Short-term solar irradiance forecasting using deep learning models

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Abstract. Population growth and evolving consumer technology have resulted in an ever-increasing demand for energy and power. Traditional energy sources such as coal, oil, and gas are not only quickly depleting but have also contributed to global pollution. As a result, the demand for renewable energy for power generation has increased tremendously. Short-term solar irradiance is a critical area in renewable energy for the optimal operation and power prediction of grid-connected photovoltaic (PV) plants and other solar energy applications. However, solar irradiance is complex to handle due to the nonuniform characteristics of inconsistent weather conditions. Deep Learning techniques have shown outstanding performance in modeling these complexities. In this paper, short-term solar forecasting models are proposed using deep learning to reliably predict the amount of solar irradiance for optimal power generation. Furthermore, it is also evaluated whether the model can forecast the amount of Global Horizontal Irradiance (GHI) within one hour given the current recorded features including air temperature, azimuth, cloud opacity, and zenith. The data for Penang, Malaysia is used in this research. A Dense Neural Network (DNN) with 32 units achieved a validation MAE of 21.33 and MSE of 1343.68 in the 6th fold. Long-Short Term Memory (LSTM) with 256 units achieved a validation MAE of 8.23 and MSE of 246.98 in the 7th fold. On test data, the DNN achieved MAE and MSE of 31.71 and 2560.80 respectively whereas the LSTM model achieved MAE and MSE of 5.78 and 106.65 respectively.

1 Introduction

The escalating demand for energy in recent years, driven by technological advancements and a growing global population, has primarily been met by fossil fuels, which accounted for 80% of energy consumption as of 2023. These fuels, derived from decomposed plants and animals, include coal, natural gas, and crude oil. However, their finite availability and environmental impact have led to a surge in interest in renewable energy sources such as sun, tides, and wind [1].Solar power has emerged as a prominent renewable energy source, with a significant increase in its usage in recent years. According to the International Energy Agency (IEA), renewable electricity generation rose by 7.1% in 2020, with solar and wind technologies accounting for nearly 60% of this increase [2]. Solar power is typically

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harnessed through photovoltaic (PV) cells, which convert sunlight into electricity. Despite being environmentally friendly, the efficiency of solar power collection can vary based on weather conditions, which can impact its popularity and stability.

High solar utilization can lead to grid stability by providing a consistent and reliable energy source, reducing dependence on fossil fuels, and mitigating the volatility associated with fuel price fluctuations. To enhance the stability of solar power generation, solar irradiance forecasting is employed. This technique predicts future power generation levels, enabling efficient management of the electric grid. Various models for solar irradiance forecasting have been proposed, including physical models, conventional statistical models, spatial correlation models, and artificial intelligence (AI) based machine learning (ML) models. Among these, AI models are often preferred due to their high forecasting accuracy and adaptability to non-linear relationships. Techniques such as Artificial Neural Networks (ANN), Dense Neural Networks (DNN), and Long-Short-Term Memory (LSTM) can further improve the performance of these models.

This paper focuses on identifying the most suitable machine learning model for short-term solar irradiance forecasting in Malaysia. We compare the performance of DNN and LSTM models. By evaluating these models, we determined the optimal approach for accurately predicting Global Horizontal Irradiance (GHI) and supporting efficient solar power generation.

2 Related works

Numerous AI techniques have been employed to forecast solar power generation. A study by Abuella M. et al. built a feed-forward ANN forecasting model to predict solar power, which outperformed the multiple linear regression and persistence model [3]. Elizabeth Michael and others evaluated the performance of a multistep convolutional neural network (CNN) stacked with LSTM for short-term solar power prediction, with the hybrid model outperforming standalone CNN and LSTM models [4]. Jaidee et al. presented a method for forecasting solar power 4 hours in advance using ML techniques [5]. Lima et al. explored Multiplayer Perceptron (MLP), Support Vector Regression (SVR), Radial Basis Function (RBF), and Deep Learning [6]. Based on the review of related works, Mandal et al. observed that the PV output strongly relies on the amount of GHI in which the total amount of radiation is received on a horizontal surface [7]. J. Ospina et al. forecasted photovoltaic plant output using a wavelet-based LSTM-DNN model, which achieved the best results [8]. Poolla et al. leveraged local weather history and global forecast data for time series modeling, developing an autoregressive model (ARX) for forecasting upcoming 18-hour irradiance [9]. Q. Qiang. et al. introduced a deep CNN to maintain the sustainability of PV power [10]. The historical time series was converted to a two-dimensional data form to ease the training process. H. Zhou et al. aimed to enhance solar energy forecasting by predicting PV energy using a clustering algorithm of a hybrid deep learning model [11]. The summary of related work is shown in Table 1. Here RMSE stands for Root Mean Square Error, MAE for Mean Absolute Error, and MAPE for Mean Absolute Percentage Error.

Accurate GHI forecasts are essential for effective solar power management, however, this is influenced by uncontrollable natural weather factors like cloud opacity and wind direction. Reliable forecasting methods enhance solar energy's reliability and efficiency in production planning and energy trading. This paper aims to forecast 1-hour GHI using variables such as air temperature and cloud opacity. It employs DNN and LSTM models, trained on 1-year data, and tested on a separate 24-hour dataset from April 20, 2023.

Table 1. Summary of ML algorithms for solar irradiance and power prediction.

Ref	Algorithms	Target variables	Performance metrics
[3]	Artificial Neural network	Solar power (kW)	RMSE = 0.0554, R^2 = 0.9707
[6]	Hybrid multistep CNN-LSTM model	Solar irradiance (kWh/m2)/ plane on Array (POA) irradiance (W/m2)	R^2=0.98, nRMSE = 0.11, MAE = 0.18 / R^2 = 0.96, nRMSE = 0.22, MAE = 29.00
[7]	Feed-forward Neural Network (W/m2)	Solar irradiation (W/m2)	nRMSE (%) = 8.13
[8]	Proposed Integration structure	Solar irradiation (W/m2)	MAPE =4.52%
[10]	Hybrid wavelet LSTM-DNN	Solar power (W)	R^2 = 0.975, MSE = 973kW, nRMSE = 0.066, MAPE = 3.555%
[11]	Hybrid CNN-LSTM model (Correlation coefficient)	Solar power (kW)	RMSE = 1.3, MAPE = 18.82%, MAE = 0.70

3 Material and methods

3.1 Data collection

The data used for this study is collected from Penang, Malaysia, located at coordinates 5.3655° N, and 100.4590° E. This region is located near the equator and experiences relatively high solar exposure, making it an optimal choice to study solar irradiance in a tropical climate. Hourly historical weather data was sourced from Solcast API (https://solcast.com/), a data modeling company that provides real-time, historical, and forecasted solar radiation data globally. Solcast provided a comprehensive dataset spanning from April 15, 2022, to April 15, 2023, ensuring the availability of sufficient data for robust model training and analysis for this region.

In single-step forecasting, the model uses the data from the past year to identify the relationship between the chosen parameters and target GHI. The four parameters air temperature, azimuth, cloud opacity, and zenith are used for training the model, and the target variable GHI was considered for forecasting. The weather data was timestamped and stored in a CSV file format, forming a matrix. The timestamp column stores the date and time at 1-hour intervals, with each step consisting of the weather parameters recorded up to the current period. Night-time weather information is ignored as it is considered unnecessary for the model. Air temperature is recorded 2 meters above the ground and is directly correlated with global irradiation. Azimuth indicates the direction of the solar beam, with angles varying from -180 to +180. Cloud opacity indicates the attenuation of incoming sunlight due to cloud presence, with values ranging from 0 to 100. Zenith indicates the angle between a line perpendicular to the horizontal surface and the sun. GHI indicates the total solar radiation incident on the horizontal surface and is widely used to forecast solar output power.

A one-day dataset with a one-hour interval on April 21, 2023, which was not included in the training and validation data, was selected as the test data to determine the model's capability for forecasting the GHI.

3.2 Deep learning models

Based on the literature review two deep learning models are selected for forecasting. DNN and LSTM. The trained models are regression models that examine the relationship between features/parameters and a single dependent variable, GHI. The models' performance is assessed and compared using different metrics such as MAE. Training is halted if the validation loss metric begins to deteriorate, a phenomenon known as overfitting. Overfitting causes the model to fit too closely to the training data, resulting in poor performance on unseen test data.

3.2.1 Dense Neural Network (DNN)

The DNN has a fully connected layer, that connects every neuron in the current layer to every neuron in the previous layer and utilizes various types of activation functions to learn complex data patterns. In this paper, a DNN was created using the open-source TensorFlow platform to test its performance on time series forecasting data. The first layer in the network is the Flatten layer, which transforms the input data into a 1-dimensional array without changing the batch size. The subsequent layers are dense layers, with 32 units and one unit, respectively. The chosen activation function is the Rectified Linear Activation Function (ReLU). This function passes the activated values at their maximum if they are positive, otherwise, it drops them to zero to disregard irrelevant contributions.

3.2.2 Long Short-Term Memory (LSTM)

LSTM, which is a modification of Recurrent Neural Network [6], is implemented to overcome the limitations of RNNs, such as the vanishing gradient problem, and to handle long sequences of data. Unlike RNNs, which contain only one interacting layer, LSTM contains four layers. In this paper an LSTM model with 256 units was designed, followed by a 1-unit dense layer.

3.3 Data normalization and validation

z-score standardization (x') is carried out on the dataset for the deep learning models. It can be easily carried out for each feature (x) by subtracting the mean (μ) and dividing by the standard deviation (σ) of the variable, as in Equation (1)

$$x' = \frac{x-\mu}{\sigma} \tag{1}$$

The performance of the models is evaluated using the k-fold cross-validation method, and the results are documented. The model is trained with the number of folds (k) ranging from 5 to 10, and the value of k that yields the best performance is recorded. The results of the models with different K-fold cross-validation are compared.

3.4 Performance metrics

The performance metrics used to evaluate the models are given in this section. Mean Absolute Error (MAE) measures the average magnitude of the errors in a set of predictions, without considering their direction. It is the average of the absolute differences between prediction and actual observation as in Equation (2). The Mean Squared Error (MSE) measures the average of the squares of the errors, that is, the difference between the estimated values and actual values, and the Root MSE (RMSE) is the square root of the average of squared differences between prediction and actual observation as in Equations (3) and (4). The Normalized RMSE (nRMSE) also known as the scatter index, is a variant of RMSE that is scaled according to the range of the target variable, yielding a scale-independent value between 0 and 1 as shown in Equation (5). R^2 is a statistical measure used in regression analysis to measure the strength of the correlation between the actual and predicted values. It ranges from 0 to 1. The formula for R^2 is given in Equation (6). R^2 value of 0.8 or above would indicate a strong correlation between weather variables and the forecasted solar output, suggesting good model performance. Here, $\hat{y}_i$ represents the predicted value, y_i is the actual value, $\bar{y}$ is the mean of the actual values and n is the number of samples.

$$MAE = \frac{1}{n}\sum|\hat{y}_i - y_i| \tag{2}$$

$$MSE = \frac{1}{n}\sum(|\hat{y}_i - y_i|)^2 \tag{3}$$

$$RMSE = \sqrt{\sum\frac{(\hat{y}_i - y_i)^2}{n}} \tag{4}$$

$$nRMSE = \frac{RMSE}{y_{max} - y_{min}} \tag{5}$$

$$R^2 = 1 - \frac{\sum(y_i - \hat{y}_i)^2}{\sum y_i - \bar{y}} \tag{6}$$

4 Experimental results and discussion

Figure 1 shows the training and validation loss metrics for DNN and LSTM model and Table 2 shows error scores and performance metrics for k-fold cross-validation. From Table 2 it can be seen that for solar irradiance forecasting, the LSTM consistently achieved lower errors and outperformed the DNN across key metrics. Since the number of samples for 1-year data is only 8760 samples which is relatively small for the deep learning model, the DNN model will be overfitted quickly and recognize only the pattern of the training set. Figures 2 and 3 show a one-week comparison of the cross-validation set for DNN and LSTM with LSTM showing better results. The trained models are used to predict the GHI on 20/04/23 with hourly features provided. The results of the two models are shown in Figure 4. Here we observe that the DNN model could only predict the flow of GHI roughly whereas the performance of the LSTM model is very accurate as most of the prediction points follow the actual GHI graph. It is also noted that the prediction points during peak hours for solar irradiance were slightly offset for the LSTM model.

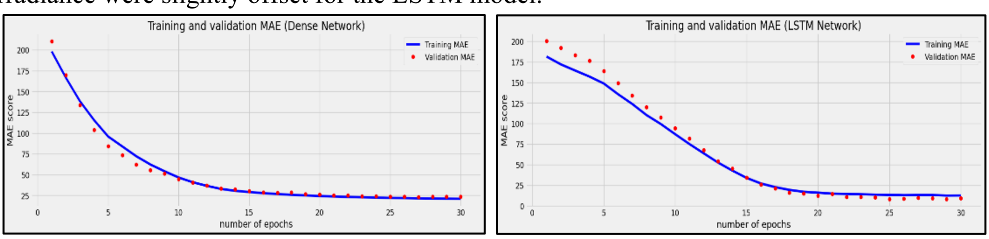

Fig. 1. Training and validation loss metrics during DNN and LSTM model training.

Table 2. Error scores and performance metrics for k-fold cross-validation, DNN, and LSTM Model.

Folds(k)	DNN				LSTM			
	MAE	**MSE**	**Fold No.**	**6 (best)**	**MAE**	**MSE**	**Fold No.**	**7 (best)**
5	21.810	1356.930	MAE	21.337	10.791	383.554	MAE	8.235
6	21.337	1343.684	MSE	1343.684	10.361	333.942	MSE	246.986
7	22.654	1509.428	RMSE	36.656	8.235	246.986	RMSE	15.716
8	23.570	1577.189	N. RMSE	0.0363	10.303	352.456	N. RMSE	0.0156
9	23.009	1582.238	R^2	0.986	8.748	248.823	R^2	0.998
10	23.293	1374.782	Training time (s)	20	10.682	356.037	Training time (s)	201

Table 3 shows the results for the testing phase where the LSTM model outperformed the DNN across all performance metrics. The LSTM achieved significantly lower errors (MAE: 5.7854, MSE: 106.6562, RMSE: 10.3274, nRMSE: 0.01255) and a higher R^2 (0.9987) compared to the DNN's results (MAE: 31.7116, MSE: 2560.8083, RMSE: 50.6044, nRMSE:

0.06149, R^2: 0.9679). LSTM took 201 seconds to run versus 20 seconds for DNN. The LSTM performed better than DNN both in terms of the test and train, metrics. This can be seen as a tradeoff between time and performance. Hence, LSTM models are highly effective for GHI forecasting and can significantly enhance the accuracy of PV system generation predictions in Penang, Malaysia, and also have better performance while dealing with time-series forecasting problems.

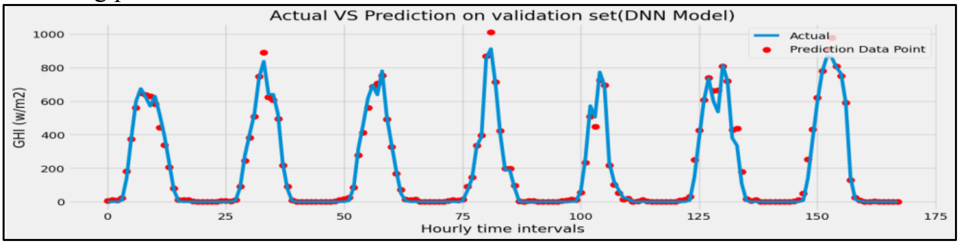

Fig. 2. One-week comparison on the cross-validation set for DNN.

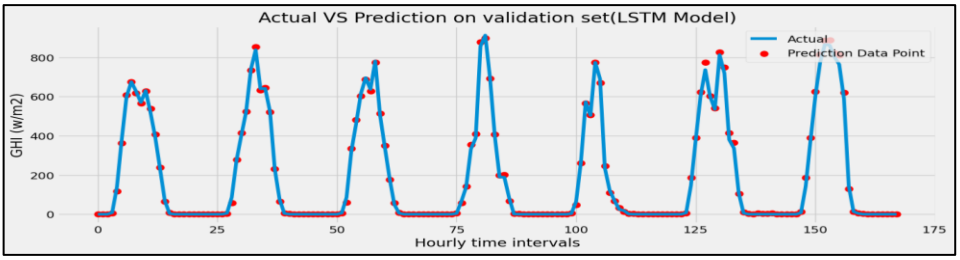

Fig. 3. One-week comparison on the cross-validation set for LSTM.

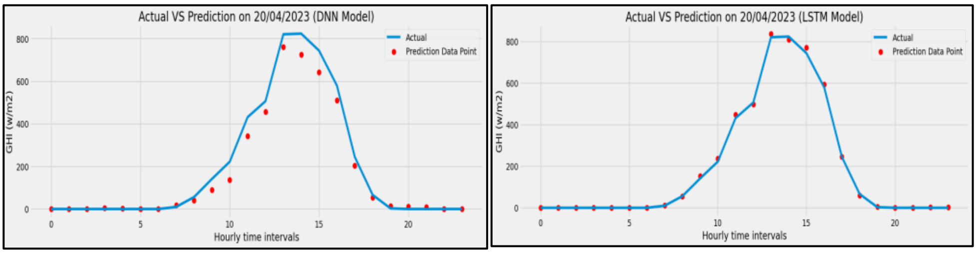

Fig. 4. Model Testing comparison between actual and predicted values on 20/04/23 DNN and LSTM.

Table 3. Model Testing performance metrics on 20/04/23 for DNN and LSTM.

Testing Performance Metrics	DNN	LSTM
MAE	31.7116	5.7854
MSE	2560.8083	106.6562
RMSE	50.6044	10.3274
Normalized RMSE	0.06149	0.01255
R^2	0.9679	0.9987

5 Conclusion

In this paper deep learning models are employed to predict the (GHI). Firstly, the models are trained to forecast GHI by learning the correlation between parameters such as air temperature, azimuth, cloud opacity, zenith, and the target GHI. Two models, DNN and LSTM are trained and validated using a complete 1-year data. The models' performance is assessed using the 24-hour test data set from April 20, 2023, and the results are visualized. The LSTM outperformed the DNN model. The LSTM model achieved an MAE of 5.5784, an MSE of 106.6562, and a nRMSE of 0.01255. Hence it can be concluded that forecasting has acceptable accuracy for predicting PV system generations for Penang Malaysia.

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