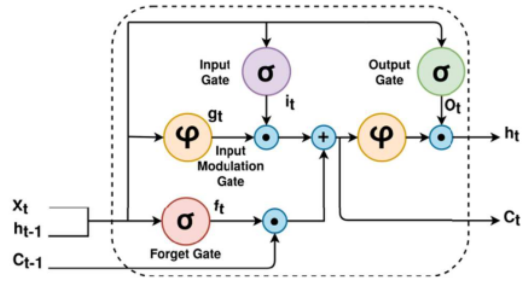

Fig. 1. LSTM cell.

information periods than RNNs. LSTM cell is illustrated in Fig. 1. Although LSTMs have advantages, these networks have a more complex structure compared to RNNs. Making LSTMs requires high computing resources and longer training time.

D. Dataset

In this study, the dataset was used in the form of a reading history of power sensors installed in the Control System Laboratory of ITN Malang. Data collection was carried out for about seven weeks, starting from 8th June 2023 to 28th July 2023 with intervals of data collection every 5 minutes. The dataset will be divided into two types, namely training data for LSTM and test data for all methods. In the LSTM training process, sensor reading data was used from 8th to 30th June. In the forecasting testing process, sensor reading data was used from 1st July to 28th July which was further divided into seven days for each experiment.

E. Research Stages

In this study, four forecasting models were used, namely Kalman Filter, ARIMA, LSTM with 3 input variables, and LSTM with 6 input variables. These models are created using the Python program code. The **statsmodels** library is required to implement ARIMA models. In addition, the **TensorFlow** library is also needed to implement the LSTM model.

The initial stage is the LSTM model training process using the dataset that has been provided. The second stage is to carry out the forecasting process using the four models that have been designed. The third stage is evaluating the performance of the model based on a comparison between forecasters and actual data. At this stage, the loss calculation for each model is carried out using the Root Mean Square Error (RMSE) method which is represented in (4).

$$RMSE = \sqrt{\frac{\sum_{t=1}^{n}(X_t - Y_t)^2}{n}} \quad (4)$$

Where X_t is the forecasted value, Y_t is the actual value read by the sensor, and n is the amount of data[19]. The lower the loss value generated, the better the forecasting results.

III. Results

The results were obtained through four short-term load forecasting experiments for seven days of data. The forecasting process is done with time interval **t** which is every five minutes. In each experiment, a comparison graph between the forecast results and the actual value is shown.

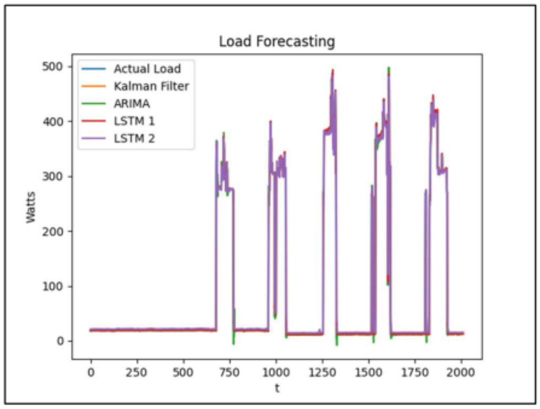

Fig. 2. First experiment chart.

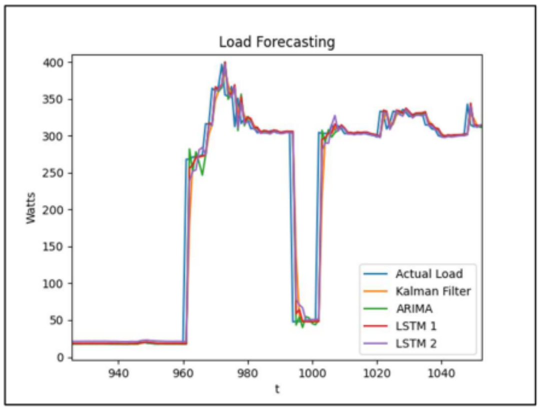

Fig. 3. First experiment chart enlargement.

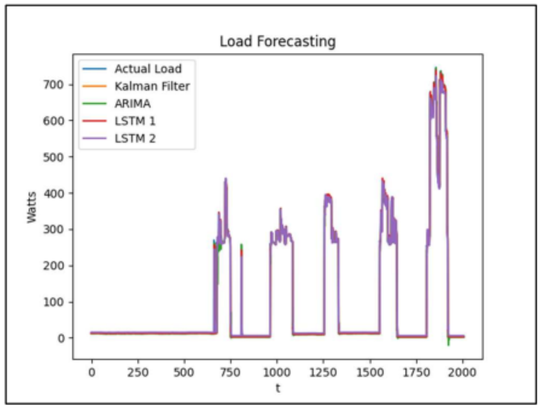

Fig. 4. Second experiment chart.

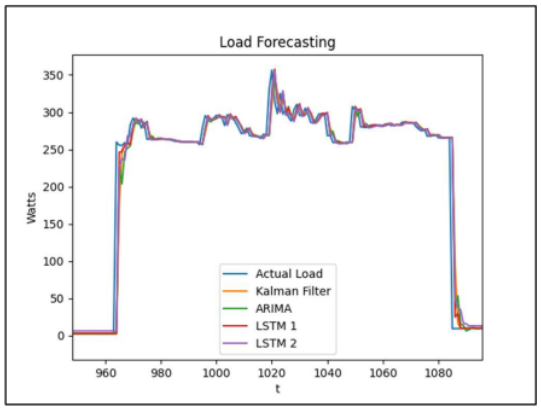

Fig. 5. Second experiment chart enlargement.

A. First Experiment

In this trial, actual data from power sensor readings from 1st July to 7th July is used as a reference for forecasting the four models that have been designed. The full-scale forecasting results are shown in Fig. 2, while the enlargement can be seen in Fig. 3.

Forecasting models that have been designed produce predictive results that are close to actual values. In the first trial, the loss value in the Kalman Filter model was 28.305, the loss value in the ARIMA model was 27.276, the loss value in the LSTM model with 3 inputs was 27.197, and the loss value in the LSTM model with 6 inputs was 27.328. In this experiment, the LSTM model with 3 inputs has the lowest loss value when compared to other forecasting models.

B. Second Experiment

In this trial, real power sensor data recorded between 8th July and 14th July serves as a basis for predicting the outcomes of the four models that were developed. The comprehensive forecasting outcomes are illustrated in Fig. 4, with a closer look available in Fig. 5.

Predictive models have been crafted to generate forecasts that closely align with real-world values. In the second trial, the Kalman Filter model resulted in a loss value of 27.772, the ARIMA model had a loss value of 27.614, while the LSTM model using 3 inputs achieved a loss value of 26.402, and the LSTM model with 6 inputs recorded a loss value of 26.458. In this experiment, it is worth noting that the LSTM model with 3 inputs displayed the most favorable performance, boasting the lowest loss value when compared to the other forecasting models.

C. Third Experiment

In this trial, actual power sensor data collected between 15th July and 21st July as a basis for predicting the outcomes of the four designed models. The comprehensive forecasting results are shown in Fig. 6, with a closer view provided in Fig. 7 for a more detailed examination.

The designed forecasting models yield predictions that closely align with the actual values. In the third trial, the Kalman Filter model had a loss value of 23.848, the ARIMA model had a loss value of 23.260, the LSTM model with 3 inputs had a loss value of 22.690, and the LSTM model with 6 inputs had a loss value of 22.944. Notably, in this experiment, the LSTM model with 3 inputs achieved the lowest loss value when compared to the other forecasting models.

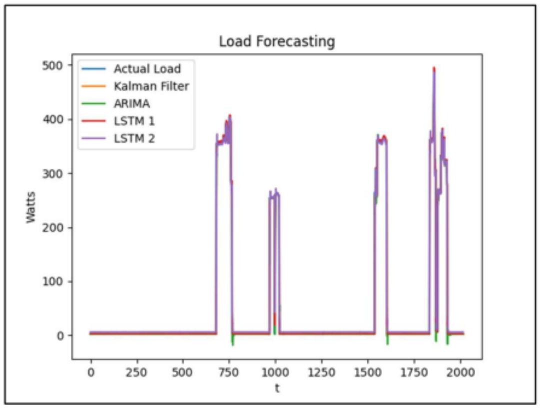

Fig. 6. Third experiment chart.

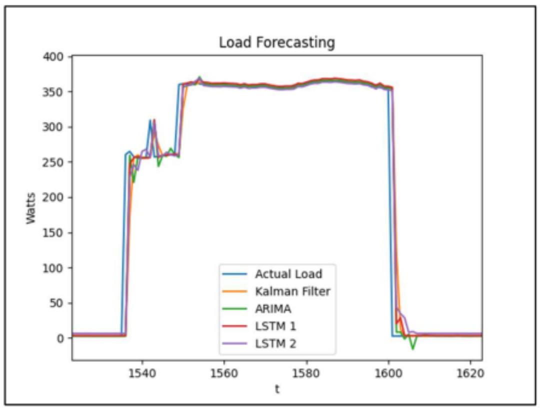

Fig. 7. Third experiment chart enlargement.

D. Fourth Experiment

In this trial, actual data from power sensor readings from 22nd July to 28th July are used as a reference for forecasting the four models that have been designed. The full-scale forecasting results are shown in Fig. 8, while the enlargement can be seen in Fig. 9.

Forecasting models that have been designed produce predictive results that are close to actual values. In the fourth experiment, the loss value in the Kalman Filter model was 37.970, the loss value in the ARIMA model was 38.395, the loss value in the LSTM model with 3 inputs was 35.434, and the loss value in the LSTM model with 6 inputs was 35.464. In this experiment, the LSTM model with 3 inputs has the lowest loss value

TABLE I. LOSS CALCUATION

Experiment	RMSE			
	Kalman Filter	*ARIMA*	*LSTM 1*	*LSTM 2*
1	28.305	27.276	27.197	27.328
2	27.772	27.614	26.402	26.458
3	23.848	23.260	22.690	22.944
4	37.970	38.395	35.434	35.464
Average	**29.474**	**29.136**	**27.931**	**28.049**

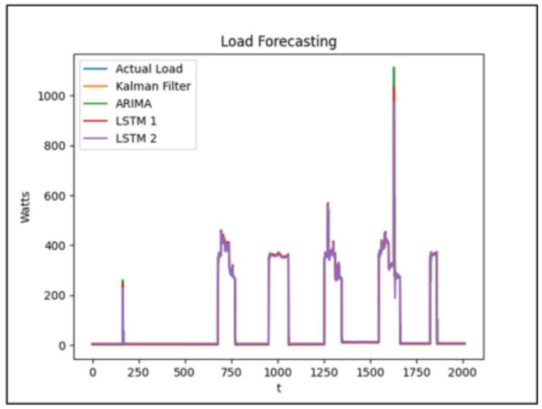

Fig. 8. Fourth experiment chart.

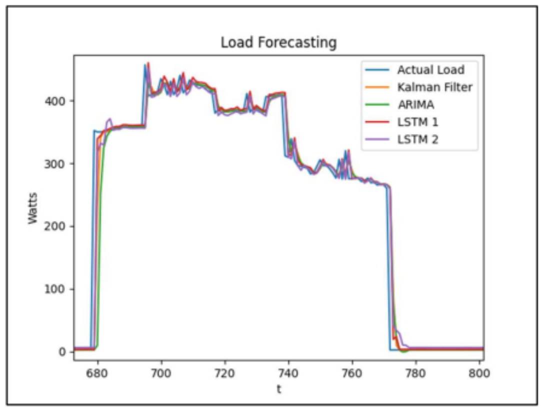

Fig. 9. Fourth experiment chart enlargement.

The comparison of the loss calculations for each model in all experiments is shown in Table 1. The average loss obtained by each model is 29.474 for the Kalman Filter, 29.136 for the ARIMA, 27.931 for the LSTM 1 model, and 28.049 for the LSTM 2 model. The lowest average loss value was obtained by the LSTM 1 model which has three inputs. The prediction results from this model also dominate in every experiment that has been carried out.

IV. CONCLUSION AND SUGGESTION

Based on a series of experiments that have been carried out, it can be concluded that short-term load forecasting can be done using three models, namely Kalman Filter, ARIMA, and LSTM. In this study, two kinds of LSTM models were designed, namely LSTM 1 which has three input variables, and LSTM 2 which has six input variables. Visually, each designed model can produce predictive results that are close to actual values.

Quantitatively, the designed forecasting model has different loss levels. In this study, loss calculations were performed using the RMSE method. Sequentially from the smallest average loss value obtained by the LSTM 1 model, namely 27.931, then obtained by the LSTM 2 model, namely 28.049, then obtained by the ARIMA model, namely 29.136, and finally obtained by the Kalman Filter, namely 29.474.

From these results it can be said that the most optimal forecasting model that has been made is the LSTM 1 model.

Further development for the LSTM model needs to be done to get a lower loss value. Experiments can be carried out to increase the number of inputs from the model or to increase the number of LSTM cells. Subsequent work can apply the LSTM model for real-time forecasting of electrical loads using embedded devices.

ACKNOWLEDGMENT

This work is supported by the research grant from the Institute for Research and Community Service of ITN Malang and the BAS Project of ITN Malang, Year 2023.

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