Forecasting Solar Irradiation on Solar Tubes Using the LSTM Method and Exponential Smoothing

Wahyu Tri Handoko, Muladi, Anik Nur Handayani
Universitas Negeri Malang, Jl. Semarang, No 5, Malang 65145, Indonesia

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ABSTRACT

Sunlight is an alternative energy source that can be used as a substitute for fossil fuels. Renewable energy potential has not been widely utilized, especially in Indonesia. Utilization of sunlight, one of which is done indoors to save electricity and the source is not limited. This study aims to predict solar irradiance to determine the value of sunlight intensity in an area as the main source of the utilization of renewable electrical energy through the solar tube system with the LSTM method. This low-cost system offers a renewable way and considers the potential for solar radiation as an energy-efficient alternative based on the intensity of light captured by the solar tube. This research uses two methods. The LSTM method is a recurrent neural network forecasting technique that can study deeply and extract temporal relationships in data because of its large architecture. The exponential smoothing method is part of the time series forecasting technique and is used when the dataset has no cyclic variance and trend. Data collection was carried out in sunny conditions because it represents a stable condition in sunlight. The results obtained from the two methods are evaluated with RMSE and MAE values to choose the optimal approach. Due to lower RMSE and MAE values in this comparison, LSTM performs better than Multiple Repeat and Exponential Smoothing in terms of performance.

Corresponding Author:

Muladi, Universitas Negeri Malang, Jl. Semarang, No. 5, Malang, Indonesia
Email: muladi@um.ac.id

1. INTRODUCTION

Indonesia is in a favorable geographical position, namely on the equator [1]. This makes Indonesia in the middle region between north and south. Therefore, here there are abundant sources of heat energy that can be used to reduce electricity consumption by using natural energy directly such as heat energy, solar energy, wind energy, and water energy in Indonesia [2] as alternative energy, such as using solar energy to heat water and capture solar radiation for lighting [3]. In Indonesia, this energy can be used directly to achieve various purposes, such as using solar energy to produce electricity or to capture solar radiation for lighting [4]. The availability of sunlight is almost always the same throughout the year, except during the rainy season and when thick clouds block sunlight [5]. So that forecasting is needed to be able to predict the condition of potential sunlight. Based on the location map, the average solar irradiation is around 4.80kWh/m^2 per day throughout Indonesia [6]. Fig. 1 shows the distribution of solar power potential in Indonesia.

In utilizing the use of distributed solar energy more efficiently, solar tubes are used. A light guide system or solar tube as an energy source with a tube model is a simpler way to estimate energy use by considering the roof and attic area of a building. A solar tube is a tool to transport or distribute natural or artificial light into a room. The process of distributing sunlight in the form of solar irradiation in solar tubes is unreliable due to natural variability which can reduce the reliability of combining solar tubes with solar panels. To overcome this problem, the technology of forecasting irradiation in solar tubes is very important to formulate scientific plans to predict the value of solar irradiation as an optimization and increase the utilization and efficiency of the economy and new energy [7].

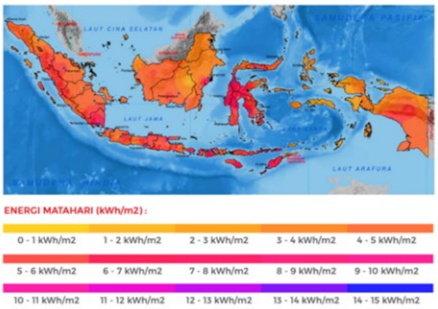

Fig. 1. Map of Potential Solar Power Locations

In general, solar irradiation forecasting methods that are often used include linear regression, fuzzy logic, ARIMA [8], and artificial nervous systems [9]. Forecasting solar irradiation in achieving accurate results also depends on many factors, such as choosing the right architecture to handle dynamic modeling data, choosing the right algorithm, choosing input variables, and adjusting the hypermeter model, and others [10].

Relevant research related to solar tubes is the analysis of solar tube designs with solar panels in residential homes [11]. The system combines solar panels with solar tubes as a means of saving electricity in residential homes [12]. In this system research, there is still no prediction of solar irradiation in Solar Tubes, so the reliability of the method is still unknown. In addition, research [13] designed and demonstrated a solar tube to convert photo-electric and photo-thermal at the same time. Based on the system design, the solar tube can obtain a total energy efficiency of 25% and is expected to be able to increase the utilization of solar energy properly. This allows improvements in estimating irradiated energy in the future.

One of the deep learning method, the Long Short-Term Memory (LSTM) model, is widely applied to predicting solar irradiation [14], [15]. A comparison study [16] uses the RNN method with results from 0.7 to 0.79 in the irradiation forecasting process. Other research regarding LSTM is shown in the discussion [17] that the utilization of solar energy, which is a variable resource, requires a prediction method to increase the availability of the entire system effectively. The deep solar hot water system used the deep learning model differently for weather conditions with a relative Mean Absolute Error of 3.45%. Based on this, LSTM on solar tube systems can be used.

Furthermore, forecasting research using exponential smoothing and recurrent methods for time series [18] obtained the best results in the Exponential Smoothing method used for seasonality removal and normalization of the time series. So, the Exponential Smoothing model can optimize the coefficients and the initial seasonal components.

From the description above, this study aims to predict solar irradiance to determine the value of sunlight intensity in an area as the main source of the utilization of renewable electrical energy through a solar tube system using the LSTM method. The reason that motivates the use of the LSTM method in forecasting this research is that LSTM is built with several layers and hidden layers which produce a more accurate level of forecasting. The main contribution of this research is implementing the LSTM and Exponential Smoothing methods in predicting light exposure. The selection of solar tubes is an innovation in utilizing direct sunlight to house buildings. This data is used as information on the potential of solar power in solar tubes with the support of solar radiation forecasting. In addition, sunlight passing through the solar tube is also used as natural lighting in the room. Section 2 describes the research methods and preparations for completing this research. Section 3 describes the results of data collection and processing using the LSTM method and exponential smoothing. Section 4 presents the results of this research contribution.

2. METHOD

In this study, two systems were designed, namely hardware and software. For hardware related to solar tubes as a room lighting system. Meanwhile, software related to language and algorithms is used in machine learning from the deep learning method with the LSTM model [19]. The design of the implemented algorithm, namely the regression and multi-repeat model, and compared with exponential smoothing.

The system flow in this study is illustrated in Fig. 2 to make it easier for researchers to analyze data, conversion of light irradiation is needed. While Fig. 3 is in the process of collecting solar irradiation data in a solar tube with a BH1750 sensor. Research [20] discussed the capabilities that can be carried out on this solar tube model, the optimal output of a light current of 1064 lumens. If converted in units of watts, the value obtained is 13.3 W/m^2. In addition, this research has been developed using sensors as input data integrated with a cloud system. So that besides being able to capture light for solar panels, light is also captured to be processed as material for this research.

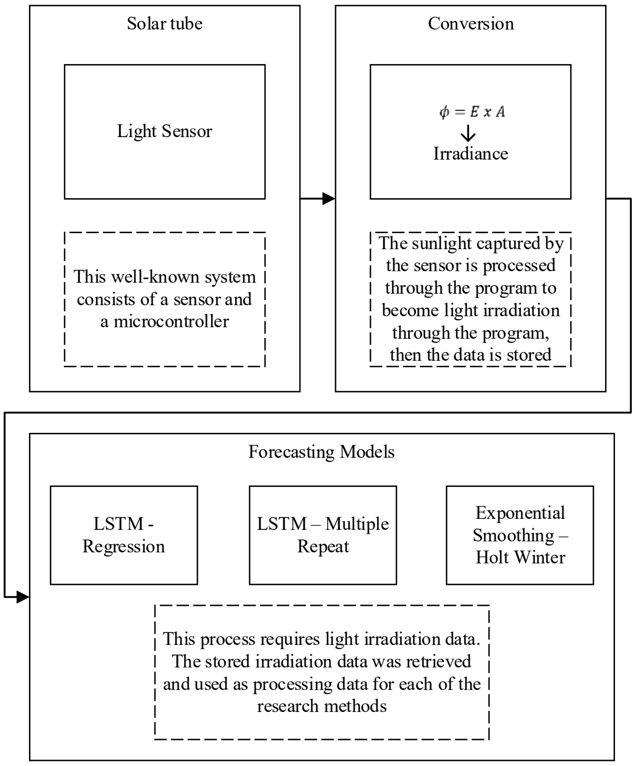

Fig. 2. Hardware (Solar Tube) and Software (Conversion and Forecasting) Block Diagram

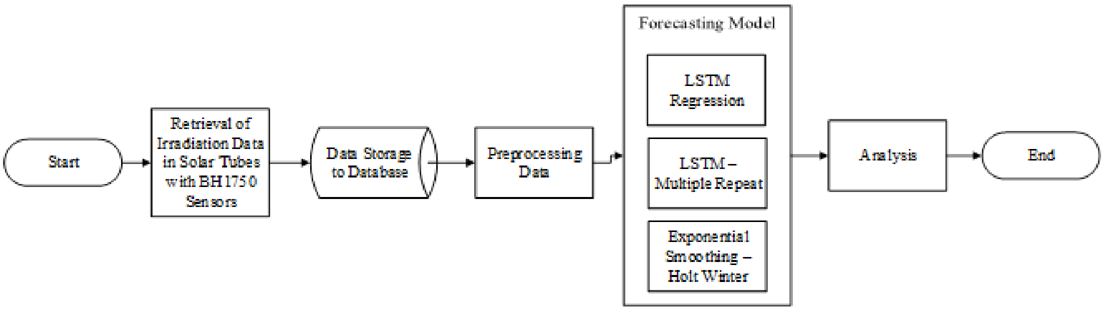

Fig 3. Flowchart of Irradiation Forecasting Process

2.1. Design Hardware

Solar Tube is designed using a tube with PVC D'5 and a dome. The dome is composed of 7 layers of convex lenses. A solar tube is used for the distribution of light into a room. The solar tube design used is shown in Fig. 4.

Based on Fig. 4, the first layer (1) is a convex lens; that serves to capture light and channel it to the collected focus points. The second (2) is a dome (a sunbeam receiver that refracts light into a tube) made using a semi-circular acrylic with a diameter of 15cm which is colored DIY (Do It Yourself); as a medium for placing convex lenses. The third (3) is a sticker attached to the PVC part as a rectifier of incoming light so that it is focused downward. Fourth (4) is PVC. Fifth (5) is a solar panel along with a light sensor installed in it, as a light intensity catcher. The six (6) are batteries, as power storage to supply sensors and lights. Seventh (7) is a lamp, as lighting at night. The eighth (8) are cables: connecting solar panels, sensors, batteries, lights, and switches. And finally (9) is an embedded system that can process and control as an on/off control for lighting. The light sensor captures the intensity of sunlight (lux) and converts it to solar irradiation, then the value of the irradiation is used as solar irradiation forecasting data.

Fig. 5 is an embedded system block that is implemented in the solar tube model of this study. The system used there are two blocks. The first block is the inner area, where there are solar panels (PV), sensors, and diodes. The inner area is used for the acquisition of data and information to be analyzed as the potential for light entering the solar tube. In addition, solar panels are used as a power generator for lighting lamps and a source for other components. Furthermore, the second block is the outer area of the solar tube (see Fig. 4(b)). This area is a charging system and data processing sent by sensors and solar panels. The data obtained by the sensor is sent to storage by the microcontroller (Node-MCU). Meanwhile, the light captured by the solar panels is sent to the SCC as a storage system in the battery. SCC receives electrical energy that has been sent by solar panels through the charging control to be stored in the battery.

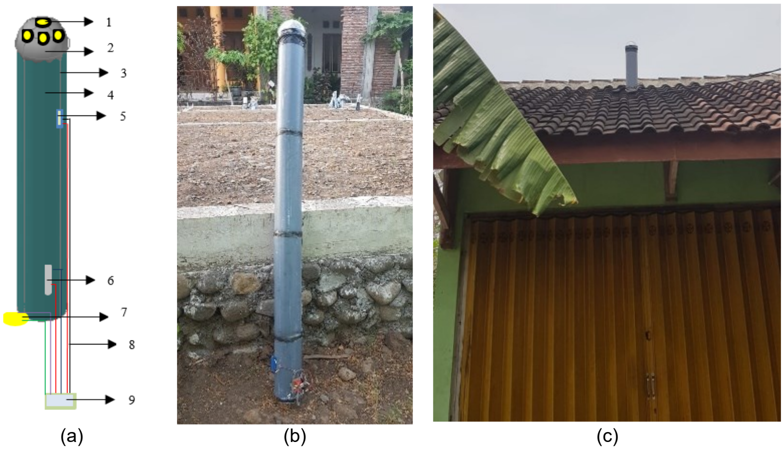

Fig. 4. (a) Design of Solar Tube, (b) Solar Tube Model, (c) Application of Solar Tube

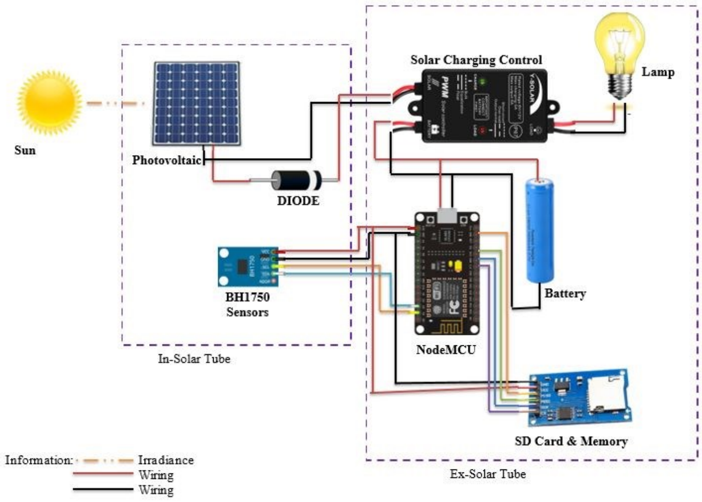

Fig. 5. Embedded System on Solar Tube

2.2. Data Preparation

Before implementing the proposed framework, some data is required for pre-processing, which includes selecting data where some data is missing or incorrectly recorded to be discarded and not included in the experiment [21]. Eliminating data and matching based on long time series of sunlight. The steps taken include collecting solar irradiation data that has been read by the sensor. Data checking is done by identifying readable data formats and data readability [22]. Data cleaning is done by making a reasonable average value [23]. An input data normalization method for forecasting solar irradiance was also carried out [24]. In this article, a normalization technique has been selected to be used. Data normalization converts actual numbers into values that range from 0 to 1 in order to reduce errors. Min-max normalization is the method for data normalization that is employed [25]. The min-max normalization equation can be seen in (1).

$$x_{norm} = \frac{x - \min(x)}{\max(x) - \min(x)} \tag{1}$$

where, x_{norm} is normalized data, x is actual data / initial data, min (x) is minimum data value, max(x) is maximum data value.

2.3. Long Short-Term Memory (LSTM)

LSTM is a kind of recurrent neural network that can learn and extract temporal relationships in data [26]. Utilizing internal memory units and gate mechanisms, LSTM overcomes the drawbacks of RNN [27]. The LSTM unit consisting of memory cells, input gates, output gates, and forget gates [28] is shown in Fig. 6. The performance of the LSTM method in reading time series is so good that it can be used for short-term forecasting [29], [30]. The stages in using the LSTM method start from collecting data, preprocessing data, modeling data, and evaluating [31]. In the data modeling section, the LSTM architecture is made so that it can be used in forecasting irradiation.

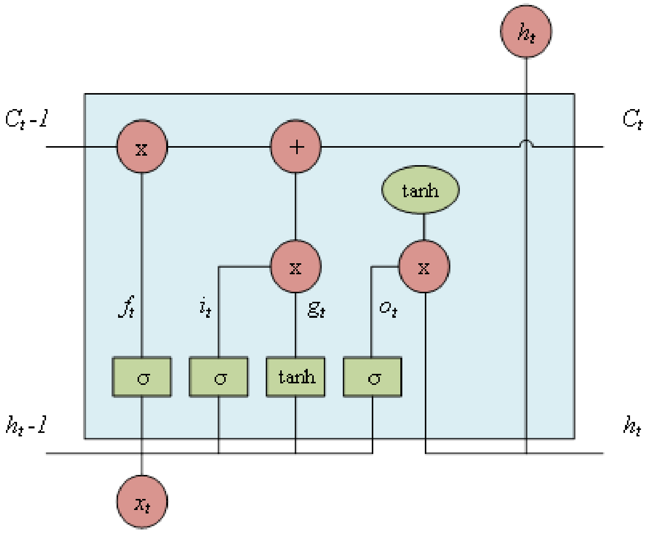

Fig. 6. LSTM Units

The main component of the LSTM is the unit cell, which is the path in memory from the previous block, C_{t-1} to the current block of memory, C_t [32]. Thus, allowing information from memory to the device. The path on the LSTM unit can be decided on all the previous information. This network can be defined in terms of functional equations:

$$f_t = \sigma(W_f.[h_{t-1}, x_t] + b_f \tag{2}$$

where h_{t-1} and x_t are linear transformations and the input is changed to a sigmoid form to get an output [33] of 0 to 1 for each cell in C_{t-1} condition. Then for the current input x_t and output h_{t-1} combined, the i_t and C_t functions [34] are obtained as follows:

$$i_t = \sigma(W_i.[h_{t-1}, x_t] + b_i \tag{3}$$

$$\tilde{C} = \tanh\,(W_c.[h_{t-1}, x_t] + b_c) \tag{4}$$

$$C_t = f_t\ x\ h_{t-1} + i_t * \tilde{C}_t \tag{5}$$

At the final stage of the LSTM cell, the output can be obtained by the unit cell.

$$o_t = (W_0.[h_{t-1}, x_t] + b_0) \tag{6}$$

$$h_t = o_t\ x \tanh\,(C_t) \tag{7}$$

where it is represented by the part of the input that will be selected as the composition of the output and ht. The steps taken in this method are shown in Fig. 7.

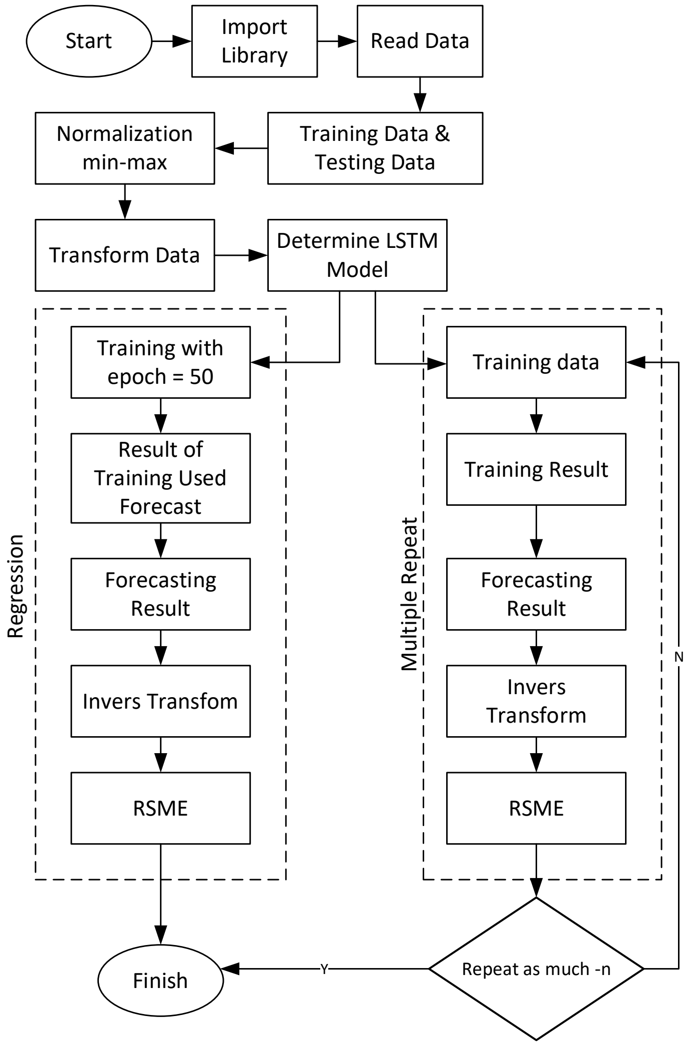

Fig. 7. Solar Irradiation Forecasting Flowchart with LSTM Regression Model and Multiple Repeats

2.4. Exponential Smoothing

Exponential smoothing methods are classified into (a) Simple Exponential Smoothing Method (b) Corrected Exponential Smoothing Method (c) Holt Winter Method [35]. The Holts exponential smoothing method is the best method for measuring estimates [36]. The Exponential Smoothing method is part of the time-series analysis technique [37]. This technique is used when the dataset has no variance and cyclic trends [38].

The Holts winter method is used to measure levels, trends, and periodicity [39]. All three are needed as a measure of increasing and decreasing trends [40]. Forecasts for future periods are presented as:

$$\hat{y}_{t+1} = (\alpha_t + b_t)C_{t+1} \tag{8}$$

where,

$$\alpha_t = \alpha\left(\frac{y_t}{C_t}\right) + (1-\alpha)(\alpha_{t-1} + b_{t-1}) \tag{9}$$

$$b_t = \beta(\alpha_t - \alpha_{t-1}) + (1-\beta)b_{t-1} \tag{10}$$

$$C_{t+1} = \gamma\left(\frac{y_t}{C_t}\right) + (1-\gamma)C_t \tag{11}$$

α, β, γ are constants to calculate the level, trend, and periodicity indices. This model is a statistical technique that can obtain seasonal information [41]. The following are the steps before calculating forecasting estimates using the exponential smoothing method shown in Fig. 8.

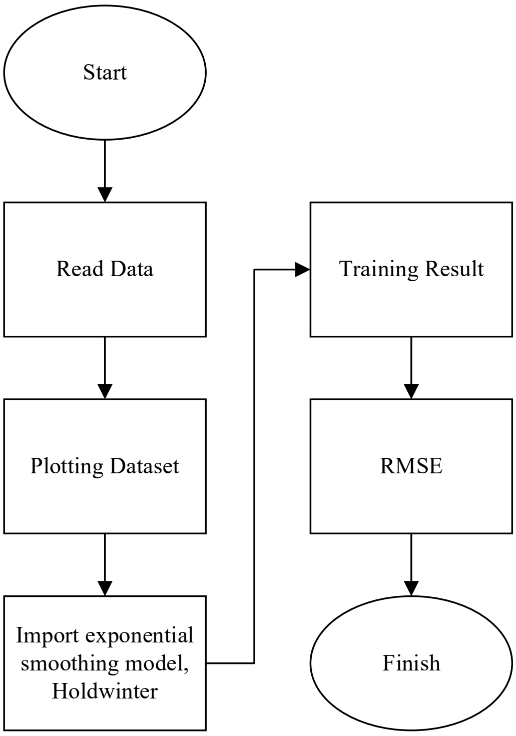

Fig. 8. Exponential Smoothing Flowchart

2.5. Index Evaluation

In forecasting case studies, it is necessary to evaluate the index by measuring the error, there are several suggestions to evaluate the performance of the forecasting model [42]. One such measurement of error is the Root Mean Square Error (RMSE) [43]. RSME is commonly used as a parameter optimization model, validation model, selection model, comparison model, and forecasting evaluation [44].

RSME in this study is by measuring the difference between the actual value and the forecast value. RMSE is used as a forecasting evaluation [45], [46]. So, a lower value indicates a better forecasting result, and it can be formulated as:

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(Pf - Pa)^2} \tag{12}$$

where N is the number of observations; Pf is the forecast value and Pa is the actual value.

As a comparison of the results of the RMSE value, the Mean Absolute Error (MAE) is used which is a method for measuring the accuracy of the prediction model [47] and can be formulated as follows:

$$MAE = \frac{1}{N}\sum_{i=1}^{N}|Pa - Pf| \tag{13}$$

3. RESULTS AND DISCUSSION

3.1. Data Collection

The data is obtained from the irradiation of light that enters through the solar tube and is stored in storage via the sensor. The data set processed in this study was obtained from measurements of solar irradiance in sunny conditions. Data collection was carried out in sunny conditions because it represents a stable condition in sunlight. Data collection began at 06.00 WIB - 18.00 WIB from 16 to 18 April 2022 at the location of Seboro Village, Krejengan District, Probolinggo Regency. This location was chosen because it is close to the researcher's residence to facilitate accessibility. Irradiation data is presented with measurements of 1 day per 30 minutes. The presentation of the data is shown in Fig. 9.

The measurement technique is carried out by reading the BH1750 sensor calibrated with the Lutron LM-8000 sensor to ensure that the readings are following the measuring device.

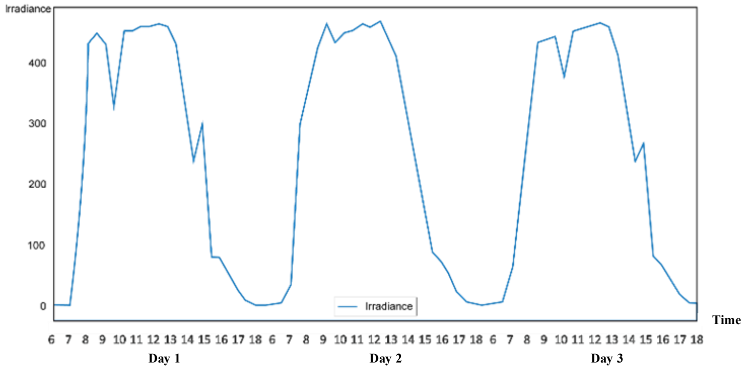

Fig. 9. Irradiance Data Graph

3.2. Forecasting

Table 1 shows the parameters used in this forecasting case. The LSTM parameter used serves as the length of time the training and testing process is carried out on the dataset to bring up the performance value of the forecast [48]. Whereas in exponential smoothing seasonality, it is used to determine the amount of seasonality that occurs in the dataset [49].

Table 1. Parameter of LSTM Model Regression, Multiple, and Exponential Smoothing

Parameter	LSTM Regression	LSTM Multiple	Exponential Smoothing
Epoch	100	100	-
Optimizer	Adam	Adam	True
Batch Size	1	1	-
Seasonal	-	-	Add (12 periods)

The results of the training data for LSTM obtained trend values that determine the forecasting of solar irradiation values shown in Fig. 10. Data training is carried out for 30-45 seconds.

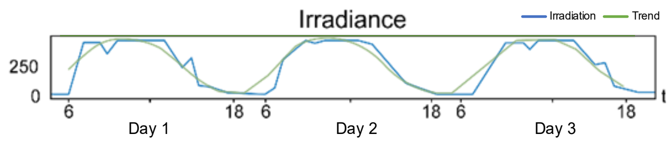

Fig. 10. Trend and Irradiation Data

The trend function reveals information about the tendency of data to vary over time. This knowledge is very helpful in predicting future values and finding long-term trends in historical data [50]. Forecasting methods can produce more precise and relevant projections by considering trends, especially if there are significant data changes from time to time.

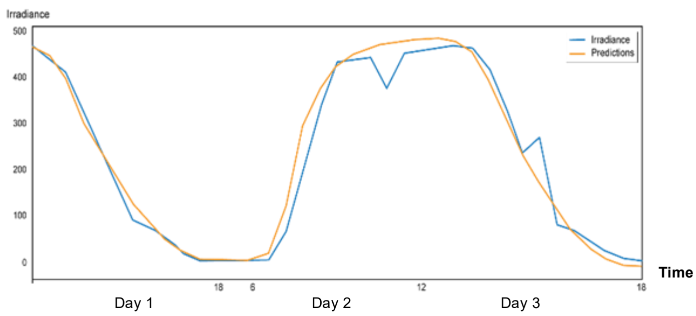

Fig. 11. Irradiation Graph and Irradiation Forecasting Result

From the forecasting results in Fig. 11, an evaluation of the RMSE value is carried out as an evaluation of the results of the accuracy of predictions with the regression model, data training is carried out for 30-45 seconds. From the LSTM Regression test that has been carried out, an average RSME of 42.60 and an MAE value of 40.21 is obtained (see Table 2).

Then carry out the solar irradiation forecasting process using the LSTM Multiple Repeats model to test different training data. In testing, the results were obtained from the multiple repeat model (see Fig. 12) and obtained the 1st and 2nd RSME and MAE values as described in Table 2.

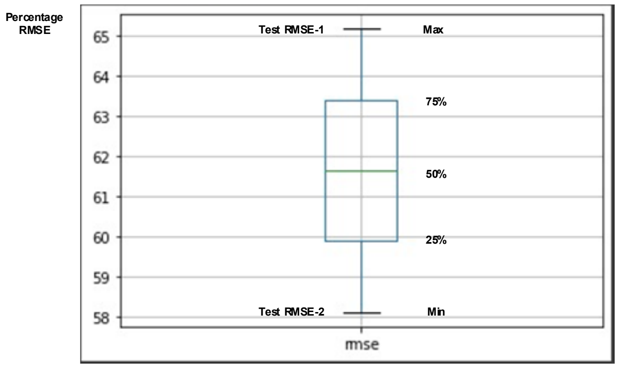

Fig. 12. Candlestick Charts use the Multiple Repeater Model LSTM Method

Furthermore, the results of forecasting with the exponential smoothing method as a comparison with the LSTM method are shown in Fig. 13. In the graph, there are three pieces of information, namely, (1) train is the training result of 60% of the data, (2) test is the test result of 40% of the data used as a forecasting test, (3) forecast is the result of forecasting using data that has been tested before. After obtaining the forecasting results, a performance evaluation is carried out through RMSE calculations and produces a value of 45.73 and an MAE value of 42.92.

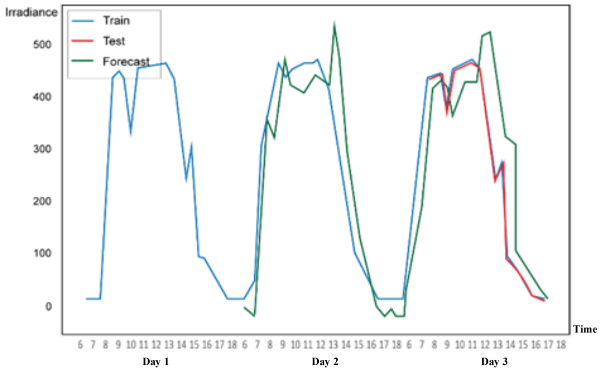

Fig. 13. Exponential Smoothing Results

Table 2. RMSE and MAE Results

Method	Model	RMSE Value	MAE Value
LSTM	Regression	42.60	40.21
	Multiple Repeat	47.16	43.87
		83.57	79.35
Exponential Smoothing	Holts Winter	45.73	42.92

The mean square root of the discrepancy between the projected value and the actual value is used by RMSE to gauge the precision of prediction error. The prediction model is more accurate with the smaller RMSE. The LSTM had the lowest RMSE in this comparison, at 42.60, indicating a considerably superior performance in predicting the true value.

The average of the absolute differences between the anticipated values and the actual values is computed to determine the magnitude of prediction error (MAE). A lower MAE suggests improved prediction accuracy. The lowest MAE in this situation is 40.21 for the LSTM, indicating that this model has a lower prediction error rate than other approaches. We must consider both the RMSE and MAE values to select the optimum approach. Due to lower values for RMSE and MAE in this comparison, LSTM performs better than Multiple Repeat and Exponential Smoothing in terms of performance.

4. CONCLUSION

Based on the forecasting results of irradiation data, RMSE and MAE values were obtained from forecasting using the regression model with an average value of 42.60 and 40.21 respectively with a test time of 35-40 seconds. Furthermore, the RSME forecasting results using the LSTM Multiple Repeats test obtained the smallest RSME and MAE results in the first test with values of 47.16 and 43.87 with a test time of 11 minutes and 9 seconds. While the RSME forecasting results with the exponential smoothing method is 45.73. Both of these methods can be used for forecasting but based on the RSME and MAE values of the two methods, the results of the LSTM regression model have a better value with RSME and MAE results of 42.60 and 40.21. The limitations of using this method are in different software and case studies. In this study, linear regression LSTM has been proven to be used with fairly accurate results.

Acknowledgments

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BIOGRAPHY OF AUTHORS

Wahyu Tri Handoko, received an A.Md. in the field of ship electrical engineering from the Surabaya State Shipping Polytechnic in 2018 and the title of S.T. in electrical engineering from Surabaya State University in 2021. Currently pursuing education to obtain an M.T. in electrical engineering from State University of Malang. His research interests include energy conversion, power systems, data science and artificial intelligence. I can be contacted at email: wahyutrihandoko.ee@gmail.com.

Muladi, received the title of S.T. and M.T. in telecommunications from the Surabaya Sepuluh Nopember Institute of Technology in 1994 and 2002 respectively, and received a Dr. degree in telecommunications from the Malaysian University of Technology in 2007. Currently a lecturer at the Department of Electrical Engineering, State University of Malang. His research interests include wireless communications, light wireless communications, source coding and error control coding, data security, communication protocol power line communications, routing in WSNs and location tracking. I can be contacted at email: muladi@um.ac.id.

Anik Nur Handayani, received the title of S.T. in electrical engineering from Brawijaya University, Malang in 2004 and received an MT in electrical engineering from the Sepuluh Nopember Institute of Technology Surabaya in 2008. After that he received the title of Dr. Eng. in science and advanced from Saga University, Japan in 2014. Currently a lecturer at the Department of Electrical Engineering, State University of Malang. His research interests include Intelligent Systems and Assistive Technology. I can be contacted at email: aniknur.ft@um.ac.id.