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A stacked LSTM model for day-ahead solar irradiance forecasting under tropical seasons in Java-Bali

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ABSTRACT

Accurate short-term solar irradiance forecasting is essential for the efficient management and planning of power generation, especially for solar energy, which holds a major role in the Indonesian Government's energy transition policy. A novel day-ahead solar irradiance forecasting is proposed using a stacked long short-term memory (LSTM) model to support the energy planning in the Java-Bali grid. The proposed model utilizes the first historical solar irradiance data of Java-Bali obtained from direct measurement to forecast the next day's hourly irradiance. The results are compared with the methods of autoregressive integrated moving average (ARIMA) and recurrent neural network (RNN). This study revealed that the proposed model outperforms ARIMA and RNN, and regarded as a highly accurate forecast since root mean square error (RMSE), mean absolute percentage error (MAPE), and R^2 are 25.56 W/m^2, 7.27%, and 0.99, respectively. The stacked LSTM produces better forecasting in the dry season than in the wet season. The MAPE indicates that the LSTM's lowest accuracy for the dry season was 13.99%, which is categorized as a good forecast. The LSTM's highest MAPE in the rainy season is 34.04%, which is categorized as a reasonable forecast. The proposed model shows its superiority and capability as a promising approach for short-term solar irradiance forecasting in Java-Bali.

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1. INTRODUCTION

The energy expansion fosters techno-economic development while addressing social and environmental concerns, such as urbanization, energy options, forestry and agriculture, and emissions [1]–[3]. The period 2005-2018 witnessed a concerning 23% increase in global greenhouse gas emissions (GHG) with the highest incidence in developing countries, coinciding with an upsurge in global economic growth, which reached an annual average of 3.5% since 2012 [4]–[6]. The energy sector, particularly power generation, stands out as one of the major contributors to the nation's emissions. Similarly, in Indonesia, the predominant use of fossil fuels, including petroleum and coal, has been identified as a key driver of the country's CO_2 emissions [7].

Indonesia's power generation landscape remains heavily reliant on fossil fuels, such as coal, oil, and gas, with the utilization of renewable energy (RE) sources currently below 15% [8]. Meanwhile, research in South American countries reveals an association between increased adoption of RE and environmental improvements. Notably, a 1% rise in the share of RE electricity is equivalent to a 0.53% reduction of CO_2 [9]. A separate study emphasizes the potential for substantial job creation (from ~57 million to ~134 million) by 2050 through a global transition to 100% RE across power, heat, transport, and desalination sectors. This shift, driven by RE's labor-intensive value chains, is likely to positively impact future economic stability and growth [10].

As one of the most potential RE in Indonesia, solar energy through photovoltaic (PV) technology presents a sustainable solution to energy poverty, environment protection such as reducing emissions and indoor air pollution, and social benefits such as employment [11], [12]. Cities globally, including Siena's medieval center, address CO_2 emissions by assessing GHG balances and adopting Intergovernmental Panel on Climate Change (IPCC) guidelines. Findings suggest energy efficiency improvements and a shift to renewables like photovoltaic panels, which could significantly reduce emissions and lead to carbon neutrality over time, especially when renewable energy powers urban needs [13].

As utility-scale solar projects increase to reach the net zero emission (NZE) target, grid-connected PV systems are projected to exhibit exponential growth. This phenomenon is leading to a significant increase in PV penetration into the grid, which can have major consequences for the performance of power systems. As a result, it will impact the stability and flexibility requirements of power systems [14]. Furthermore, at increasing grid penetration levels, solar power's variability causes issues with the price of reserves, dispatchable power, and supplementary power. Consequently, high-accuracy forecast systems for numerous time horizons related to regulating, dispatching, scheduling, and unit commitment are necessary [15].

PV power output forecasting is required to maintain sufficient resources in an electrical grid [16]. Forecasting can also be characterized as short-term, medium-term, and long-term forecasting based on a time horizon. For example, time series and statistical models are ideal for less than one hour to six hours of forecasting horizon. While, a numerical weather prediction can be utilized for one day to one year of forecasting horizon [17].

There are many forecasting methods developed and used in various cases. The autoregressive integrated moving average (ARIMA) model is a forecasting approach based on statistical serial correlation. It may estimate daily and monthly solar radiation due to its ease and accuracy, minimal data input demand, and easy computing procedure. ARIMA outperforms exponential smoothing approaches when the data is sufficiently lengthy and the correlation between prior observations is stable [18], [19].

Artificial neural network (ANN) approaches outperform traditional methods in predicting solar radiation. The input parameter combinations, training methods, and architectural configurations all affect how accurately an ANN model predicts outcomes [20]. The study examines the possibility of developing artificial neural network model that might be applied to anticipate monthly average daily total solar irradiation on a horizontal surface for locations in Uganda has been conducted. The results showed good agreement between anticipated and measured actual solar irradiation values. With root mean square error (RMSE) and mean bias error (MBE) are 0.131 MJ/m^2 and 0.018 MJ/m^2, a correlation coefficient of 0.997 was found. Overall, the accuracy of the artificial neural networks model was 0.1% of the typical absolute percentage error [21].

A study compares the accuracy of long short-term memory (LSTM) to alternative methods in 21 sites, 16 of which are in continental Europe and 5 in the United States. According to empirical studies, LSTM outperforms a broad range of competing methods by a significant margin, with a mean forecast accuracy of 52.2% over the persistence model. Because of its recurrent design and memory units, LSTM networks can represent temporal fluctuations in PV output power. Compared to other approaches, applying LSTM further reduces predicting inaccuracy [22]–[24]. The clearness index was established in a study using the LSTM model, to increase prediction accuracy on cloudy days. These two conditions define an actual-time condition and its impact on the forecasting results [25].

Aside from solar forecasting, the LSTM approach has some other applications. The LSTM is used to forecast carbon emissions in China. To compare the LSTM approach, it employs back propagation neural network (BPNN) and gaussian process regression (GPR). The simulation results reveal that LSTM has a higher forecast accuracy of carbon emissions than BPNN and GPR [26]. LSTM also fits crude oil prices to improve the preciseness of oil market price prediction. Transfer learning presents an efficient data extension strategy for improving prediction accuracy by increasing the size of the training set [27]. In addition, the stacked LSTM model is also utilized to enhance forecasting performance. In order to fine-tune the prediction model with the best weighting, stacking LSTM units gives hierarchical-level of information [28].

According to the literature above, solar irradiance forecasting is needed to enhance the solar power plant penetration to the grid. LSTM shows excellent historical prediction studies with the smallest error value. Therefore, the LSTM-based method is chosen, studied, and developed for a novel short-term prediction in this work, and two other models, ARIMA and RNN, have been established to validate the stacked LSTM approach in varying weather and location.

2. STACKED LSTM

In 1997, Hochreiter and Schmidhuber [29] suggested long short-term memory (LSTM) to avoid long-term dependency through targeted design. Figure 1 shows the LSTM unit's architectural layout. To address the vanishing gradient issue of RNN, LSTM models were created [30]. The difference between an LSTM and an RNN with a single hidden layer is that by includes a cell state unit C, which serves as the accumulator of state information [31]. The fundamental components of the memory unit of LSTM are a cell state, an input gate (i), an output gate (o), and a forget gate (f). In LSTM, there are working memory (h_t) which serves as the output, and memory cells (c_t) which regulate how the sequence is retained. The current memory section that needs to be written is managed by o. The i controls the writing of the data for present state (h_{t-1}) and present input (x_t) to c_t. The known time-series data act as the input, while the predicted results are the output. The memory of the prior sequence is managed by the f. To determine the current information x_t and the previous state h_{t-1}, non-linear activation (σ) is applied. The (1)-(6) can be used to demonstrate how the LSTM design was derived.

$$f_t = \sigma\left(w_f \times [h_{t-1}, x_t] + b_f\right) \tag{1}$$

$$i_t = \sigma(w_i \times [h_{t-1}, x_t] + b_i) \tag{2}$$

$$\tilde{c}_t = tanh(w_c \times [h_{t-1}, x_t] + b_c) \tag{3}$$

$$c_t = (f_t \times c_{t-1}) + (i_t \times \tilde{c}_t) \tag{4}$$

$$o_t = \sigma(w_o \times [h_{t-1}, x_t] + b_o) \tag{5}$$

$$h_t = o_t \times tanh(c_t) \tag{6}$$

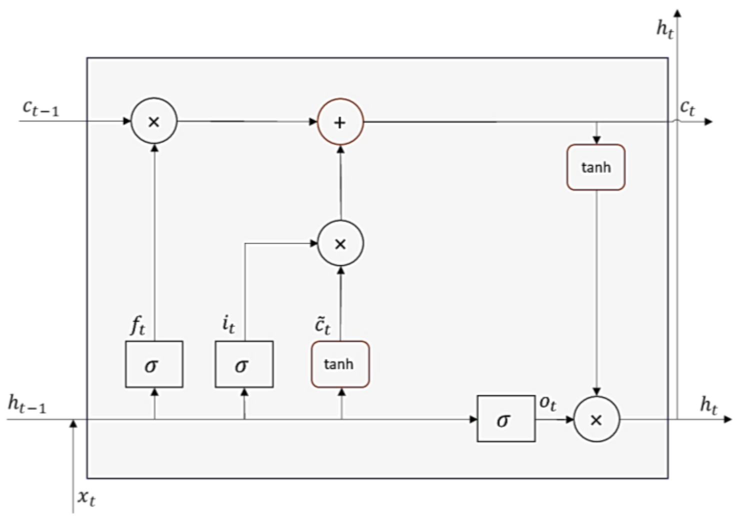


Figure 1. LSTM's architecture

In this study, a stacked LSTM model is proposed, consisting of several hidden LSTM layers. Through the addition of layers, input observations are substantially abstracted by merging previously learned representations. Stacking LSTM units provides hierarchical-level information that can be used to fine-tune the prediction model with the best weighting. In other words, higher LSTM layers are thought to be able to capture abstract ideas in the sequences, which could enhance the accuracy of the forecasts [32].

According to the author's understanding, many studies on irradiance forecasting, especially in the Java-Bali region, have predominantly relied on historical solar irradiance datasets derived from platforms employing estimation approaches or models to determine irradiance values at specific locations as the input features of the model development. The stacked LSTM has been more widely employed in other cases; however, the study of its application in irradiance forecasting, especially at specific locations within the Java-Bali electricity grid area and its correlation with tropical season characteristics, remains limited. Thereby, based on these comprehensions, the novel stacked LSTM model developed using measured data of actual solar irradiance characteristics in the Java-Bali region is proposed in this study to achieve highly accurate irradiance forecasting performance. The utilization of actual measurement data of solar irradiance as the input features contribute to developing the proposed model in weights and biases optimization. In other words, the learning process of the proposed model is based on actual characteristics instead of estimated characteristics. Figure 2 shows the architecture of a stacked LSTM network.

In this study, the mechanism of the additional layer is by adding specific neurons, activation function, and dropout layer in separated layers before entering the dense layer. The number of neurons in the additional layer is 40, and the ReLu activation function is applied. Meanwhile, the dropout by 0.1 is also configured. By doing so, the first layer generates a complete set of hidden states for every time-step that passes through it. Therefore, instead of only receiving a single value from the layer above it, the layer beneath receives a series of outputs. The implementation of the proposed model is elaborated in section 3.3.

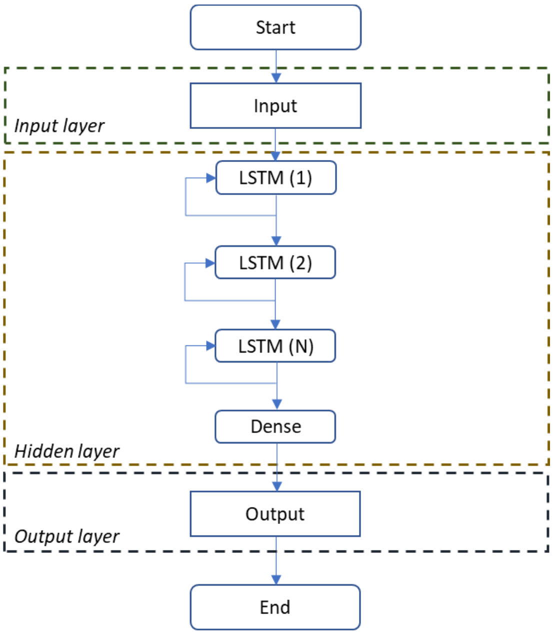


Figure 2. A stacked LSTM architecture

3. RESEARCH METHOD

Several essential principles of the research process are needed to provide the foundation for the inquiry of solar irradiance forecasting. This study employed the scientific method, which comprised data collection, data pre-processing, algorithm implementation and model development, followed by model performance analysis. Historical solar irradiance and sky images are collected, and then data pre-processing is performed to ensure that the data conforms to the input requirements of the model. This study involves algorithm implementation and model development using a neural network-based model, specifically the proposed stacked LSTM model, which is the essential phase in this study. To ensure the validity and reliability of the drawn conclusions, the proposed model undergoes a precise evaluation and analysis based on the performance metrics parameters. This evaluation process leverages the Python programming language and its extensive libraries, including Keras and Scikit-learn for deep learning, Pandas for data manipulation, Matplotlib for data visualization, and numerous additional mathematical libraries. Additionally, Jupyter notebook serves as the computational environment for the entire study, facilitating seamless code execution, interactive analysis, and clear documentation.

3.1. Dataset collection

This research takes the data from an online platform, indonesiasolarmap.com, a collaboration project between AESI and PT Synkrona Enjiniring Nusantara of Indonesia which has been measured solar irradiation for 1.5 years as the first Java-Bali's historical solar irradiance data platform obtained from distributed direct measurement. They deployed pyranometers across Java, Madura, and Bali islands representing the Java-Madura-Bali grid in Indonesia. As a representative point, this study divides the area into four sections, they are: i) Cilegon is on the western tip of Java, ii) Purwodadi stands for Central Java, iii) Situbondo replaces the eastern part of Java, and iv) Amlapura represents Bali Island. The coordinates of each location mentioned in

Figure 3. This study also requires satellite imagery of the Java-Bali area throughout the day within a predetermined time to describe the cloud cover level in the area. Therefore, this study takes images from the open-weather platform of Kochi University, Japan.

Figure 3. The distribution of pyranometers with the selected coordinates

3.2. Dataset pre-processing

The hourly data of solar irradiance are chosen to describe each daily characteristic from January 2022 until February 2023. In each daily data, irradiance data from 07:00 to 17:00 are used while the other hours are neglected because of low and undetected solar irradiance values. To determine whether seasonal changes have an impact on the forecasting techniques and the necessity of studying the effects of these sorts of input parameters, multi-seasonal data can be used [33]. Therefore, the raw data is divided into two periods, describing tropical seasons in Indonesia. Each period is then determined by a single date as a time-series sequence index.

3.3. Implementation of the algorithm and proposed model

The forecasting algorithm is described in Figure 4. Hourly irradiance data of Cilegon, Purwodadi, Situbondo, and Amlapura from January 2022 until February 2023 which has been divided into dry and rainy seasons, has been loaded into python notebook by Pandas library. Another python library and package needed for time-series forecasting were also imported, such as Keras, Sklearn.

The irradiance dataset's time and date were chosen as the index values for the input data. These datasets were split for training and testing. The Min-Max scaler in the Sklearn package normalizes the irradiance data and transforms it in the range of 0 to 1 as (7), x stands for the related irradiance value.

$$x_{normalized} = \frac{x - x_{min}}{x_{max} - x_{min}} \quad (7)$$

An input layer, stacked hidden layer structure, and output layer make up the model in this work. In detail, there are sequence input layer, ReLu function layer, LSTM layer, dropout layer, dense layer, and evaluation layer. A network receives sequence data from the sequence input layer. Each input component is put through a threshold action by the ReLu function layer to reduce gradient dispersion by quick calculation [34]. The Keras package in python is used for building the LSTM model. Because higher LSTM layers can serially capture theoretical ideas and enhance prediction outcomes, it is crucial to stack LSTM layers [35]. To prevent overfitting, the dropout layer randomly sets input elements to zero with a specified probability, this is crucial since overfitting in neural networks is a major issue [36]. Moreover, there is a dense layer, its neuron receives feedback from all neurons in the previous layer, so it is also known as a fully connected layer [37]. It is employed to change the output's dimensionality so that the model can more easily define the link between the data values. Between the forecasted and the actual value as the target, the evaluation layer computes the gradient in the hidden layer using mean squared error (MSE) as the commonly used loss function [38]. A backpropagation algorithm is used for adjusting the weights. Every learning iteration uses the adaptive moment estimation (Adam) optimizer to handle sparse gradients in noisy problems by combining the best aspects of AdaGrad and RMSProp, so this method is very fast and converges rapidly [39]. The prediction value as the output of the model is denormalized to get the forecasted irradiance value. The model performance metrics are utilized to assess the accuracy of the models based on the actual and forecasted irradiance values. As comparison studies, time-series forecasting using ARIMA and RNN models were also developed. The forecasting results from each model are evaluated using performance metrics parameters; there are RMSE, MAPE, and R^2.

Table 1 shows the configuration of the proposed model and comparative models. The stacked LSTM model consists of two LSTM layers with 40 neurons on each layer. The RNN model is a single layer configuration with 50 neurons. Then the ARIMA model is built with *p* which stands for the autoregressive processes, *d* as the quantity of nonseasonal deviations required for stationarity, and *q* number is describing the moving average calculation.

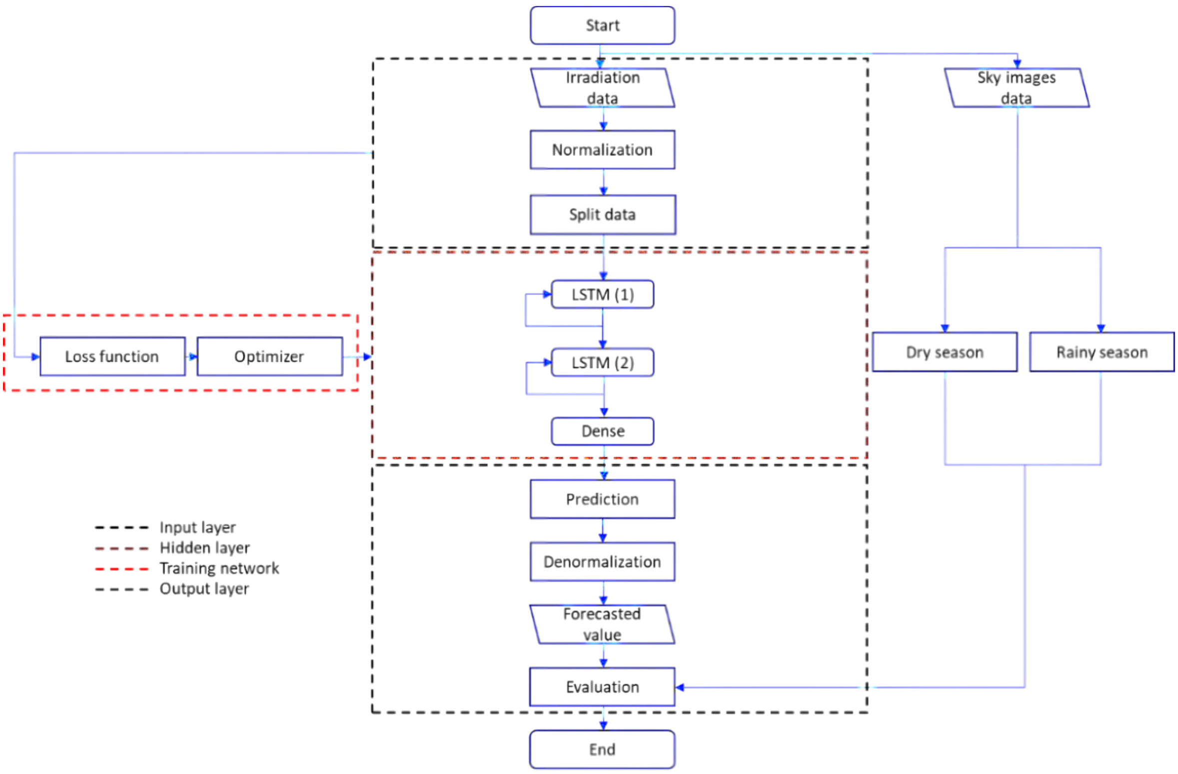


Figure 4. Forecasting algorithm

Table 1. Model configuration

Model	Configuration
Stacked LSTM	model.add (LSTM (40, return_sequences=True, input_shape=(n_input, n_features))) model.add (Activation ('relu')) model.add (Dropout (0.1)) model.add (LSTM (40, return_sequences=False)) model.add (Activation ('relu')) model.add (Dropout (0.1)) model.add (Dense (1)) model.compile (optimizer = "adam", loss = 'mse')
RNN	model.add (SimpleRNN (50, return_sequences=False, input_shape=(n_input, n_features))) model.add (Activation('relu')) model.add (Dropout (0.1)) model.add (Dense (1)) model.compile (optimizer = "adam", loss = 'mse')
ARIMA	ARIMA (p, d, q)

3.4. Model performance evaluation

An important phase in the development of a forecasting model is evaluating its applicability for projecting future values. Deterministic estimations forecast accuracy is assessed by calculating the difference between predicted and observed values using a variety of parameters [40]. The following error metrics are used in this work for model evaluation. There are three types of error metrics used: root mean square error (RMSE), mean absolute percentage error (MAPE), and coefficient of determination (R^2). In the specific metrics listed below: N is the data size, while F and A are the forecast and actual value, respectively.

The average of the squared discrepancies between forecasted and actual values is the root mean square error, or RMSE. The relatively lower values of RMSE indicates better prediction. The RMSE is given by (8).

$$RMSE = \sqrt{\left(\frac{1}{N}\sum_{i=1}^{N}(F_i - A_i)^2\right)} \tag{8}$$

The absolute percentage inaccuracies of forecasts are averaged to get the MAPE. It represents the percentage inaccuracy to real value, as in (9).

$$MAPE = \frac{1}{N}\sum_{i=1}^{N}\left|\frac{F_i - A_i}{A_I}\right| \times 100\% \tag{9}$$

The interpretation of the MAPE for defining the performance of the model has been described by Lewis, C. D. in 1982 [41], as shown in Table 2. The performance of the model is classified into highly accurate, good, reasonable, and inaccurate. R^2 gauges how much of the variance in forecast errors may be accounted for by the variance in actual values. Ranging from 0 to 1, this metric quantifies the relative deviation between the actual and predicted values, as in (10).

$$R^2 = 1 - \frac{\sum_{i=1}^{N}(F_i - A_i)^2}{\sum_{i=1}^{N}(\overline{A_i} - A_i)^2} \tag{10}$$

Table 2. Interpretation of MAPE [41]

MAPE	Accuracy	MAPE	Accuracy
MAPE < 10%	Highly accurate	21% <MAPE < 50%	Reasonable
11% < MAPE < 20%	Good	51% < MAPE	Inaccurate

4. RESULTS AND DISCUSSION

In this study, to support the energy planning of solar power plants in the Java-Bali grid, we propose a stacked LSTM model for short-term solar irradiance one-day ahead forecasting. The proposed model forecasts the hourly solar irradiance for the following day, from 07:00 to 17:00. This study uses past solar irradiance data as input features from the first Java-Bali's historical solar irradiance monitoring and database platform, which obtained from distributed direct measurement devices. The distribution area for Java and Bali is covered by four selected locations: Cilegon, Purwodadi, Situbondo, and Amlapura. As a comparative study, the forecasting results with their performance metrics are compared with the ARIMA model as a statistical-based forecasting method and the RNN model as another artificial neural network-based method. Besides, the weather conditions may affect the forecasting result. It caused different behaviors and resulted in various ranges of errors [42]. Therefore, this study is conducted throughout the year to cover tropical seasons in Indonesia: dry and rainy.

4.1. Forecasting during dry season

The input features for the dry period encompass irradiance data spanning from January to August 2022. Figures 5(a)-5(d) depicts the forecasting results for the dry season in: Figure 5(a) Cilegon, Figure 5(b) Purwodadi, Figure 5(c) Situbondo, and Figure 5(d) Amlapura. A distinctive trend observed in Cilegon, as illustrated in Figure 5(a). Notably, Cilegon exhibits a unique irradiation fluctuation in the afternoon, a phenomenon absents in other locations. The actual measurements account for this fluctuation, signifying its importance in accurate forecasting. A closer examination using satellite images in Figures 6(a)-6(d) validates the distinct characteristics of cloud cover patterns observed across Indonesia at: Figure 6(a) 09:00 UTC+7, Figure 6(b) 11:00 UTC+7, Figure 6(c) 13:00 UTC+7, and Figure 6(d) 15:00 UTC+7 during a dry season day. The imagery confirms that the western part of Java experiences intermittent cloud cover, ranging from wispy to thick clouds, on several occasions. Conversely, Purwodadi, Situbondo, and Amlapura maintain relative clarity throughout the day; these solar irradiance conditions and their forecasting results are also shown in Figures 5(b)-5(d) respectively, with characteristics of a roof profile that relatively less fluctuating and more closely approaches the ideal form related to solar irradiance on a clear day. This divergence in cloud cover contributes to the varied trends observed in the forecasting, emphasizing the need for nuanced considerations in predicting irradiance for different regions during the dry season.

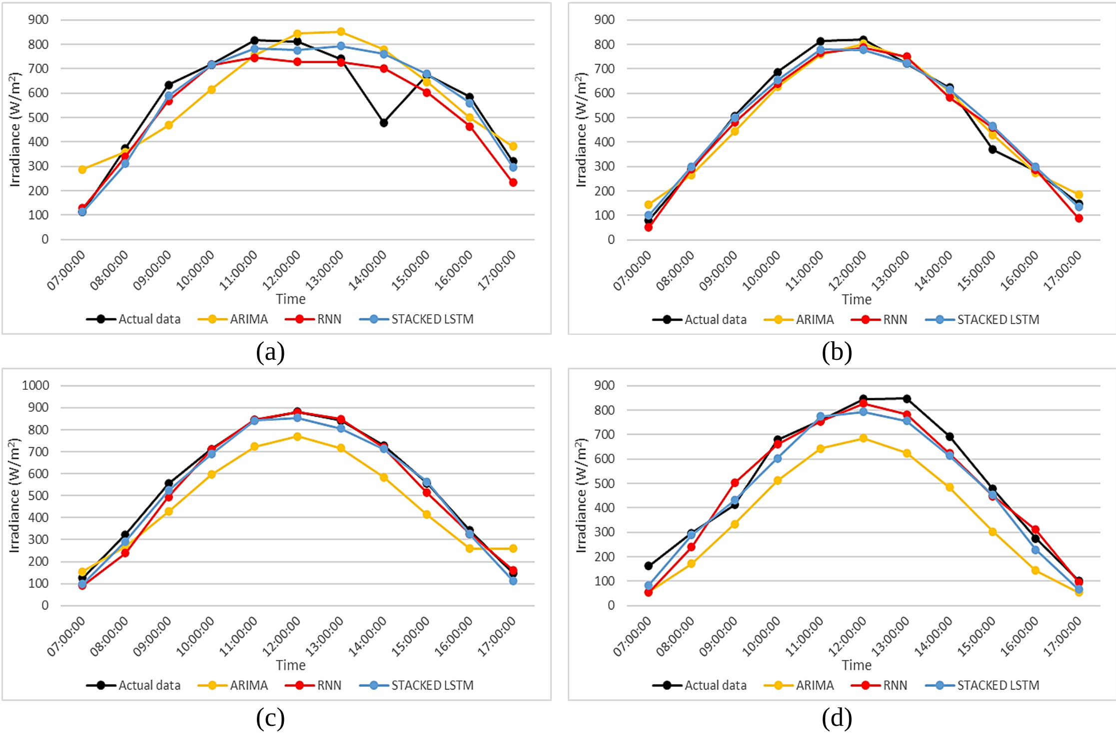


Figure 5. Solar irradiation forecasting during dry season on August 11th, 2022: (a) Cilegon, (b) Purwodadi, (c) Situbondo, and (d) Amlapura

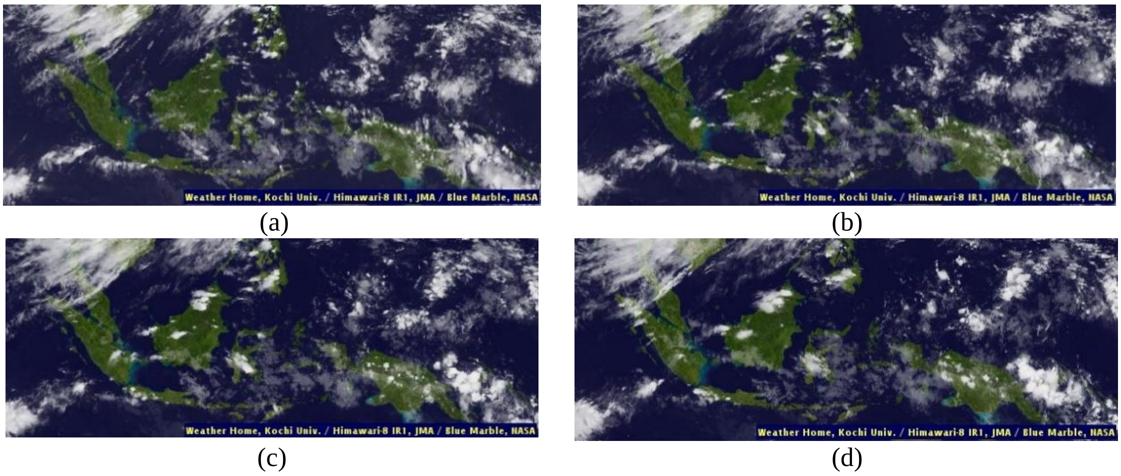


Figure 6. The satellite images of Indonesia on August 11th, 2022: (a) 09:00, (b) 11:00, (c) 13:00, and (d) 15:00

Table 3 and Figure 7 present the performance assessment of the model during the dry season. In the context of irradiance forecasting in Cilegon during this season, the RMSE for stacked LSTM, RNN, and ARIMA are documented as 91.22 W/m^2, 92.68 W/m^2, and 130.53 W/m^2, respectively. Concurrently, the MAPE is recorded as 10.08%, 14.44%, and 29.70%. Stacked LSTM exhibits significantly superior performance in comparison to ARIMA and marginally outperforms RNN. These performance attributes are similarly observed in the irradiance forecasts for Situbondo and Amlapura. In the case of Situbondo, LSTM yields an RMSE and MAPE of 25.56 W/m^2 and 7.27%, respectively, while RNN records 35.88 W/m^2 and 7.99%. ARIMA, in contrast, demonstrates markedly inferior performance relative to stacked LSTM and RNN. Likewise, for Amlapura, LSTM produces performance metrics of 55.74 W/m^2 and 13.99%, while RNN yields 56.55 W/m^2 and 14.16%. These error metric outcomes also signify superior performance when compared to ARIMA. A slightly different phenomenon is seen in Purwodadi. The RMSE of LSTM, RNN, and ARIMA are 36.31 W/m^2, 44.12 W/m^2, and 44.13 W/m^2, while their MAPE is 8.15%, 12.51%, and 15.28%. Those values show good forecasting performance for this site. However, LSTM still performs better than RNN and ARIMA.

Table 3. Evaluation of forecast performance at dry season for chosen locations

Location	Model	RMSE (W/m^2)	MAPE (%)	R^2
Situbondo	ARIMA	106.56	24.36	0.82
	RNN	35.88	7.99	0.98
	Stacked LSTM	25.56	7.27	0.99
Purwodadi	ARIMA	44.13	15.28	0.97
	RNN	44.12	12.51	0.97
	Stacked LSTM	36.31	8.15	0.98
Cilegon	ARIMA	130.53	29.70	0.63
	RNN	92.68	14.44	0.81
	Stacked LSTM	91.22	10.08	0.82
Amlapura	ARIMA	148.77	33.91	0.67
	RNN	56.55	14.16	0.95
	Stacked LSTM	55.74	13.99	0.95

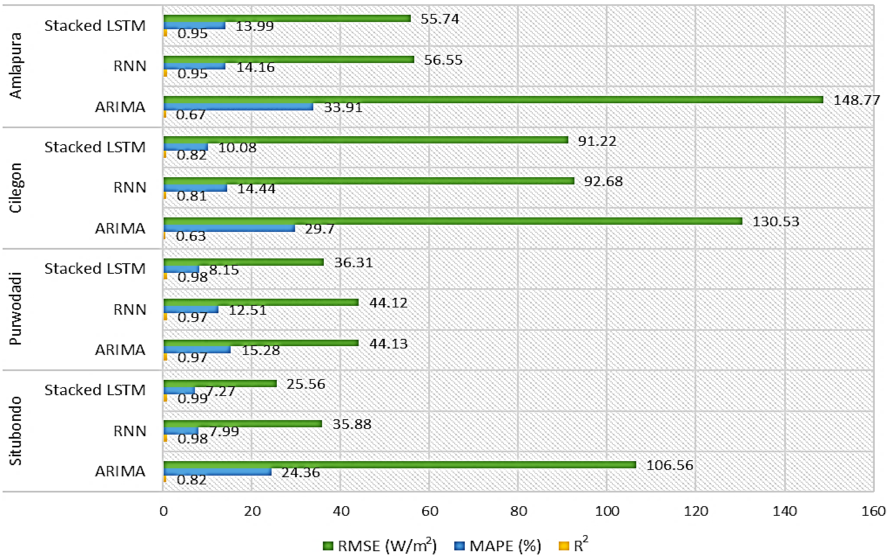
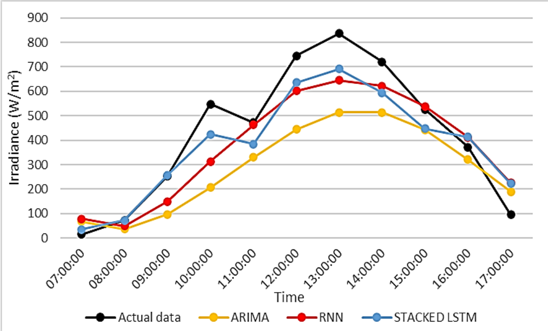


Figure 7. Evaluation of forecast performance at dry season

4.2. Forecasting during wet season

To evaluate the efficacy of forecasting models across different seasons, the irradiance data spanning from August 2022 to February 2023 are employed as input features specifically during the rainy season. Figure 8 shows the comparison of forecasting results in Figure 8(a) Cilegon, Figure 8(b) Purwodadi, Figure 8(c) Situbondo, and Figure 8(d) Amlapura. Moreover, Figure 9 shows satellite images at several particular times of cloud movement on February 22nd, 2023, during a wet season day at Figure 9(a) 09:00 UTC+7, Figure 9(b) 11:00 UTC+7, Figure 9(c) 13:00 UTC+7, and Figure 9(d) 15:00 UTC+7. As it shown in Figure 9, most of the sky conditions in Indonesia throughout that period were cloudier than on August 11th, 2022. In light of these circumstances, it is evident that the actual irradiation measurements are fluctuating at three of the four chosen locations. Amlapura has the most fluctuating actual irradiance data compared to other chosen locations, followed by Cilegon and Purwodadi. More obvious performance differences between the three models can be seen regarding these characteristics. The values of performance metrics as shown in Table 4 and Figure 10 are not as good as the forecast for the dry season, especially in the Cilegon and Amlapura cases. The stacked LSTM's MAPE in Cilegon and Amlapura is about 30%, but it is still classified as reasonable forecasting. Those values are much better than RNN and ARIMA models in this study, they even reach 66.51% and 70.94% respectively, which means they are not suitable for solving related conditions. Furthermore, the stacked LSTM model in this study still requires further development to improve its performance when predicting extremely fluctuating irradiance values. On the other hand, the forecast of Purwodadi and Situbondo shows good results, with the maximum MAPE is 25.36% obtained by the ARIMA model. RNN's performance values are slightly better than ARIMA's. Whereas the best performance values obtained by the stacked LSTM with RMSE, MAPE and R^2 are 65.31 W/m^2, 7.45%, and 0.96.



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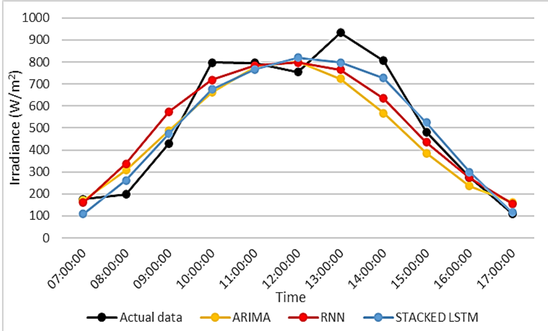

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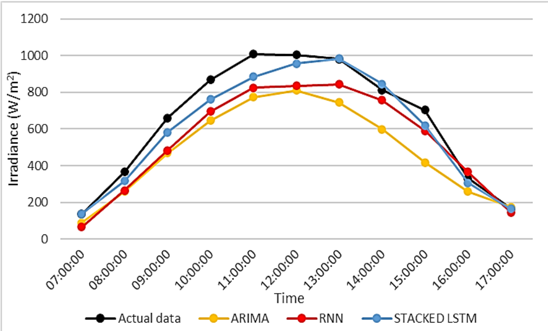

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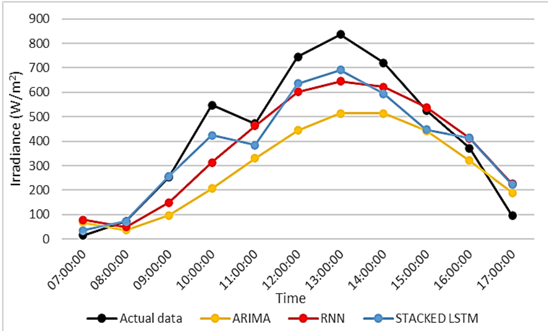
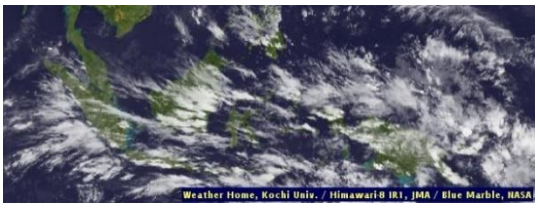
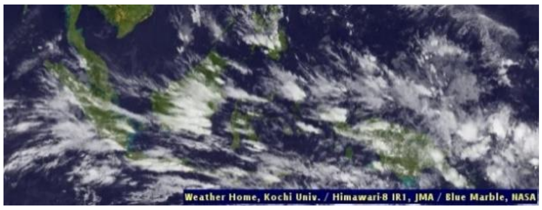


(d)

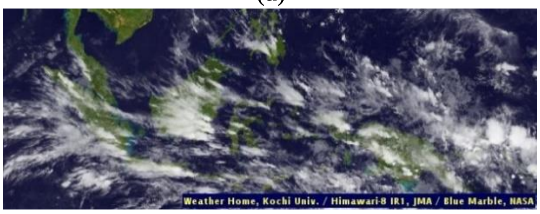
Figure 8. Solar irradiation forecasting during rainy season on February 22nd, 2023: (a) Cilegon, (b) Purwodadi, (c) Situbondo, and (d) Amlapura



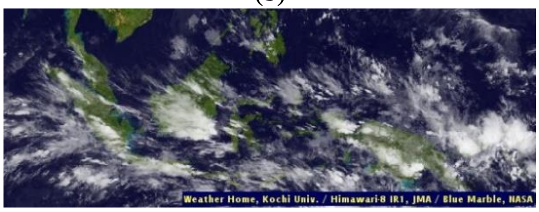
(a)



(b)



(c)



(d)

Figure 9. The satellite images of Indonesia on February 22nd, 2023: (a) 09:00, (b) 11:00, (c) 13:00, and (d) 15:00

Table 4. Evaluation of forecast performance at wet season for chosen locations

Location	Model	RMSE (W/m^2)	MAPE (%)	R^2	Location	Model	RMSE (W/m^2)	MAPE (%)	R^2
Situbondo	ARIMA	186.44	25.36	0.66	Cilegon	ARIMA	196.04	70.94	0.48
	RNN	126.35	20.02	0.84		RNN	119.46	66.51	0.81
	Stacked LSTM	65.31	7.45	0.96		Stacked LSTM	93.69	34.04	0.88
Purwodadi	ARIMA	117.12	21.10	0.84	Amlapura	ARIMA	143.94	43.50	0.65
	RNN	100.35	20.03	0.88		RNN	129.64	33.20	0.71
	Stacked LSTM	72.55	14.10	0.94		Stacked LSTM	115.90	32.11	0.77

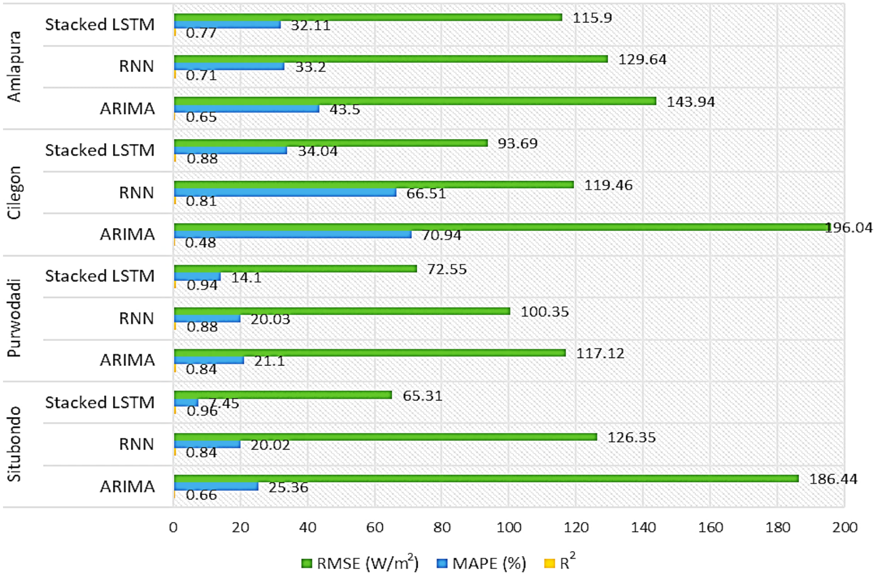


Figure 10. Evaluation of forecast performance at wet season

5. CONCLUSION

The global demand for fossil-based energy, particularly in developing nations, amplifies environmental and social concerns, including GHG emissions. Solar energy, especially through PV technology, presents a sustainable solution. However, high penetration of solar energy significantly impacts power system performance. Consequently, accurate forecast systems become essential for effective regulation, dispatch, scheduling, and unit commitment. In this study, a novel day-ahead forecasting of solar irradiance using a stacked LSTM model has been demonstrated for forecasting one-day ahead hourly solar irradiance in the Java-Bali region.

In this research, it is observed that weather conditions caused different solar irradiance characteristics and resulted in various ranges of errors in forecasting. As a result, the proposed stacked LSTM model provides better forecasting results during the dry season than in the rainy season since the clouds are less developed during the dry season. Nevertheless, the lowest accuracy of the stacked LSTM model during the dry season obtained by the value of MAPE is 13.99%, which is still classified as a good forecast. In the rainy season on the other hand, the stacked LSTM's MAPE reached 34.04%. Despite of its high MAPE, the model is still categorized as a reasonable forecast. In comparison, the proposed stacked LSTM model outperforms both ARIMA as statistical-based method and RNN as another ANN-based method. The best RMSE, MAPE, and R^2 during dry season were obtained by the stacked LSTM with 25.56 W/m^2, 7.27%, and 0.99 which is classified as a highly accurate forecast. While the best results using RNN and ARIMA obtain the MAPE about 7.99% and 24.36%, which are much less accurate forecasts as compared to the proposed model. During the rainy season however, the stacked LSTM model provides the best RMSE, MAPE, and R^2 of 65.31 W/m^2, 7.45%, and 0.96 respectively. The best MAPE of RNN and ARIMA in contrary, are 20.03% and 25.36% respectively. This also demonstrated that the ANN-based method is more robust for stochastic and fluctuated data than the statistical method.

The proposed model demonstrates an excellent performance for fluctuated solar irradiance across the Java-Bali Islands. Therefore, it would be well-suited as a method for solar irradiance forecasting and the proposed method could be used for all conditions in Java-Bali area. The model development would potentially promote the more widespread solar PV electric generation utilization and hence could contribute to national solar energy development. As a continuation of the research, further work on enhancing the performance of the proposed model by considering the significance of other related meteorological parameters would be recommended. The study of supporting methods for data preprocessing and clustering would also be necessary for more profound model research and increasing accuracy.

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