

Solar Irradiation Forecasting via Feedforward and LSTM Neural Networks: Insights from Learning Algorithms

Lovdeep Grover, Vikas Gupta

Research Scholar, Associate professor Guru Kashi University; Bhatinda, Punjab

Corresponding Author Email: glovdeep@gmail.com

Abstract - Accurate estimation of solar radiation is essential for numerous industrial applications, energy management, and agricultural planning. This study investigates the effectiveness of advanced machine learning models for solar radiation prediction in Indian Location utilizing a comprehensive set of meteorological variables. Following rigorous quality control procedures and correlation-based feature selection, the dataset was divided into training (80%) and testing (20%) subsets. Two Neural Network, namely Long Short-Term Memory (LSTM) with the Adam optimizer and Feed-Forward Neural Network (FFN) were developed and trained under six input scenarios, employing various learning algorithms including Levenberg–Marquardt (LM), Bayesian Regularization (BR), Gradient Descent (GD), and Resilient Propagation (RP) at both daily and monthly timescales. The results indicate that the FFN-BR model under scenario 6, incorporating a wide range of meteorological inputs, yielded the highest accuracy for monthly radiation estimation ($R^2 = 0.90$, ARE = 2.6%). For daily radiation prediction, the LSTM model under scenario 4 provided superior performance ($R^2 = 0.91$, ARE = 1.35%). These findings underscore the importance of model selection and input configuration in enhancing solar radiation estimation accuracy, offering valuable insights for renewable energy resource assessment in arid regions.

Keyword- Solar radiation, Artificial Neural Network, LSTM, FFN, Machine Learning Models.

1. Introduction

Solar radiation plays a critical role in numerous sectors, including health, tourism, agriculture, and energy production. Recognizing its significance is crucial for maintaining the sustainability of energy-dependent processes in the natural world [1][2][3]. Solar radiation directly influences various natural phenomena such as photosynthesis, temperature, evapotranspiration, and humidity [4]. It serves as a vital input for models that forecast the growth, development, and performance of agricultural products [5]. With the global population steadily increasing, the demand for energy has risen significantly. The necessity for renewable energy sources has become more urgent, and solar energy is gaining prominence as a sustainable and renewable option [6][7]. Consequently, having access to accurate solar radiation data is essential for maximizing the benefits derived from solar power.

The most precise approach for determining solar radiation levels involves the installation of direct measurement tools like Pyranometers and Pyrheliometers. However, this method can be expensive and necessitates specialized equipment [8][9][10]. As an alternative, numerous experimental models have been developed globally to estimate solar radiation. These models utilize various meteorological variables and empirical coefficients to estimate the radiation levels. However, all of these models incorporate empirical constants that are dependent on the season and geographical location of a specific area [11]. Consequently, if any of these models were to be applied to a different region, calibration would be necessary.

Artificial Intelligence (AI) has brought about a revolution in various domains, and radiation data estimation is no exception. The incorporation of AI algorithms capabilities has significantly enhanced the accuracy and efficiency of estimating radiation data. Therefore, AI-powered radiation data estimation is undoubtedly the way forward. Researchers have employed diverse AI techniques such as artificial neural networks (ANNs), genetic algorithms, fuzzy logic, and hybrid approaches to estimate solar radiation, considering different time scales, meteorological variables, and geographical coordinates [12][13]. Qazi et al [14] conducted a study utilizing ANN to simulate solar radiation, demonstrating that this technique yields accurate predictions with errors below 20%. Compared to other experimental models, ANN has the advantage of incorporating multiple meteorological variables as inputs, thereby increasing the model's accuracy. Abdulazeez [15] employed a feed-forward-backpropagation

neural network to estimate the monthly average global solar radiation in Gusau, Nigeria. Input parameters included sunshine hours, maximum temperature, and relative humidity, while solar radiation served as the output parameter. The research findings reported an RMSE of 0.0028, indicating a strong agreement between the estimated and measured values of solar radiation. A comprehensive review of previous studies confirms the efficiency of ANNs in radiation estimation.

Accurately estimating solar radiation requires careful consideration of input parameters, algorithms, and network structures. This study aims to compare the efficacy of various training algorithms for feed-forward neural networks (FFN) and Long Short-Term Memory Networks (LSTM) in estimating both daily and monthly radiation. Prior to developing the networks under different scenarios and learning algorithms, the correlations between solar radiation and meteorological variables are calculated and analyzed on a daily and monthly scale. Subsequently, the accuracy of each model in estimating daily and monthly radiation is assessed independently. Based on the analysis results, the study suggests the best model to be used in the specific study area.

2. Materials and Methods

2.1. Study area

Mohali (Sahibzada Ajit Singh Nagar) district, located in the northwestern region of India in the state of Punjab, is an important urban and industrial hub within the Chandigarh Tricity area. Geographically, it lies between 30° 40' to 30° 50' North latitude and 76° 38' to 76° 45' East longitude. The district is situated at an average elevation of approximately 316 meters above sea level. Mohali experiences a subtropical climate, with an average annual temperature of around 24 °C and a mean annual rainfall of approximately 1,100 millimetres, most of which occurs during the southwest monsoon season. Meteorological data for the study area have been collected from the local weather station for the period extending from January 2018 to December 2019.

2.2. Validation and quality control of radiation data

Accurate and reliable radiation observational data is of utmost importance [16]. In order to achieve this, the study utilized Moradi's algorithm for radiation data quality control [17]. The quality control process consists of three stages to ensure the accuracy and reliability of radiation observational data, as follows:

2.2.1. Comparing Global Daily Solar Radiation with Extraterrestrial Daily Radiation

In the first step, the global daily solar radiation (R_s) is compared with the extraterrestrial daily radiation (R_0) received at the horizontal surface outside the Earth's atmosphere. The comparison is made using Equation [1]:

$$0.03R_0 \leq R_s < R_0 \quad (1)$$

2.2.2. Limiting Daily Solar Radiation with Clear Sky Radiation

The second step involves ensuring that the observed solar radiation (R_s) does not exceed a certain threshold represented by the small amount of daily clear sky radiation (R_{cd}) observed under very clear sky conditions. Equation [2] defines this condition:

$$R_s < 1.1R_{cd} \quad (2)$$

2.2.3. Checking Radiation Stability using the Radiation Index

The third stage consists of stability checks that utilize the relationship between daily global solar radiation and the sunshine hours fraction. In this step, a new index called the radiation index (i_n) is calculated and compared to its lowest limit (LL) using Equation [3]. The radiation index takes into account the atmospheric clearness index (K_T), which is the ratio of observed solar radiation (R_s) to extraterrestrial radiation (R_0), and the sunshine hours fraction (N_n).

$$i_n = \begin{cases} K_T & \text{if } n < 0.05 \text{ or } K_T < 0.1 \\ \frac{K_T}{N_n} & \text{else} \end{cases} \quad (3)$$

The lower limit of the index is determined using the Equation [4]. incorporates several parameters: a, which represents the second quartile of K_T for all days when the sunshine hours fraction (n/N) is greater than 0.9; b, which represents the first quartile of data with n/N values less than or equal to 0.1; and c, which is the ratio of n/N [17].

$$i_n = \begin{cases} a \frac{n}{N} & \text{if } \frac{n}{N} \geq c \\ b & \text{else} \end{cases} \quad (4)$$

Overall, these three stages provide a comprehensive approach to quality control for radiation data, ensuring that the observed values are consistent with the expected ranges and relationships.

2.3. Feature Selection

To introduce ANN and determine the suitable features for it, Pearson correlation was utilized to calculate the correlation between radiation and meteorological variables-based Equation [5]. Where, COV represents the covariance, σ_x denotes the standard deviation of a meteorological variable, and σ_y represents the standard deviation of the solar radiation data [18][19]. Correlation calculations were performed at both daily and monthly scales, allowing to identify of the correlation values. These correlation values are crucial in selecting the appropriate variables as inputs to the ANNs and determining the selection of scenarios.

$$\rho_{x,y} = \frac{COV(X,Y)}{\sigma_x \sigma_y} \quad (5)$$

2.4. ANN Development

ANN is a powerful tool within the field of AI that serves various purposes such as nonlinear function estimation, data classification, pattern recognition, optimization, clustering, and simulation. The structure of an ANN consists of several components, including the input layer, hidden layer(s), output layer, weights, biases, activation function, and neurons. During the training phase, the network utilizes these weights and biases to minimize the error function and generate the desired output. The learning process involves the application of specific algorithms and training courses [13]. For this research, FFN was employed to develop the model. The FFN architecture will be introduced further in subsequent sections. Additionally, the research proposes an estimating method for radiation based on LSTM techniques. LSTM, known for its ability to analyze relationships among time series data through its memory function, enhances the model's capabilities in capturing temporal patterns and dependencies.

2.4.1. FNN

FFN holds a significant position among ANNs due to its distinctive structure devoid of cycles or loops [20]. The FFN architecture comprises an input layer connected to a hidden layer, and it is common for ANNs to have only one hidden layer, with rare instances of networks having more than two hidden layers [21]. In FFN, the connections between neurons are unidirectional and established through weights. Figure 1 illustrates a simple FFN structure with one hidden layer. Where m represents the number of inputs, n denotes the number of neurons in the hidden layer, and O signifies the output. The FFN's operation involves calculating the weighted sum of inputs to a node, followed by the application of an activation function. Various activation functions exist, but the sigmoid function is widely utilized and popular [20]. In this study, the sigmoid function was chosen for activation. Mathematically, the process can be represented as Equation [6] [22], where f_k denotes the activation function, I_m

represents a vector of inputs (independent variables), b_m signifies the bias vector, and W_{mn} represents the connected weight between input m and hidden layer n .

$$H_n = f_k \left(b_n + \sum_{m=1}^m w_{mn} I_m \right) \quad (6)$$

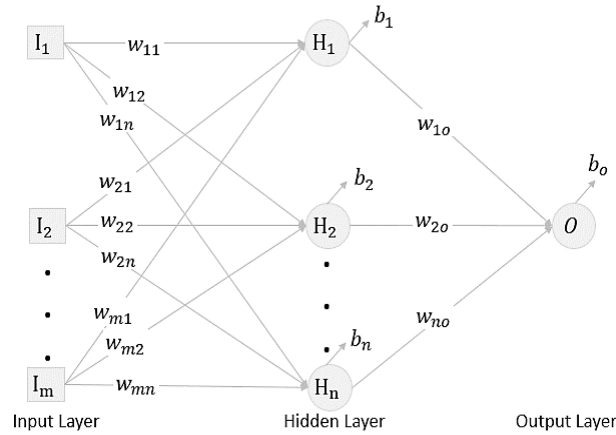


Figure 1. A simple architecture of FFN

The key advance is the introduction of a learning algorithm, which finds the weight and offset parameters of the network for a particular problem [20]. In this study, four learning algorithms were selected to train FFN, including Bayesian Regularization (BR), Levenberg-Marquardt (LM), Resilient Back-propagation (RP), and Gradient Descent (GD). A brief description of these algorithms is given in the following subsections.

The BR learning algorithm: The BR algorithm uses Bayes' rule to update the weights of the ANN and mitigate overfitting. The cost function (CF) for the BR learning algorithm is defined by Equation [7]. Where n represents the number of input data, m represents the number of neurons in the output layer, Δ_{ij} , α , and β is determined by Equation [8], Equation [9], and Equation [10], respectively. T_{ij} represents the network target and O_{ij} denotes the network output for a given input i and neuron j of the output layer.

$$F = CF_{SD} + \beta \sum_{k=1}^p \sum_{l=1}^q \quad , \quad CF_{SD} = \alpha \sum_{i=1}^n \sum_{j=1}^m \Delta_{ij}^2 \quad (7)$$

$$\Delta_{ij} = T_{ij} - O_{ij} \quad (8)$$

In the Equation [9] and [10], m represents the maximum posterior, and γ corresponds to the number of parameters that have a greater relative impact on reducing the CF value. W_{kl} denotes the weight between neurons k and l .

$$\alpha = \frac{n - \gamma}{2 \sum_{i=1}^n \sum_{j=1}^m \Delta_{ij}^2 (w^M)} \quad (9)$$

$$\beta = \frac{\gamma}{2 \sum_{k=1}^p \sum_{l=1}^q w_{kl}^2 (w^M)} \quad (10)$$

The distribution of weights follows a Gaussian function, as expressed in Equation [11]. Where P represents the probability function, W represents the weights vector, and P represents the input data vector [23].

$$P(W|P, \alpha, \beta) = \frac{P(P|W, \alpha)P(W|\beta)}{\sum P(P|W, \alpha)P(W|\beta)\Delta W} \quad (11)$$

The LM learning algorithm: The weights of the FFN are typically updated using the steepest descent (SD) algorithm, as shown in Equation [12]. However, the SD algorithm has a relatively slow convergence rate. To address this, a stable and fast learning algorithm called the Levenberg-Marquardt (LM) algorithm is employed by combining the Gauss-Newton (GN) method with the SD algorithm, as presented in Equation [13]. The GN method is defined by Equation [14], where J represents the Jacobian matrix, E represents the error matrix, and I represent the identity matrix [23].

$$\Delta w_{ij} = \frac{\partial CF_{SD}}{\partial w_{ij}} \quad (12)$$

$$\Delta w_{LM} = \Delta w_{GN} + \left(\frac{1}{\alpha} I \right)^{-1} J E \quad (13)$$

$$\Delta w_{GN} = (J^T J)^{-1} J E \quad (14)$$

The GD learning algorithm: The core principle of the Gradient Descent (GD) learning algorithm involves iteratively updating the dynamic parameters in the direction opposite to the gradient of the error (E), aiming to minimize this discrepancy. This update process is described by Equation [15], where μ represents the learning rate, w denotes the weight of the neuron, and b signifies the bias [24].

$$\Delta w = -\mu \frac{\partial E}{\partial w}, \Delta b = -\mu \frac{\partial E}{\partial b} \quad (15)$$

The RP learning algorithm: The RP algorithm is an enhanced version of the traditional batch back-propagation algorithms, known for its fast convergence for many problems. It offers rapid local adaptation by utilizing only the sign of the back-propagated gradient to update the network's biases and weights, rather than considering the magnitude of the gradient itself. In other words, the direction of the weight/bias update is determined solely by the sign of the derivative. The weight adjustments are made according to Equation [16] and Equation [17] [25][26][27]. The values $0 < \mu^- < 1 < \mu^+$ are empirically set as 0.5 and 1.2, respectively.

$$\Delta_{ij}(t) = \begin{cases} \mu^+ \cdot \Delta_{ij}(t-1), & \text{if } \frac{\partial E}{\partial w_{ij}}(t-1) \cdot \frac{\partial E}{\partial w_{ij}}(t) > 0 \\ \mu^- \cdot \Delta_{ij}(t-1), & \text{if } \frac{\partial E}{\partial w_{ij}}(t-1) \cdot \frac{\partial E}{\partial w_{ij}}(t) < 0 \\ \Delta_{ij}(t-1), & \text{otherwise} \end{cases} \quad (16)$$

$$w_{ij}(t) = \begin{cases} -\Delta_{ij}(t), & \text{if } \frac{\partial E}{\partial w_{ij}}(t) > 0 \\ +\Delta_{ij}(t), & \text{if } \frac{\partial E}{\partial w_{ij}}(t) < 0 \\ 0, & \text{otherwise} \end{cases} \quad (17)$$

The weight update process in the RP algorithm can be summarized as follows: When the partial derivative of the error function (E) with respect to a specific weight w_{ij} changes its sign, it indicates that the previous update was too large, causing the algorithm to overshoot a local minimum. In such cases, the updated value is decreased by a certain factor. Conversely, if the derivative maintains its sign, the updated value is slightly increased by the factor to facilitate faster convergence in shallow regions. Once the updated values for all weights are adjusted, the weight update itself adheres to a straightforward rule: If the derivative is positive (indicating an increasing error), the weight is decreased by its update value. Conversely, if the derivative is negative, the update value is added to the weight [25].

2.4.2. LSTM

LSTM is a variant of Recurrent Neural Network (RNN) that incorporates additional components such as a cell, input gate, output gate, and forget gate [28] [29]. This architecture enables an LSTM layer to effectively capture long-term dependencies, making it particularly suitable for time series prediction tasks. In a typical configuration, an LSTM layer consists of multiple LSTM cells and a dense output layer. Figure 2 depicts the fundamental structure of an LSTM cell, comprising three key gates: the input gate (i_t), forget gate f_t , and output gate O_t , along with the candidate value $\hat{C}_t$ at each time step [33]. The relationships between these gates are mathematically defined by the following Equations [28].

$$f_t = \alpha(w_{f,x} \cdot x_t + w_{f,h} \cdot h_{t-1} + b_f) \quad (18)$$

$$i_t = \alpha(w_{i,x} \cdot x_t + w_{i,h} \cdot h_{t-1} + b_i) \quad (19)$$

$$o_t = \alpha(w_{o,x} \cdot x_t + w_{o,h} \cdot h_{t-1} + b_o) \quad (20)$$

$$\hat{C}_t = \tanh(w_{\hat{c},x} \cdot x_t + w_{\hat{c},h} \cdot h_{t-1} + b_{\hat{c}}) \quad (21)$$

In the LSTM architecture, there are weight matrices denoted as $w_{(i,x)}$, $w_{(i,h)}$, $w_{(f,x)}$, $w_{(f,h)}$, $w_{(o,x)}$, $w_{(o,h)}$, $w_{(c,x)}$ and $w_{(c,h)}$. These weight matrices consist of parameters ranging from 0 to 1. A parameter value closer to 1 implies that more information is retained, with 1 indicating complete preservation and 0 indicating complete forgetting. Additionally, there are bias vectors b_i , b_f , b_o and b_c . The current input is represented by x_t , the output of the LSTM at the previous time is denoted as $h_{(t-1)}$, and α denotes the activation function. The forget gate determines the amount of prior memory value to be discarded from the cell state, while the input gate determines the new input to be added to the cell state. Finally, the cell state c_t is calculated as the Equation [22]:

$$c_t = f_t * c_{t-1} + i_t * \hat{C}_t \quad (22)$$

The output h_t of the LSTM at the time t is derived as Equation [23]:

$$h_t = O_t * \tanh(C_t) \quad (23)$$

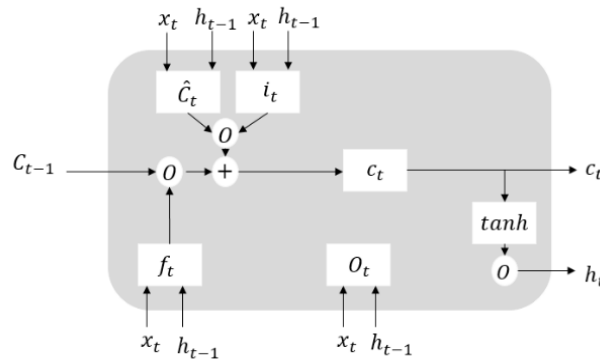


Figure 2. The schematic structure of an LSTM cell

In this study, a single-layer LSTM architecture was utilized with the number of neurons determined proportionally to the number of inputs, as indicated in Table 3. To update the parameters of the LSTM model, we utilized the Adam optimizer, which is renowned in the field of deep learning for its self-adaptive learning rate and fast convergence speed. 80% of the dataset was used for training and 20% as a test dataset.

2.5. Model evaluation

To assess the performance and reliability of the developed models, several error evaluation criteria were utilized, including MAE (Mean Absolute Error), RMSE (Root Mean Squared Error), MBE (Mean Bias Error), ARE (Absolute Relative Error), and R^2 (R-square). The equations for these evaluation metrics can be found in Table 1. In the equations (24) to (28), O_i represents the observed values, X_i is the estimated values, N represents the number of data points, RSS represents the Sum of Squares of Residuals, and TSS represents the Total Sum of Squares.

Table 1 Error evaluation criteria and their relationship

Formula	Number of Equation
$MAE = \frac{1}{N} \sum_{i=1}^N X_i - O_i $	(24)
$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^N (X_i - O_i)^2}$	(25)
$MBE = \frac{1}{N} \sum_{i=1}^N (X_i - O_i)$	(26)
$ARE = \frac{1}{N} \sum_{i=1}^N \frac{X_i - O_i}{O_i} \times 100$	(27)
$R^2 = 1 - \frac{RSS}{TSS}$	(28)

3. Results and Discussion

3.1. Feature selection

The results of the correlations are presented in Table 2 and Figure 3. As indicated in Table 2, the correlations tend to be stronger on a monthly scale compared to a daily scale. On a monthly scale, the highest correlation with radiation is observed for evaporation, while the lowest correlation is observed with the average dew point temperature. On a daily scale, the highest correlation with radiation is found with sunshine hours, whereas the lowest correlation is observed with maximum wind speed. Except for the average dew point temperature, all meteorological parameters exhibit similar correlations on both daily and monthly scales. Parameters such as average pressure, average vapor pressure, precipitation, average cloudiness, maximum cloudiness, maximum relative humidity, minimum relative humidity, average relative humidity, maximum pressure, minimum pressure, and dew point temperature exhibit a negative correlation with radiation on a daily scale.

A study conducted in Nigeria investigated the impact of relative humidity on solar radiation intensity, revealing that an increase in relative humidity leads to a decrease in solar radiation and vice versa [30]. These findings align with a study by Jebli et al [31] which explored the correlation between solar radiation and meteorological variables such as relative humidity, air pressure, temperature, and wind speed. Similarly, a study discovered strong correlations (greater than 0.5) between solar radiation and variables such as temperature, soil temperature, relative humidity, sunshine hours, and saturated vapor pressure [32]. These results are consistent with the findings of the present study.

The study identified several variables that play a significant role in determining the amount of daily and monthly radiation. For the daily scale, the variables found to be influential were the fraction of sunshine hours (n / N), mean saturated vapor pressure, mean temperature, relative humidity, and mean soil temperature. For the monthly scale, the most important features were identified as mean temperature, mean saturated vapor pressure, soil temperature, sunshine hours, and relative humidity, respectively. Utilizing the degree of correlation as a basis, the selection of scenarios for ANNs was performed based on the information provided in Table 3.

Table 2. Correlation between R_s and variables on daily scale and monthly scale

Parameter	Correlation on the monthly scales	Correlation on the daily scale
Horizontal visibility	0.2605	0.2589
Maximum wind speed	0.4261	0.0728
Mean wind speed	0.5801	0.1761
Maximum temperature	0.9225	0.7442

n/N	0.8700	0.9314
Minimum temperature	0.9140	0.5747
Mean temperature	0.9327	0.7230
Mean pressure	-0.7600	-0.4359
Mean vapor pressure	0.1861	-0.1622
Precipitation	-0.3850	-0.3095
Mean cloudiness	-0.5636	-0.5905
Maximum cloudiness	-0.5286	-0.5162
Maximum relative humidity	-0.8061	-0.6475
Minimum relative humidity	-0.7218	-0.6141
Mean relative humidity	-0.7983	-0.6857
Sunshine hours	0.8676	0.8005
Radiation	1	1
Evaporation	0.9441	0.6656
Dew point temperature	0.2218	-0.1142
Wet bulb temperature	0.8858	0.5715
Mean soil temperature	0.9107	0.5666
Minimum soil temperature	0.9107	0.5666
Maximum pressure	-0.7864	-0.4540
Minimum pressure	-0.7390	-0.4136
Saturated vapor pressure	0.9141	0.7177

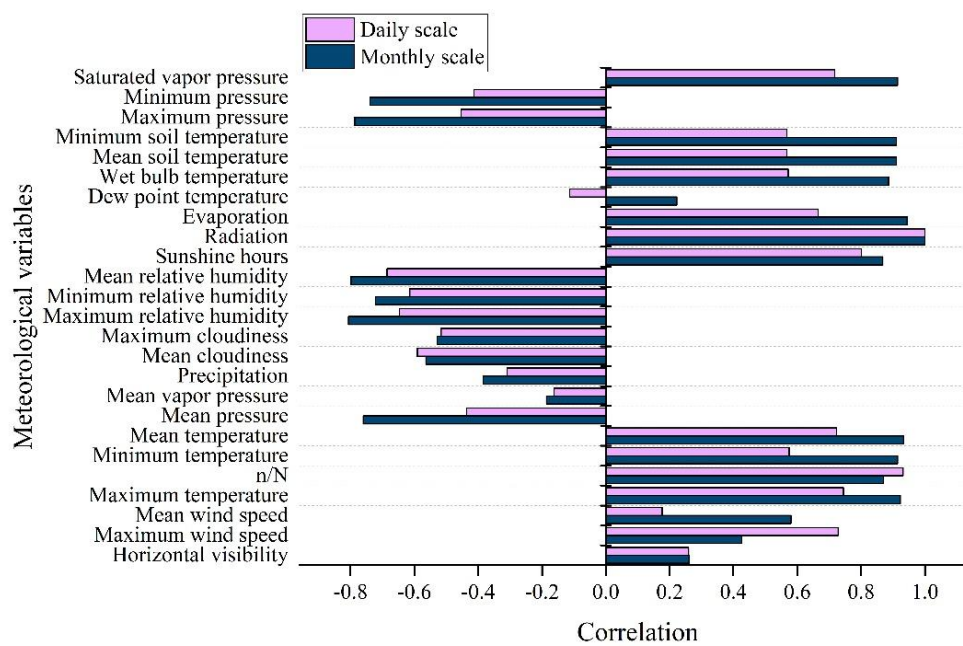


Figure 3. Correlation between R_s and variables on daily and monthly scale

Table 3. LSTM/FFN scenarios and structure on the daily/monthly scale

Scenario	Number of neurons	Output	Inputs
1	1	R_s/R_0	n/N
2	2	R_s/R_0	n/N, SVP
3	3	R_s/R_0	n/N, SVP, MAT
4	4	R_s/R_0	n/N, SVP, MAT, MRH
5	4	R_s/R_0	n/N, SVP, MAT, MRH, MST
6	10	R_s/R_0	n/N, SVP, MAT, MRH, MST, HV, MW, C, DP, WB, P

3.2. Result of developing models

Tables 4 and Table 5 present the error values for training and testing data of FFN using various learning algorithms, including LM, BR, GD, and RP. The error values are displayed for both daily and monthly scales. Additionally, Table 6 and Table 7 display the error values for training and testing data of LSTM models, also on a daily and monthly scale. In the subsequent sections, the performance of the FFN models trained with different learning algorithms across different scenarios were analysed and compared, considering both time scales. Furthermore, the top-performing FFN models with the LSTM models were compared to determine the most effective approach.

3.3. Comparison of FFNs under different learning algorithms

The accuracy of the FFNs was assessed using various metrics such as RMSE, MAE, MBE, ARE, and R^2 , considering both the training and test datasets at monthly and daily intervals. According to the findings from Table 4, the most accurate FFN model for estimating daily radiation at the Kerman synoptic station is the model implemented in scenario 6 using the BR algorithm. This particular model demonstrates an ARE of 4.5% and an R^2 value of 0.92. On the other hand, the FFN models developed using the GD algorithm exhibit lower accuracy compared to other algorithms across all scenarios, with a higher incidence of errors. Notably, the models generated by the GD algorithm display an ARE exceeding 18% and an R^2 as low as 0.1 for the test dataset, indicating a poor fit between the estimated values and the observed data. Consequently, it is not recommended to utilize the GD algorithm for estimating daily radiation values at this specific station.

Contrary to earlier observations, the test results reveal that scenario 1 demonstrates superior performance for the GD algorithm compared to other scenarios utilizing the same algorithm. Furthermore, the accuracy achieved by the GD algorithm in scenario 1 is comparable to that of the RP algorithm, with only slight variations from the accuracy of the LM and BR algorithms. Nevertheless, upon examining the ARE values computed for the test data, it becomes apparent that the GD algorithm consistently exhibits the highest error rate across all scenarios, except for scenario 3. In scenario 3, the RP algorithm displays the highest ARE following the GD algorithm. On the other hand, both the LM and BR algorithms consistently yield similar levels of accuracy in each scenario. Notably, the BR algorithm consistently achieves the lowest ARE and the highest R^2 values in every scenario, a trend that holds true for the training data as well. Additionally, the RMSE results obtained using the BR and LM algorithms are highly comparable.

Table 4 also provides insights into the performance of the model under the LM algorithm. It is observed that the accuracy of the model improves as the number of inputs and the complexity of the model increase, as indicated by the corresponding values. When examining the MBE values for the training data, it becomes evident that all scenarios and algorithms have a tendency to overestimate the radiation values. However, for the test data, the estimated radiation values are consistently underestimated, and some scenarios and algorithms even produce negative values.

Based on the information presented in Table 5, the monthly ARE values for the test dataset range from 2.7% to 13.6%. The most precise model for estimating monthly radiation at the Kerman synoptic station is the FFN model under scenario 6, utilizing the BR algorithm. The ARE of the test dataset is 2.7%, and the R^2 value is 0.92. During the training phase, the R^2 value is 0.96. This particular model exhibits the lowest values for ARE, MAE, and RMSE in both the training and testing phases. Notably, when considering the RMSE, R^2 , and ARE values for the test dataset across all scenarios, models developed using the GD algorithm demonstrate lower accuracy when compared to models developed using other algorithms.

After evaluating the ARE values for both the test and train datasets, it was evident that the GD algorithm consistently yielded the highest ARE across all scenarios. These models, developed using the GD algorithm, exhibited the lowest R^2 values in each scenario, suggesting a poor fit between the estimated values and the observed data. Consequently, it is not advisable to employ the GD algorithm for estimating radiation values on a monthly scale. Even in scenario 1, where the GD algorithm shared the same R^2 value as the other algorithms for both the test and train datasets, it still proved less accurate when assessed using the ARE criterion. In contrast, models based on the RP algorithm outperformed those generated by the GD algorithm in all scenarios, as evidenced by their superior performance in terms of ARE, R^2 , and RMSE.

However, the RP algorithm cannot be regarded as the most efficient algorithm when compared to the LM and BR algorithms. The results obtained from both the BR and LM algorithms exhibit similarities across all scenarios, albeit with slight variations in their ARE, R^2 , RMSE, and MAE values. In certain scenarios, the LM algorithm

performs better, whereas in others, the BR algorithm yields superior outcomes. Analyzing the R^2 values of the test data reveals that the LM algorithm outperforms the BR algorithm in scenarios 6, 5, and 1. Conversely, under scenarios 2, 3, and 4, the BR algorithm surpasses the LM algorithm. Except for the GD algorithm under scenario 4, the MBE values for the test dataset are positive. This implies that, in all scenarios and algorithms except for the GD algorithm under scenario 4, the estimated radiation values for the test dataset are overestimated. The evidence presented in Table 5 strongly suggests that the LM and BR algorithms excel in minimizing errors and adjusting the network's weights and biases to accurately estimate monthly radiation data. Therefore, it is highly recommended to utilize the LM and BR algorithms to ensure utmost precision in estimating this parameter.

The significance of learning algorithms in determining the accuracy of ANN models for radiation estimation should not be underestimated. It is essential to thoroughly explore various ANN structures in order to derive optimal models. By emphasizing this critical step, we can guarantee the highest level of precision in radiation estimations.

3.4. Comparison of LSTM networks

Examining Table 6 at the daily scale, the LSTM models exhibit ARE values ranging from 1.3% to 13.6% for the test dataset in all scenarios, and R^2 values ranging from 0.91 to 0.49. Similarly, for the training dataset, the LSTM models display ARE values ranging from 1.5% to 14.26% and R^2 values ranging from 0.92 to 0.41 across all scenarios. The positive MBE values in all scenarios for the test dataset indicate that the developed models tend to overestimate radiation estimates. Notably, scenario 6 yielded unsatisfactory results compared to the other scenarios, as evident from Table 6. Considering the R^2 and ARE values for both the test and training datasets, it can be concluded that scenario 4 produced the most favorable outcomes. In scenario 4, the test dataset achieved an R^2 value of 0.91 and an ARE value of 1.35%, while the training dataset exhibited an R^2 value of 0.92 and an ARE value of 1.5%.

Analyzing Table 7 at the monthly scale, the LSTM models exhibit ARE values ranging from 5.2% to 12.4% for the test dataset in all scenarios, and for the training dataset, the range is from 4.9% to 12.3%. The R^2 values for the test dataset range from 0.89 to 0.56, and for the training dataset, they range from 0.90 to 0.56 across all scenarios. Notably, the test dataset displays negative MBE values in all scenarios except scenario 6, indicating an underestimation of radiation estimates by the developed models in scenarios 1 to 5. Consistent with the findings at the daily scale, the LSTM model's performance in estimating radiation data on a monthly scale under scenario 6 is inadequate, as indicated by Table 7. The R^2 values for the test dataset indicate that scenario 4 yields the most favorable outcomes. Although there are slight variations in the R^2 values from scenario 1 to 5, ranging from 0.86 to 0.89. Therefore, it can be concluded that the LSTM model is not suitable for accurately estimating radiation data on a monthly scale under scenario 6.

3.5. Comparison of FFN and LSTM

Comparing Table 4 and Table 6, it is evident that in scenario 4, the LSTM model demonstrates higher accuracy compared to the FFN model across all algorithms for both the test and training datasets. However, when examining scenario 6, the results of R^2 and MAE indicate that the FFN model outperforms the LSTM model under the BR algorithm, as well as across all algorithms for both the test and training datasets. Thus, for estimating radiation data, LSTM under scenario 4 may be a preferable option to certain FFN models under scenario 4. However, when comparing the best FFN algorithm (using the BR algorithm under scenario 6) with LSTM, it is observed that the FFN model achieves slightly better results in terms of R^2 values for estimating radiation data on a daily scale, although this is not the case for ARE values. Based on the ARE results at the daily scale, LSTM performs better than FFN in all scenarios except scenario 6. The optimal FFN algorithm and scenario yield an ARE value of 4.5%, while LSTM under scenario 4 achieves an ARE value of 1.3%. Furthermore, comparing the RMSE values for LSTM under scenario 4 and FFN under the BR algorithm and scenario 6, it can be concluded that, at the daily scale, the LSTM model under scenario 4 outperforms the developed FFN models.

Comparing Tables 10 and Table 8, it is evident that LSTM models, under scenarios 1 to 5, are more suitable for estimating radiation data compared to certain FFN networks under RP and GD algorithms in specific scenarios. However, when comparing the best FFN algorithm with LSTM, it can be concluded that the FFN model, under scenario 6 and the BR algorithm, outperforms the LSTM model in all scenarios based on ARE values for both the

test and training datasets. Specifically, the FFN model achieves an ARE of 2.6%, an RMSE of 0.0013, and an R^2 of 0.9 for the test dataset when estimating radiation data on a monthly scale. In contrast, the LSTM model yields an ARE of 5.1%, an RMSE of 0.0015, and an R^2 of 0.9 for the test dataset. Similarly, for the training dataset, the FFN model achieves an ARE of 0.9%, an RMSE of 0.0065, and an R^2 of 0.96, while the LSTM model yields an ARE of 4.96%, an RMSE of 0.0015, and an R^2 of 0.90. Therefore, the FFN model under the BR algorithm and scenario 6 demonstrates the highest accuracy for estimating radiation data on a monthly scale.

The type of ANNs and their structure plays a crucial role in determining the accuracy of radiation estimation models, whether on a monthly or daily scale. It is essential to conduct a comprehensive analysis of various ANN architectures in order to obtain the most optimal models. Failing to prioritize this critical step can result in inaccurate estimations. Therefore, emphasizing the importance of this process is vital to ensure the highest level of precision in radiation estimations, benefiting numerous industries and applications.

Table 4. Training error and testing error for FFN on the daily scale

Information		Test					Train				
Scenario	Algorithm	RMSE	MAE	MBE	ARE	R^2	RMSE	MAE	MBE	ARE	R^2
1	LM	0.0020	0.0368	0.0027	5.939	0.8718	0.0021	0.0365	0.0120	6.0666	0.8739
	BR	0.0021	0.0368	0.0019	5.91	0.8718	0.0021	0.0364	0.0113	6.0092	0.8743
	GD	0.0025	0.04	0.0021	6.4747	0.8528	0.0024	0.039	0.0112	6.4973	0.8549
	RP	0.0023	0.0383	-0.0008	6.2549	0.8585	0.0023	0.0373	0.0081	6.3069	0.8622
2	LM	0.0015	0.0307	0.0009	5.0639	0.9037	0.0019	0.0332	0.0116	5.5771	0.8897
	BR	0.0015	0.0306	0.0006	5.0351	0.9042	0.0019	0.0332	0.0115	5.5543	0.8898
	GD	0.0113	0.0871	-0.0039	15.6181	0.3707	0.0115	0.0861	0.0107	15.7133	0.3653
	RP	0.0016	0.0313	0.0002	5.1693	0.9008	0.0019	0.0335	0.0104	5.6502	0.8874
3	LM	0.0015	0.0304	-0.0008	4.9874	0.9061	0.0018	0.0326	0.0108	5.4452	0.8943
	BR	0.0015	0.0305	-0.0008	4.9763	0.9063	0.0018	0.0325	0.0107	5.4202	0.8952
	GD	0.0173	0.099	-0.0102	18.0399	0.123	0.0172	0.0958	0.0187	17.957	0.1164
	RP	0.0015	0.0305	0.0001	4.9857	0.9066	0.0018	0.0328	0.0119	5.4699	0.8954
4	LM	0.0015	0.0302	0.0003	4.9656	0.9071	0.0017	0.0319	0.0111	5.3617	0.8992
	BR	0.0014	0.0297	-0.0005	4.8402	0.9107	0.0017	0.0321	0.011	5.3622	0.8984
	GD	0.0084	0.0695	0.0139	12.4382	0.4899	0.0123	0.0868	0.0253	15.2132	0.3034
	RP	0.0016	0.0314	0.0002	5.2248	0.8974	0.0018	0.0325	0.0102	5.5294	0.8931
5	LM	0.0015	0.0301	0.0005	4.9097	0.9083	0.0017	0.0321	0.0111	5.3367	0.899
	BR	0.0014	0.03	-0.0006	4.8589	0.9098	0.0017	0.0317	0.0102	5.2534	0.9007
	GD	0.0104	0.0786	-0.0002	13.5461	0.4139	0.0088	0.0704	0.007	12.7073	0.486
	RP	0.0016	0.0312	-0.0004	5.1395	0.8995	0.002	0.0344	0.0098	5.7848	0.8782
6	LM	0.0014	0.0294	-0.0032	4.7788	0.9127	0.0016	0.0306	0.0067	5.0899	0.9045
	BR	0.0013	0.0279	-0.0007	4.5406	0.919	0.0015	0.0299	0.0094	4.9118	0.9113
	GD	0.0056	0.0564	0.0053	9.2974	0.6754	0.0071	0.0663	0.0066	10.799	0.6228
	RP	0.0016	0.0308	-0.0005	5.0917	0.8988	0.0019	0.0335	0.0113	5.6144	0.8875

Table 5. Training error and testing error for FFN on the monthly scale

Information		Test					Train				
Scenario	Algorithm	RMSE	MAE	MBE	ARE	R ²	RMSE	MAE	MBE	ARE	R ²
1	LM	0.0324	0.0286	0.0283	4.3763	0.8172	0.0197	0.0159	-0.0039	2.2852	0.8464
	BR	0.0352	0.0316	0.0315	4.8451	0.816	0.0193	0.0159	-0.0014	2.2957	0.8485
	GD	0.0714	0.0604	0.0594	9.5134	0.8018	0.063	0.0518	0.0295	7.8709	0.8447
	RP	0.0349	0.0311	0.0311	4.7605	0.8116	0.0209	0.0175	0.0008	2.5481	0.824
2	LM	0.0318	0.0302	0.0302	4.6042	0.9159	0.0133	0.0106	-0.0031	1.5335	0.9314
	BR	0.0314	0.0297	0.0297	4.5371	0.9181	0.0134	0.0107	-0.0033	1.5539	0.9305
	GD	0.0931	0.0879	0.0879	13.6437	0.4656	0.0711	0.0577	0.0565	8.8611	0.7023
	RP	0.0309	0.0288	0.0288	4.3908	0.9053	0.0144	0.0113	-0.0023	1.6637	0.9170
3	LM	0.0366	0.035	0.035	5.3559	0.8993	0.0125	0.0098	-0.0003	1.4306	0.9355
	BR	0.0317	0.0303	0.0303	4.6264	0.9269	0.0131	0.0105	-0.0032	1.5222	0.9351
	GD	0.0745	0.0573	0.0529	8.9812	0.0013	0.0695	0.0596	0.0222	8.8349	0.0014
	RP	0.0376	0.0352	0.0352	5.3622	0.8662	0.0146	0.0118	-0.0017	1.7162	0.9142
4	LM	0.0298	0.028	0.028	4.2953	0.916	0.0132	0.0103	-0.0025	1.4822	0.9322
	BR	0.0303	0.0286	0.0286	4.3826	0.9164	0.0128	0.0102	-0.0026	1.4721	0.9365
	GD	0.0723	0.0585	-0.0267	8.8196	0.5796	0.1051	0.0888	-0.0497	12.5938	0.7756
	RP	0.0354	0.0327	0.0326	4.9927	0.8511	0.0152	0.0118	-0.0007	1.7344	0.9055
5	LM	0.0262	0.0239	0.0237	3.6477	0.9031	0.0131	0.0104	-0.0024	1.5185	0.9337
	BR	0.0258	0.0227	0.0223	3.5534	0.8645	0.0127	0.01	-0.0029	1.4423	0.937
	GD	0.055	0.0455	0.0439	7.1515	0.1023	0.0467	0.0407	0.0072	6.0116	0.1285
	RP	0.0254	0.0228	0.0226	3.4944	0.8889	0.0168	0.0136	-0.0028	1.9756	0.8871
6	LM	0.0262	0.0235	0.0235	3.5765	0.9025	0.0123	0.0096	0	1.3971	0.9381
	BR	0.0229	0.0176	0.0175	2.6646	0.8993	0.0098	0.0065	-0.0006	0.9633	0.961
	GD	0.0957	0.077	0.0709	12.1146	0.3595	0.0756	0.0627	0.0213	9.4259	0.2645
	RP	0.031	0.0269	0.0252	4.1016	0.7933	0.0155	0.0116	0.0002	1.6875	0.9098

Table 6. Training error and testing error for LSTM on the daily scale

scenario	Test					Train				
	RMSE	MAE	MBE	ARE	R ²	RMSE	MAE	MBE	ARE	R ²
1	0.028058	0.0241	0.0237	3.73	0.8154	0.022934	0.0173	-0.01039	2.47	0.829
2	0.021411	0.0193	0.0189	2.96	0.9128	0.017056	0.0134	-0.00652	1.95	0.897
3	0.014093	0.0112	0.0060	1.73	0.8672	0.01907	0.0157	-0.00392	2.30	0.856
4	0.011021	0.0088	0.0032	1.35	0.9129	0.013837	0.0103	0.001759	1.52	0.922
5	0.013642	0.0100	0.0042	1.56	0.8638	0.016435	0.0120	-0.00305	1.74	0.895
6	0.009453	0.0761	0.0587	13.65	0.4896	0.009511	0.0789	0.04891	14.25	0.415

Table 7. Training error and testing error for LSTM on the monthly scale

Scenario	Test					Train				
	RMSE	MAE	MBE	ARE	R ²	RMSE	MAE	MBE	ARE	R ²
1	0.002258	0.0369	-0.0100	5.89	0.865	0.001985	0.034	-0.0004	5.734	0.875
2	0.001939	0.0332	-0.0104	5.51	0.886	0.001936	0.033	-0.001	5.635	0.878
3	0.001758	0.0321	-0.0096	5.19	0.896	0.00176	0.032	0.0021	5.442	0.889
4	0.001574	0.0318	-0.0173	5.10	0.899	0.001526	0.029	-0.001	4.962	0.904
5	0.001873	0.0331	-0.010	5.42	0.889	0.001638	0.030	0.0013	5.192	0.897
6	0.008192	0.0634	0.0257	12.37	0.565	0.008145	0.060	0.0271	12.300	0.559

4. Conclusion

Solar radiation estimation plays a vital role in various fields, including energy production, architecture, health, and agriculture. In agriculture, it aids in assessing plant light requirements, irrigation planning, crop selection, optimizing crop performance, and weather forecasting. Consequently, it serves as a powerful tool for enhancing productivity and performance in the agricultural sector. The accuracy of radiation estimates in different scientific disciplines related to this essential parameter can be improved by collecting comprehensive and precise solar radiation data and addressing any statistical gaps.

The objective of this research is to enhance the accuracy of solar radiation estimation. Despite the complexity of meteorological variables, there exist varying correlations among different weather parameters, which depend on the influences and interactions between these variables. Initially, the correlation between meteorological variables and radiation was calculated at both monthly and daily scales. Variables exhibiting high correlations were selected for modeling purposes. FFN models were then trained using the chosen meteorological variables and various learning algorithms such as LM, BR, GD, and RP to estimate solar radiation under six different scenarios. LSTM network models were developed under similar scenarios. The performance of the models was evaluated using error evaluation criteria such as RMSE, MAE, ARE, MBE, and R² at both daily and monthly scales.

The research findings indicate that the LSTM model, under scenario 4, utilizing inputs including the sunshine hours fraction, saturated vapor pressure, mean daily temperature, and mean relative humidity, with the Adam algorithm, yields the best results for estimating daily radiation. It achieves an R² of 0.91 for the test dataset and an ARE of 1.35%. On a monthly scale, the FFN model, under the same scenario 6, employing the BR algorithm, demonstrates the highest performance for estimating the radiation variable. It achieves an R² of 0.96 for the training dataset, 0.92 for the testing dataset, and an ARE of 2.66% for the test dataset. Overall, the use of ANNs provides more precise estimations of radiation data in both short-term and long-term time scales compared to deep learning networks. Furthermore, the comparison of learning algorithms highlights the significant influence of ANN structure on the accuracy of model training. Therefore, conducting further research to evaluate the performance of different ANNs with varying structures in radiation estimation is imperative. By doing so, we can enhance the accuracy and reliability of radiation data, which holds significant implications across various fields.

Nomenclature

<i>ANN</i>	Artificial Neural Network
<i>FFN</i>	Feed-Forward Neural Network
<i>LSTM</i>	Long Short-Term Memory
<i>GD</i>	Gradient Descent Learning Algorithm

<i>BR</i>	Bayesian Regularization Learning Algorithm
<i>RP</i>	Resilient Propagation Learning Algorithm
<i>LM</i>	Levenberg–Marquardt Learning Algorithm
<i>R_s</i>	observed solar radiation (W/m ²)
<i>R_{cd}</i>	daily clear sky radiation (W/m ²)
<i>R₀</i>	extraterrestrial daily radiation (W/m ²)
<i>N_n</i>	sunshine hours fraction
<i>SVP</i>	Saturated Vapor Pressure (mb)
<i>MAT</i>	Mean Air Temperature (°C)
<i>MRH</i>	Mean Relative Humidity (%)
<i>MST</i>	Mean Soil Temperature (°C)
<i>HV</i>	Horizontal Visibility (m)
<i>MW</i>	Mean Wind speed (m/s)
<i>DP</i>	Dew Point temperature (°C)
<i>WB</i>	Wet Bulb temperature (°C)
<i>P</i>	Pressure (mb)
<i>C</i>	Cloudiness (Okta)
<i>MAE</i>	Mean Absolute Error
<i>RMSE</i>	Root Mean Squared Error
<i>MBE</i>	Mean Bias Error
<i>R²</i>	R-square

Conflict of Interest: There is no conflict associated with this manuscript

Funds Association: There is no fund associated with this manuscript

References

- [1] Wild M. (2009). Global dimming and brightening: a review. *Journal of Geophysical Research*, 114. <http://doi.org/10.1029/2008JD011470>.
- [2] Asaf, D., Rotenberg, E., Tatarinov, F., Dicken, U., Montzka, S.A., and Yakir, D. (2013). Ecosystem photosynthesis inferred from measurements of carbonyl sulphide flux. *Nature Energy*, 6(3), 186–190. <https://doi.org/10.1038/NGEO1730>.
- [3] Gurel, A., Agbulut, U., Bakır, H., Ergun, A., and Yıldız, G. (2023). A state of art review on estimation of solar radiation with various models. *Heliyon*, 9(2), 13167. <https://doi.org/10.1016/j.heliyon.2023.e13167>
- [4] Gueymard, C.A., and Myers, D.R. (2008). Validation and ranking methodologies for solar radiation models. In *Modeling Solar Radiation at the Earth's Surface*. Springer, Berlin, Germany, 479–481. https://doi.org/10.1007/978-3-540-77455-6_20.
- [5] Abraha, M.G., and Savage, M.J. (2008). Comparison of estimates of daily solar radiation from air temperature range for application in crop simulations. *Agricultural and Forest Meteorology*, 148(3), 401–416. <https://doi.org/10.1016/j.agrformet.2007.10>.

- [6] Bouat, K., Othman, A., and Besbes, M. (2018). Estimation of Global and Direct Solar Radiation in Tunisia Based on Geostationary Satellite Imagery. IEEE PES/IAS PowerAfrica, 190-194. <http://doi.org/10.1109/PowerAfrica.2018.8521155>.
- [7] Meenal, R., and Selvakumar, A.I. (2017). Review on artificial neural network based solar radiation prediction. International Conference on Communication and Electronics Systems (ICCES), Coimbatore, 302-305. <https://doi.org/10.1109/CESYS.2017.8321285>.
- [8] Zeng, J., and Qiao, W. (2011). Short-Term Solar Power Prediction using an RBF Neural Network. IEEE Power and Energy Society General Meeting, <https://doi.org/10.1109/PES.2011.6039204>
- [9] Shamshirband, S., Mohammadi, K., Chen, H.L., Samy, G.N., Petkovic, D., and Ma, C. (2015). Daily global solar radiation prediction from air temperatures using kernel extreme learning machine: A case study for Iran. Journal of Atmospheric and Solar-Terrestrial Physics, 134, 109–117. <http://doi.org/10.1016/j.jastp.2015.09.014>
- [10] Ertekin, C., and Yaldız, O. (1999) Estimation of monthly average daily global radiation on horizontal surface for Antalya (Turkey). Renewable Energy, 17(1), 95–102. [https://doi.org/10.1016/s0960-1481\(98\)00109-8](https://doi.org/10.1016/s0960-1481(98)00109-8).
- [11] Besharat, F., Dehghan, A.A., and Faghih, A.R. (2013). Empirical models for estimating global solar radiation: A review and case study. Renewable and Sustainable Energy Reviews, 21, 798–821. <https://doi.org/10.1016/j.rser.2012.12.043>.
- [12] Camacho, E.F., Berenguel, M., Rubio, F.R., and Martínez, D. (2012). Control of Solar Energy Systems. Springer, London, UK, <http://dx.doi.org/10.1007/978-0-85729-916-1>.
- [13] Yadav, A.K., and Chandel, S.S. (2014). Solar radiation prediction using Artificial Neural Network techniques: A review. Renewable and Sustainable Energy Reviews, 33, 772–781. <https://doi.org/10.1016/j.rser.2013.08.055>.
- [14] Qazi, A., Fayaz, H., and Wadi, A. (2015). The artificial neural network for solar radiation prediction and designing solar systems: A systematic literature review. Journal of Cleaner Production, 104, 1–12. <https://doi.org/10.1016/j.jclepro.2015.04.041>.
- [15] Abdulazeez, M.A. (2011). Artificial neural network estimation of global solar radiation using meteorological parameters in Gusau, Nigeria. Archives of Applied Science Research, 3(2), 586–595.
- [16] Bian, Z., Chong, W., Ding, L., and Yang, W. (2019). Analysis and research on quality control method of global radiation observation data. The Journal of Engineering, 23, 8975-8979. <https://doi.org/10.1049/joe.2018.9161>.
- [17] Moradi, I. (2009). Quality control of global solar radiation using sunshine duration hours. Energy, 34, 1-6. <https://doi.org/10.1016/j.energy.2008.09.006>.
- [18] Benesty, J., Chen, J., and Huang, Y. (2008). On the importance of the Pearson correlation coefficient in noise reduction. IEEE Transactions on Audio, Speech, and Language Processing, 16(4), 757–765. <https://doi.org/10.1109/TASL.2008.919072>.
- [19] Edelman, D., Mori, T.F., and Szekely, G.J. (2021). On relationships between the Pearson and the distance correlation coefficients. Statistics & Probability Letters, <https://doi.org/10.1016/j.spl.2020.108960>.
- [20] Bohat, V.K., and Arya, K.V. (2018). An effective gbest-guided gravitational search algorithm for real-parameter optimization and its application in training of feedforward neural networks. Knowledge-Based Systems, 143, 192–207. <https://doi.org/10.1016/j.knosys.2017.12.01>.
- [21] Heaton, J. (2008). Introduction to Neural Networks with Java 26-29. <http://www.heatonresearch.com/book/programming-neural-networks-java.html>.
- [22] Okut, H. (2016). Bayesian Regularized Neural Networks for Small n Big p Data. Artificial Neural Networks Models and Applications, <https://doi.org/10.5772/63256>.
- [23] Moshkbar-Bakhshayesh, K. (2021). The ensemble approach in comparison with the diverse feature selection techniques for estimating NPPs parameters using the different learning algorithms of the feedforward neural network. Nuclear Engineering and Technology, 53(12), 3944–3951. <https://doi.org/10.1016/j.net.2021.06.030>.
- [24] Moshkbar-Bakhshayesh, K. (2019). Development of a modular system for estimating attenuation coefficient of gamma radiation: comparative study of different learning algorithms of cascade feedforward neural network. Journal of Instrumentation, 14(10), 10010. <https://doi.org/10.1088/1748-0221/14/10/p10010>.
- [25] Yang, F., Gao, P., and Lu, Y. (2016). Evolving Resilient Back-Propagation Algorithm for Energy Efficiency Problem. MATEC Web of Conferences 77, 06016. <https://doi.org/10.1051/mateconf/20167706016>.

- [26] James, T.O., Gulumbe, S.U., and Danbaba, A. (2018). Resilient Back-Propagation Algorithm in the Prediction of Mother to Child Transmission of HIV. *Open Access Library Journal*, 5, 1-7. <https://doi.org/10.4236/oalib.1104538>.
- [27] Reddy, L.R., Patel, P., Rajendra, S.K. (2020). Utilization of Resilient Back Propagation Algorithm and Discrete Wavelet Transform for the Differential Protection of Three Phase Power Transformer. 21st National Power Systems Conference (NPSC), <https://doi.org/10.1109/npsc49263.2020.9331861>.
- [28] Hochreiter, S., and Schmidhuber, J. (1997). Long short-term memory. *Neural Computation*, 9, 1735–1780. <https://doi.org/10.1038/nature14539>.
- [29] Pan, B., Yu, H., Cheng, H., Du, S., Cai, S., Zhao, M. (2023). A CNN–LSTM Machine-Learning Method for Estimating Particulate Organic Carbon from Remote Sensing in Lakes. *Sustainability*, 5(17), 13043. <https://doi.org/10.3390/su151713043>.
- [30] Tasie, N., Israel-Cookey, C., and Banyie, L. (2018). The Effect of Relative Humidity on the Solar Radiation Intensity in Port Harcourt, Nigeria. *International Journal of Research*, 5,128-136. <https://pen2print.org/index.php/ijr/>
- [31] Jebli, I., Belouadha, F.Z., Kabbaj, M.I., and Tilioua, A. (2021). Prediction of solar energy guided by pearson correlation using machine learning. *Energy*, 224,120109. <https://doi.org/10.1016/j.energy.2021.120109>
- [32] Fraihat, H., Almbaideen, A.A., Al-Odienat, A., Al-Naami, B., De, Fazio, R., and Visconti, P. (2022). Solar Radiation Forecasting by Pearson Correlation Using LSTM Neural Network and ANFIS Method: Application in the West-Central Jordan. *Future Internet*, 14-79. <https://doi.org/10.3390/fi14030079>
- [33] Fischer, T., and Krauss, C. (2018). Deep learning with long-term memory networks for financial market predictions. *European Journal of Operational Research*. FAU Discussion Papers in Economics., <https://ideas.repec.org/p/arx/papers/1803.06386.html>