

M/LSTM-GRU HYBRID MODEL FOR SOLAR RADIATION ESTIMATION

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Received on March 22, 2024

Presented by Ch. Roumenin, Member of BAS, on April 29, 2025

Abstract

Solar energy is acknowledged as an environmentally friendly and clean renewable energy source, making it a crucial research topic. Estimation of the future radiation levels before and during the use of this source is vital for proper planning and operation of a photovoltaic (PV) system. In this study, a solar energy forecasting method was developed, utilizing both Long Short-Term Memory and Gated Recurrent Units models. The performance of the developed method was tested using various metrics on real-time, multivariate solar radiation data from a specific region in Turkey. Examining the results reveals lower RMSE, MSE, MAE performance values and higher R^2 values compared to many similar studies in the literature. This indicates the success of the proposed model, positioning it as a viable alternative.

Key words: solar radiation, estimation, M/LSTM-GRU

Introduction. The most important parameter that affects the output of a PV system is the intensity of solar radiation falling on the panel. Solar radiation data is inherently non-stationary. On the other hand, solar radiation intensity data contains unstable continuous variations. These unstable continuous variations cause prediction uncertainties [1]. Solar radiation reflected from PV modules and irregular cloud movements are known to be the main sources of these uncertainties. Such situations cause rapidly changing random fluctuations on the power output

<https://doi.org/10.7546/CRABS.2025.06.12>

of PV modules. Sudden changes in the network, frequency fluctuations, and random voltage changes can pose major problems in terms of energy supply and reliability. In order to eliminate these problems, it is necessary to develop high accuracy and reliability prediction models [2]. For this reason, accurate estimation of solar radiation intensity data changes over time is of vital importance for solar energy system designers and grid operators. Estimation models are necessary to establish accurate prediction models for regions with a certain solar potential and to reduce grid integration costs [3].

When the literature is examined, it is understood that there are various models developed for estimating solar radiation intensity. Statistical techniques and machine learning models are among the most commonly used models in this field [4, 5]. WENTZ et al. [6] compared the performances of Artificial Neural Networks (ANN) and Long Short Term Memory (LSTM) models for solar radiation estimation. It is understood that in the forecast model presented for this purpose, various meteorological data are used as input to artificial neural networks. In the study, it is understood that the LSTM model gives more accurate results with a MAPE value of 19.5%. In the study by BOU-RABEE et al. [7], a bidirectional approach based on long short-term memory (BLSTM) was developed for irradiance estimation in continental climate regions. The performance of the developed approach was tested for sunny and cloudy days. The study found that the BLSTM model outperformed other deep learning networks in estimating solar radiation. The RMSE values were calculated as 4.24 and 20.95 for sunny and cloudy days, respectively. In the study of ALI-OU-SALAH et al. [8], a hybrid structure of seasonal clustering technique and ANN model were used for solar radiation estimation. The results of the study show that the hybrid model is more successful compared to the individual ANN model.

Materials and methods. Solar radiation. Solar radiation intensity can be defined as the amount of solar radiation falling per unit area. The energy distributed in the form of radiation from the solar surface circulates in the space between the sun and the earth's atmosphere. As it is known, in the studies conducted, the annual amount of radiation outside the earth's atmosphere is considered to be approximately 1376 W/m^2 .

Data set. Turkey has a geographical location in the sun belt. Turkey's annual total sunshine duration is calculated as 2741 hours on average, and the annual total incoming solar energy is calculated as 1527 kWh/m^2 on average [9]. In this study, solar radiation data and other meteorological data from Van province, which is located at the coordinates of $38^{\circ}30'30.06'' \text{ N}$ and $43^{\circ}22'28.22'' \text{ E}$ and has the highest solar energy potential in Turkey, were used. The data set used in the study was taken from the General Directorate of State Meteorology (GDSM) [10]. The data set consists of 17 520 rows and 10 columns. Some parameters of the data set are year, month, day, hour, heat, pressure, wind direction, wind speed, solar radiation and humidity.

Data preprocessing. It is important to detect outliers in the raw data measured in the field, to detect data resulting from undesirable situations such as short-term power outages or sensor malfunctions, and to develop strategies for them. In the study, it is clear that some data obtained from the General Directorate of Meteorology could not be measured due to different external factors. These data, which could not be measured during the pre-processing stage, were completed by taking the average of each month. On the other hand, outliers in the data set were completed by taking the average of the values before and after the outliers. The ratio of the number of data exposed to the pre-processing stage in the total data is less than 1%, and this ratio is at a level that does not affect the overall success of the model. Another important issue that needs to be done before creating a prediction model is feature selection. Feature selection is an important factor that increases the accuracy of the model and affects the learning process. When a correct feature selection is made, unnecessary and unimportant information can be removed from the model. In this way, computational costs can be reduced and critical features for the model can be preserved. Temporal and various meteorological data such as day, month, year are considered effective input parameters for different deep learning models. For this purpose, in the study, optimum features for the model were determined using the Pearson correlation method. These detected features are highly related to radiation intensity. In this step, it is aimed to create an accurate prediction model with a high success rate. The heat map showing the correlation matrix between the data is presented in Fig. 1. The heat map presented is based on Pearson correlation. The mathematical expression of this correlation is given in the following equation [11]

$$(1) \quad r = \frac{\sum (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum (x_i - \bar{x})^2 \sum (y_i - \bar{y})^2}}.$$

Here, r is the correlation coefficient, x_i is the value of the x variable, $\bar{x}$ is the average of the values of the x variable, y_i is the value of the y variable and $\bar{y}$ is the average of the values of the y variable. In the correlation matrix, values close to -1 are interpreted as a negative correlation, while correlation coefficient values close to $+1$ indicate a positive relationship. On the other hand, the value “0” indicates that there is no relationship between the variables [11]. The heat map presented in Fig. 1 shows the existence of a positive and negative correlation between variables within the datasets. It shows that temperature and humidity meteorological data with a calculated correlation value of over 0.5 with solar radiation may be more effective on the success of the prediction model than other parameters.

In deep learning models, it is necessary to use normalized values instead of the data themselves. In order to reduce the computational load on the model and improve its performance, data with a value equal to zero (representing hours when there is no sunlight) were removed from the data set. The measured and pre-processed data were converted into training and test data to be used in deep

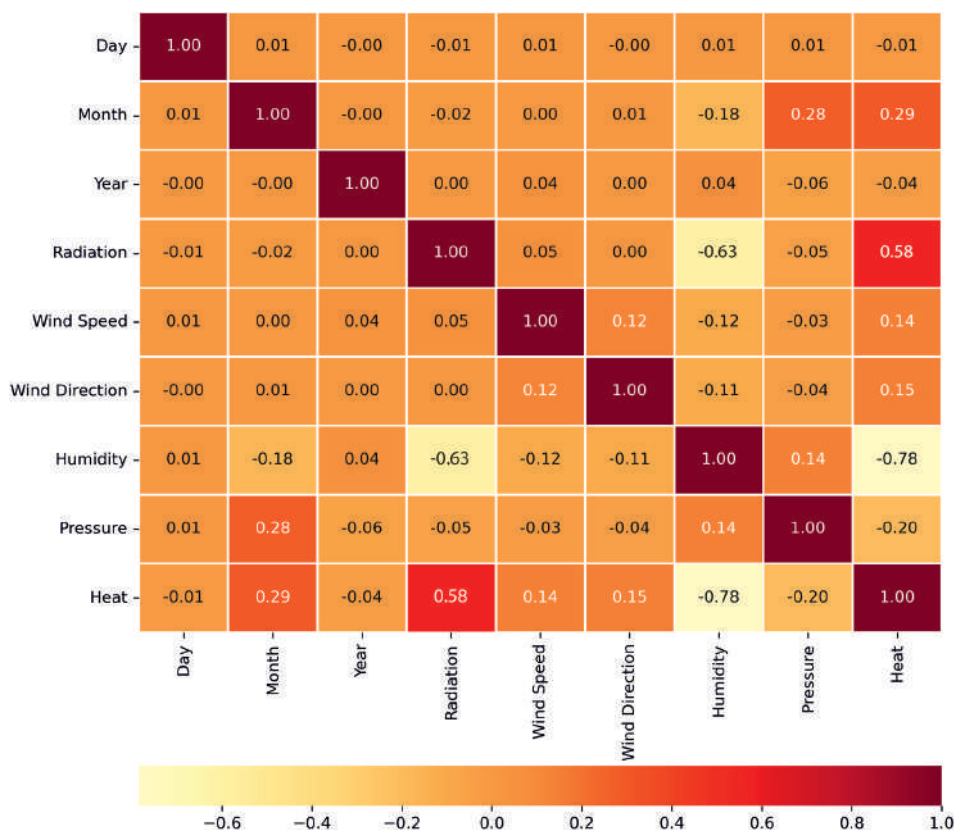


Fig. 1. Correlation matrix

learning models for solar radiation estimation. Seventy percent of the total number of data was used for training and 30% for testing. The data used in the study was scaled between (0–1) using the min-max method presented in the following equation [11]

$$(2) \quad x_{\text{new}} = \frac{x - x_{\min}}{x_{\max} - x_{\min}}.$$

Here, x_{new} indicates the normalized data, x indicates the original data to be normalized, $x_{\max}$ indicates the maximum value of the data sample, $x_{\min}$ indicates the minimum value of the data sample.

Proposed model. In this study, a method was developed in which M-LSTM/GRU hybrid models are used together to estimate hourly solar radiation using real-time solar radiation data and external meteorological variables. The performance of the proposed hybrid model is compared with the M-LSTM/LSTM model. There are four basic neural network layers in an LSTM structure: cell

state, input gate, forget gate, and output gate [12]:

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

$$(4) \quad f_t = \sigma(W_f[h_{t-1}, x_t] + b_f)$$

$$(5) \quad C_t = f_t C_{t-1} + i_t \cdot \tanh(W_c[h_{t-1}, x_t] + b_c)$$

$$(6) \quad o_t = \sigma(W_o[h_{t-1}, x_t] + b_o)$$

$$(7) \quad h_t = o_t \cdot \tanh(C_t).$$

In equations (3)–(7), W_i , W_f , W_c , W_o are the weight matrices, σ is the sigmoid activation function, b_i , b_f , b_c , and b_o are the bias weights of each gate. f_t represents the forget gate, o_t represents the output gate, C_t represents the cell outputs [12]. GRU architecture is also fundamentally similar to LSTM architecture. However, the GRU architecture contains only two gates instead of the three gates found in LSTM. Therefore, the GRU architecture requires less computation overall. Therefore, the time spent for the training process is relatively shorter. The cell state includes a reset gate and an update gate [12]. In equations (8)–(10), x_t is the input value, h_t is the output, z_t is the update gate, r_t is the reset gate, and W , U , b are the learning parameters:

$$(8) \quad Z_t = \sigma_g(W_z x_t + U_z h_{t-1} + b_z)$$

$$(9) \quad r_t = \sigma_g(W_r x_t + U_r h_{t-1} + b_r)$$

$$(10) \quad h_t = z_t \cdot h_{t-1} + (1 - z_t) \cdot \tanh(W_h x_t + U_h (r_t \cdot h_{t-1}) + b_h).$$

The hybrid model proposed in this study includes the use of both LSTM and GRU architectures together. As can be seen from the next section, this proposed hybrid hierarchy exhibits a better performance in solar irradiance estimation. It is considered that this situation arises from the fact that the hybrid model uses the learning capabilities of the LSTM model and the calculation speed and power of the GRU model. In the study, the data set was first applied to the LSTM layer in the hybrid LSTM-GRU model. The LSTM layer, which has high learning success, largely solves the problem of vanishing gradients in backpropagation. Then the output of LSTM is transmitted to GRU. GRU increases model calculation power and speed. Another feature that affects the success of this study is that temperature and humidity meteorological parameters, as well as time data affecting the radiation intensity, are presented as input to the network. Since there are many additional parameters, the method used in the study is called hybrid Multivariate LSTM/GRU architecture. In time series problems, t represents the current time and $t + 1$ represents the next time. In this case, all data in the dataset is transformed into a supervised learning problem by shifting it one step into the future to create multivariate input sequences [12]. The general configuration of the hybrid forecasting model used in the study is given in Fig. 2.

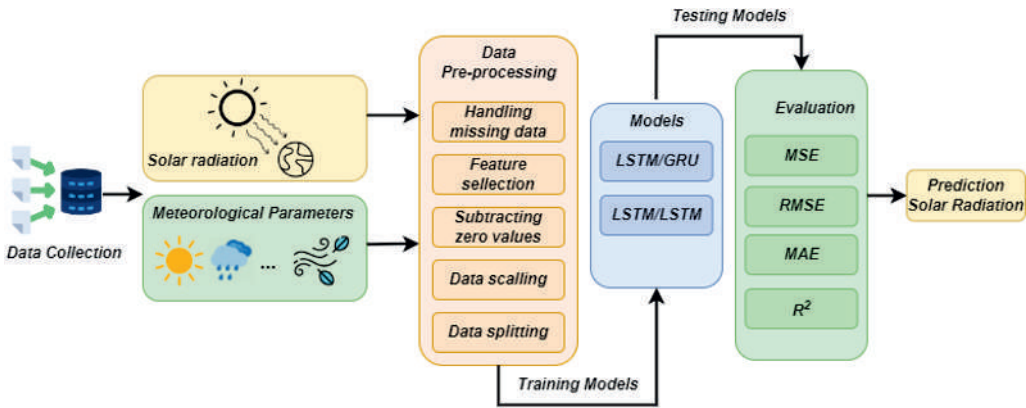


Fig. 2. Process implemented for forecasting solar radiation

Performance metrics. Mean squared error (MSE), mean absolute error (MAE), root mean square error (RMSE) and R^2 value were used to evaluate the performance of the models. The MAE metric is used to determine the absolute deviation of the predicted value from the observed value. The calculation of MAE is given in the following equation [13]

$$(11) \quad \text{MAE} = \frac{1}{N} \sum_{L=1}^N |Y_L - \hat{Y}_L|,$$

where Y_L represents the observed true value, $\hat{Y}_L$ represents the estimated value, and N represents the number of data points in the dataset.

Mean Square Error (MSE) is used to determine the average square difference between the observed values and the estimated values. MSE is calculated by the following equation

$$(12) \quad \text{MSE} = \frac{1}{N} \sum_{L=1}^N (Y_L - \hat{Y}_L)^2.$$

On the other hand, the mathematical expression of RMSE is used to calculate the standard deviation of the differences between the observed value and the predicted value [13].

$$(13) \quad \text{RMSE} = \sqrt{\frac{1}{N} \sum_{L=1}^N (Y_L - \hat{Y}_L)^2}.$$

Finally, the coefficient of determination

$$(14) \quad R^2 = 1 - \frac{\sum_{L=1}^N (Y_L - \hat{Y}_L)^2}{\sum_{L=1}^N (Y_L - A_L)^2}$$

expresses the ratio of variance in the dependent variables to the independent variables estimated. An R^2 value close to 1 is desired, and the closer it is to 1, the more variation is explained by the model. A_L represents the average value [13].

Results. This study has been conducted in Python environment. Before the training phase, 70% of the data set has been separated for training and 30% for testing. In addition to time data, meteorological parameters affecting radiation intensity have been presented as input. At this stage, the parameters to be presented as input data were determined with the help of a heat map extracted according to Pearson correlation. The most important advantage of the proposed M-LSTM/GRU model is the high learning success of LSTM. Thanks to the created model structure, very successful results have been achieved in solar radiation prediction. The results obtained from M-LSTM/GRU and M-LSTM/LSTM models are given in Table 1.

T a b l e 1
Experimental results of M-LSTM/GRU and M-LSTM/LSTM

Performance metrics	Solar radiation (W/m ²)	
	M-LSTM/GRU	M-LSTM/LSTM
MSE	33.219	38.426
RMSE	5.764	6.199
MAE	4.762	4.842
R^2	0.996	0.987

Another advantage of modelling is the high computational power and speed of GRU. When the second layer of the same network structure is LSTM, the model speed has decreased. In order to observe the success of both models in terms of time, only the second layer of the model has been changed to GRU. All other parameters have been left the same. The computer on which the algorithms are executed runs on an Intel[®] Core i7-9750H (2.6 GHz) processor with 8 GB of RAM, and has Windows 10 operating system. In conclusion, it was observed that the LSTM-LSTM block reached the result in 44.74 s, while the LSTM-GRU block reached the result in 25.63 s.

The estimated value graphs of the proposed model in Fig. 3 are shown along with the actual values.

Discussion and conclusion. The output power of PV panels varies depending on various meteorological factors. Solar radiation is known as the most important parameter that affects the output power of PV systems. Accurately predicting this parameter is of great importance in energy planning activities. Due to its nature, the intensity of solar radiation has variable characteristics and is influenced by various meteorological events, making it difficult to predict accurately due to uncertain changes. In this study, an M-LSTM/GRU model has been devel-

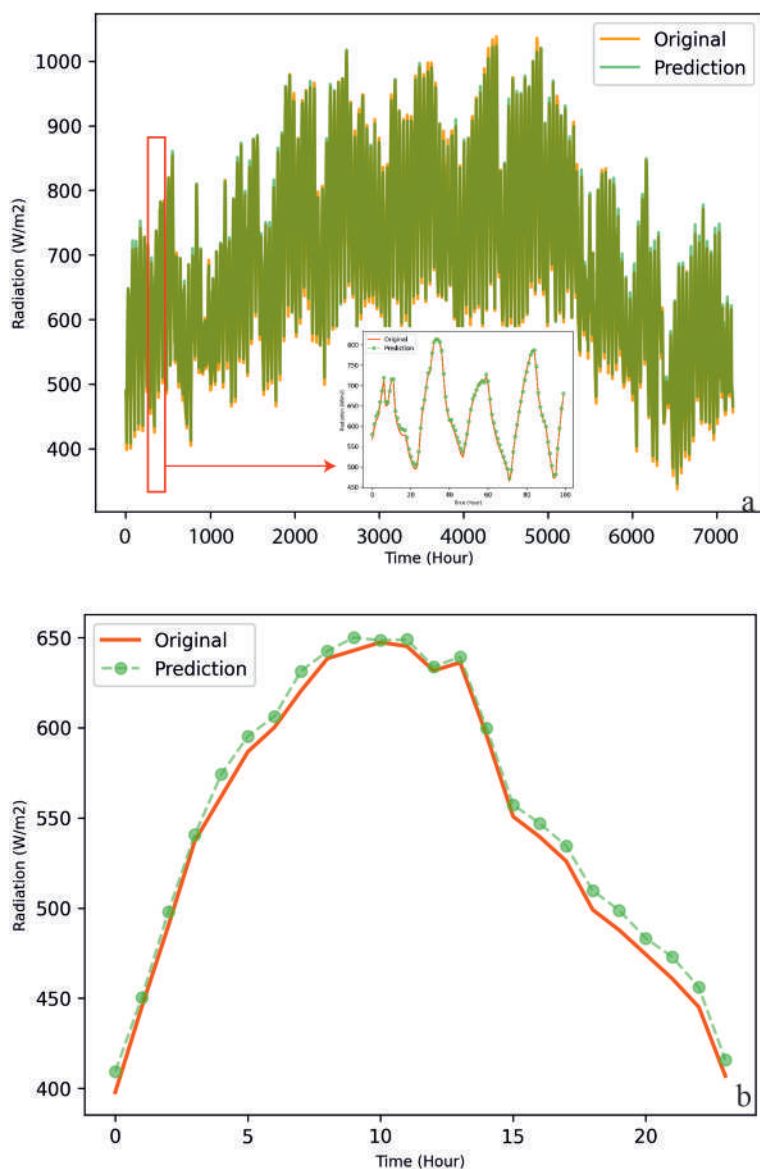


Fig. 3. Original-predicted values (a); Magnified original-predicted values (b)

oped to predict solar radiation. The performance of the model has been tested on real-time data obtained from a specific location in Turkey. Before the model was created, the dataset was subjected to a detailed analysis and correlations between each variable were calculated. According to the correlation coefficients, it was determined that the features affecting solar radiation are temperature and humidity values. In order to increase the effectiveness of the study, time data along with the features obtained from the correlation matrix were presented as inputs to the

model. The proposed method can accurately and reliably predict fluctuations in solar energy systems. The MSE, RMSE, and MAE values between the developed model outputs and the measured data are calculated as 33.219, 5.764, and 4.762, respectively. Another important result obtained from the study is the reduction in prediction times thanks to the proposed approach. Therefore, it is considered that the proposed model can be used in the development of early warning systems against fluctuations in solar energy systems.

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