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One-Step-Ahead Solar Radiation Forecasting Using Bi-LSTM and GRU Models in Semi-Desert Climates

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Solar Radiation Forecasting, Solar Energy, Time series, Artificial Neural Networks.

ABSTRACT

The increasing demand for energy and the imperative to reduce greenhouse gas emissions have heightened the need for renewable energy sources. Hence, there has been a notable surge in research efforts focused on advancing solar energy forecasting. The aim of this study is to forecast solar radiation using Deep Neural Network models, including Bidirectional Long Short-Term Memory (BiLSTM) and Gated Recurrent Unit (GRU), based on historical solar radiation values recorded at half-hour intervals in a semi-desert climate over a two-year period starting in January 2020.

To assess and compare the accuracy of the two Deep Neural Networks (DNNs), various evaluation metrics were used, including Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), Maximum Error, and R-squared (R^2). Solar radiation predictions were carried out based on the values recorded over the previous twenty-four hours at half-hour intervals. The results obtained indicate that both forecasting models achieve exceptional accuracy in one-step-ahead solar radiation prediction, with correlation coefficients exceeding 97.2%. This highlights the strong potential of Gated Recurrent Unit (GRU) and Bidirectional Long Short-Term Memory (BiLSTM) models for optimizing and estimating solar radiation. Consequently, these models can be effectively used to estimate solar energy production, thereby enhancing the control and efficiency of solar energy systems. However, the study also highlights challenges in forecasting under partial cloud cover, where sudden fluctuations in solar radiation adversely

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affect prediction accuracy. Addressing these complexities could further improve the robustness of forecasting models and enhance their practical applicability in semi-desert climates.

التنبؤ بإشعاع الشمس بخطوة واحدة باستخدام نماذج Bi-LSTM و GRU في المناخات شبه الصحراوية

عبد اللطيف ايت منصور، يوسف البوطاهري، أمين تيليوا

ملخص: أدى تزايد الطلب على الطاقة والضرورة الملحة للحد من انبعاث الغازات الدفيئة إلى زيادة الإقبال على مصادر الطاقة المتجددة، مما نتج عنه ارتفاع ملحوظ في الأبحاث العلمية في مجال التنبؤ بالطاقة الشمسية. تهدف هذه الدراسة إلى التنبؤ بالإشعاع الشمسي باستخدام شبكات عصبية عميقة (DNNs)، بما في ذلك الشبكات العصبية ثنائية الاتجاه ذات الذاكرة القصيرة والطويلة (BiLSTM) والوحدات المتكررة المغلقة) GRU(، وذلك باستخدام بيانات الإشعاع الشمسي المسجلة بفاصل نصف ساعة في منطقة ذات مناخ شبه صحراوي على مدى عامين بدءًا من يناير 2020. لتقييم ومقارنة دقة النموذجين، تم استخدام مقاييس تقييم مختلفة ،منها الجذر التربيعي لمتوسط الخطأ التربيعي) RMSE(، متوسط الخطأ المطلق) MAE(، الخطأ الأقصى(ME)، ومعامل تحديد التباين (R^2). تم إجراء التنبؤات استنادًا إلى القيم المسجلة خال الأربع وعشرين ساعة الماضية. أظهرت النتائج قدرة النموذجين على التنبؤ بدقة استثنائية بالإشعاع الشمسي لخطوة واحدة مقدمة، حيث تجاوزت معامات تحديد التباين 2.97 %، مما يشير إلى الإمكانات الواعدة لنموذجي وحدة التكرار المغلقة (GRU) والذاكرة طويلة وقصيرة الأمد ثنائية الاتجاه (BiLSTM) في تحسين توقعات الإشعاع الشمسي. وبالتالي، يمكن استخدامهما لتقدير كمية إنتاج الطاقة في أنظمة الطاقة الشمسية، مما يساهم في تحسين كفاءة هذه الأنظمة وتسهيل التحكم فيها. كما كشفت الدراسة تحديات في التنبؤ خال الطقس المغيم جزئيًا، حيث تؤثر التقلبات المفاجئة في الإشعاع الشمسي على دقة التنبؤ. ويمكن لمعالجة هذه التعقيدات أن تسهم في تحسين نماذج التنبؤ وتعزيز تطبيقها العملي في المناخات شبه الصحراوية.

الكلمات المفتاحية – لتنبؤ بإشعاع الشمس؛ الطاقة الشمسية؛ السلاسل الزمنية؛ الشبكات العصبية الاصطناعية.

1. INTRODUCTION

The world is currently at a turning point in its search for green and sustainable energy [1], which will help both to fulfill the growing global energy demand [2] and to lower greenhouse gas (GHG) emissions by decreasing reliance on fossil fuels [3]. Among renewable energy sources (RES), solar energy has emerged as a prominent and environmentally friendly option for power generation [4], due to its high scalability [5], rapid growth, low operation and maintenance costs [6], and the widespread availability of sunlight [7]. According to the IEA's 2023 report on renewables [8], global renewable electricity capacity additions reached approximately 507 GW, an increase of nearly 50% compared to the previous year. This remarkable acceleration was primarily driven by the People's Republic of China, which saw substantial growth in both the solar PV (+116%) and wind (+66%) markets. Projections suggest that by 2028, global renewable electricity generation could reach around 14,400 TWh, representing a significant 70% increase compared to 2022 levels. The solar photovoltaic (PV) and wind sectors are expected to continue their expansion in the coming years, accounting for 96% of total renewable power capacity additions by 2028. Furthermore, solar PV is projected to surpass nuclear electricity generation by 2026, and wind power by 2028. Despite the promising future of solar PV, solar energy systems still face several challenges. Since their production depends directly on sunlight availability, they are sometimes referred to as unreliable source due to their unpredictability and intermittency, because of their dependency on weather conditions such as cloud cover and daylight hours [9,10].These factors make it difficult to integrate this source into electrical grids and balance supply with demand. To address these challenges, accurate solar radiation forecasting is essential for increasing the potential and profitability of solar energy as a clean and sustainable power source [11]. It enables better planning of energy distribution and grid management, optimizes energy production to meet demand, reduces dependency on fossil fuels, and helps mitigate greenhouse gas (GHG) emissions [12]. This, in turn, leads to cost reductions associated with solar energy systems [6]. It is therefore essential to consider accurate solar radiation forecasting, for the purpose of maximizing solar energy production, integrating solar power into the grid, facilitating energy trading, guiding infrastructure planning, evaluating environmental impacts, managing risks, and assessing solar resources. In this context, deep neural network (DNN) models have emerged as an innovative approach due to their ability to approximate complex functions, particularly nonlinear ones [13]. They can identify hidden correlations in large and complex datasets and leverage them to make both short- and long-term predictions. In recent years, research has increasingly focused on developing advanced forecasting strategies using DNNs for both one-step and multistep ahead predictions. Since their introduction to the field of solar energy forecasting, deep neural network (DNN) time series models have demonstrated notable accuracy, often outperforming traditional methods for one-step ahead forecasting [14]. Despite these promising results, the use of Bidirectional Long Short-Term Memory (Bi-LSTM) and Gated Recurrent Unit (GRU) models remains relatively uncommon in this field [11]. The aim of this study is to forecast solar radiation using deep neural network (DNN) models, specifically Bidirectional Long Short-Term Memory (Bi-LSTM) and Gated Recurrent Unit (GRU), based on real solar radiation data measured in a semi-desert region in southern Morocco. The investigation focuses on evaluating the accuracy of these models while also addressing the challenges of forecasting under partial cloud cover. The following sections detail the methods used in this study, with particular emphasis on assessing and improving the predictive performance of the two DNN models.

2. RELATED WORKS

The power output of a photovoltaic (PV) panel depends on its technology, geometric characteristics, and environmental parameters such as solar radiation and temperature [15,16]. It can be estimated using the following equation:

$$P_{out,PV} = C_{R,PV} \frac{G_T}{G_{T,STC}} [1 + \alpha_P (T_C - T_{C,STC})] \tag{1}$$

where:

$C_{R,PV}$ is the rated power of the PV array (W), G_T and $G_{T,STC}$ are the solar radiation incident on the PV array in the current time step and at standard test conditions (W/m^2). α_P is the temperature coefficient of power (%/°C), while T_C and $T_{C,STC}$ are PV cell temperature in current time step and standard test conditions (°C).

Estimating the power output of PV panels is challenging due to the intermittent and chaotic nature of solar radiation, as well as atmospheric conditions that are inherently unpredictable, as highlighted by Law et al. [17]. Nevertheless, forecasting solar radiation in advance enables better management of electricity production by maximizing the use of this renewable energy source. Numerous studies have been conducted to address the challenges of solar energy forecasting. For instance, Jebli et al. [16] evaluated the predictive performance of four machine learning (ML) models—Linear Regression (LR), Random Forest (RF), Support Vector Regression (SVR), and Artificial Neural Network (ANN)—using a dataset collected in the Errachidia region between 2016 and 2018. Their results showed that RF (MAE = 67.33; R^2 = 0.58) and ANN (MAE = 30.3; R^2 = 0.93) outperformed LR (MAE = 79.2; R^2 = 0.31) and SVR

(MAE = 77.4; R^2 = 0.44). Among all the models tested, ANN delivered the most accurate predictions for daily solar energy.

M. Neshat et al. [18] introduced a novel method for predicting solar radiation one hour ahead, which integrates a hybrid deep residual learning model with gated Long Short-Term Memory recurrent networks, enhanced by a differential covariance matrix adaptation evolution strategy (ADCMA). Their research highlights that employing (ADCMA) significantly improves the accuracy of solar radiation predictions. Consequently, their approach demonstrates superior performance compared to other machine learning and hybrid deep learning techniques. To address the uncertainty associated with cloud evolution, A. Carpentieri et al. [19] introduced a probabilistic surface solar radiation forecasting method based on cloud-scale-dependent autoregressive advection. In their study, they present a probabilistic optical flow model, called SolarSTEPS, which simulates the temporal variability of cloud cover. The model is implemented in Python using the Pysteps library, originally designed for precipitation nowcasting. SolarSTEPS improves forecast accuracy by decomposing cloudiness into multiple spatial scales, resulting in a 9% reduction in Root Mean Square Error (RMSE).

3. METHODS

3.1. About the dataset

The dataset used in this study was collected in Errachidia, a region in southern Morocco characterized by a semi-desert climate. Solar radiation measurements were recorded at half-hour intervals over a two-year period, starting in January 2020. In total, 35,040 samples were collected, equivalent to 48 samples per day over two years.

3.2. Forecasting strategies

This study aims to predict the future value of solar radiation based on both current ($\hat{y}_{t+1}$) and past measurements ($y_t, y_{t-1}, y_{t-2}, \ldots, y_{t-k}$). The forecasting problem can be formulated as follows:

$$\hat{y}_{t+1} = f(y_t, y_{t-1}, y_{t-2}, \ldots, y_{t-k}) \tag{2}$$

Where:

f represents the forecasting model, and y_t, y_{t-1}, y_{t-2}, …, y_{t-k} are the actual and past values of the time series which will be utilized to predict the anticipated $\hat{y}_{t+1}$.

To this end, the dataset was transformed into a float array with 34,992 rows and 48 columns. It was then split into three parts: training set (70%), testing set (15%), and validation set (15%). The choice of 48 columns corresponds to the data recorded over the past 24 hours, allowing the model to estimate the next value based solely on this timeframe

3.2. About the DNNs

In this study, Bi-LSTM and GRU models were selected for their proven ability to effectively handle sequential dependencies, capture temporal patterns, and manage long-term relationships in time-series data. The bidirectional structure of Bi-LSTM enables learning from both past and future contexts, resulting in more comprehensive pattern recognition, while the simplified architecture of GRU reduces computational complexity without sacrificing performance. These characteristics make both models well-suited for accurately forecasting solar radiation, where historical patterns and temporal dynamics are critical. Despite their advantages, these models have been rarely applied to solar radiation prediction, which adds a novel aspect to this research. Both deep neural network models were implemented using the Keras library. Table 1 illustrates the architecture of these models. They were compiled using the Adam optimizer with a learning rate of 0.001.

Table 1: The architecture of the two studied Deep Neural Networks.

Model	Layer Type	Output Shape	Number of Parameters	Total Parameters
GRU	GRU	(None, 64)	12,864	13,393
	Dense	(None, 8)	520	
	Dense	(None, 1)	9	
Bi-LSTM	Bidirectional LSTM	(None, 128)	33,792	34,833
	Dense	(None, 8)	1,032	
	Dense	(None, 1)	9	

3.3. Performances evaluation

Evaluating the precision of a machine learning model is essential for assessing its effectiveness and understanding its ability to generalize to unseen data. To evaluate the performance of the proposed deep neural network models, several metrics have been employed, including Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), Maximum Error, and the coefficient of determination (R^2). These metrics are defined by equations (2) through (5), respectively.

$$MAE = \frac{1}{N}\sum_{i=1}^{N} \mid y_i - \hat{y}_i \mid \tag{3}$$

$$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^{N}(y_i - \hat{y}_i)^2} \tag{4}$$

$$ME = \max_{1 \le i \le N} \mid y_i - \hat{y}_i \mid \tag{5}$$

$$R^2 = 1 - \frac{SS_{res}}{SS_{tot}} \tag{6}$$

Where: N refers to the number of samples, y_i is the measured solar radiation value, $\hat{y}_i$ is the predicted solar radiation value, SS_{res} refers to the sum of squares of residuals and SS_{tot} Sum of Squares Total denotes the total sum of squares.

4. RESULTS AND DISCUSSION

This section presents and analyzes the results obtained from the proposed deep neural network forecasters. Table 2 summarizes the performance of the models using various error metrics, along with the coefficient of determination (R^2). The values of MAE, ME, and RMSE—which quantify the magnitude of errors between actual and predicted solar radiation—are found to be consistent across the training, testing, and validation datasets. This consistency indicates that the models exhibit robust generalization capabilities, performing effectively on unseen datasets.

Figure 1 illustrates the measured and forecasted solar radiation using (a) BiLSTM and (b) GRU models across the training, validation, and testing phases over a two-year period. The first 70% of the dataset, shown in blue, was used for training, while the remaining 30% was equally divided between validation (15%, green) and testing (15%, cyan).

The plots display a characteristic bell-shaped profile for each year, representing seasonal variations, with daily peaks corresponding to maximum solar radiation levels. Both models effectively capture these daily fluctuations, demonstrating their ability to learn and generalize temporal patterns present in the data.

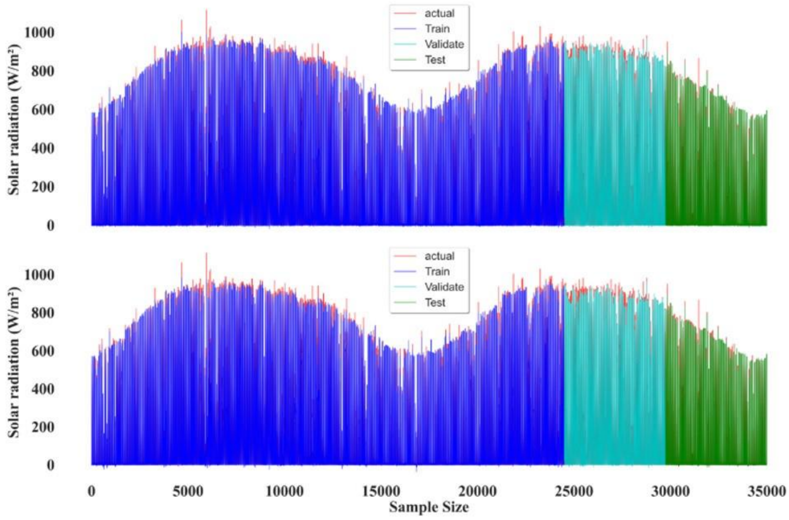

Figure 1: Measured and forecasted solar radiation using a) BiLSTM and b) GRU during training, validation, and testing.

The high sampling frequency of 48 observations per day allows for a detailed representation of solar radiation dynamics, resulting in a close match between the measured and predicted values.

Table 2: Statistical errors metrics for the two forecasters.

		ME	MAE	RMSE	R2 (%)
Bi LSTM	train	731	15.54	41.04	98.2
	validate	542	18.20	48.89	97.9
	test	468	12.85	35.20	97.9
GRU	train	719	15.57	40.99	98.2
	validate	531	18.65	48.82	97.9
	test	460	12,23	34.69	97.9

Table 3: Confidence intervals for key performance metrics for BiLSTM.

Metric	Train	Test	Validate
ME	[520.1, 731.3]	[364.9, 468.7]	[411.5, 542.7]
MAE	[15.07, 15.99]	[12.00, 13.74]	[16.97, 19.41]
RMSE	[39.43, 42.55]	[32.11, 38.40]	[45.28, 52.60]
R^2	[0.980, 0.983]	[0.975, 0.982]	[0.975, 0.982]

Table 4. Confidence intervals for key performance metrics for GRU

Metric	Train	Test	Validate
ME	[513.0, 719.6]	[381.3, 460.0]	[402.6, 531.4]
MAE	[15.11, 16.08]	[11.40, 13.09]	[17.42, 19.85]
RMSE	[39.40, 42.78]	[31.62, 37.78]	[45.36, 52.39]
R^2	[0.980, 0.983]	[0.976, 0.983]	[0.976, 0.982]

The low values of MAE and RMSE, combined with R^2 scores ranging from 97.9% to 98.2% as presented in Table 2, demonstrate the high predictive accuracy of both models. These results highlight the strong potential of GRU and Bi-LSTM architectures for reliable solar radiation forecasting, making them promising tools for energy planning and grid management applications. The R2 values reflect the model's ability to explain the observed variance within the data, with higher R2 values indicating a more robust linear correlation between predicted and actual values of solar radiation. Both DNNs models achieve remarkable R2 scores surpassing 97.9%, indicating an exceptionally high level of explained variance. This implies that the models are effectively capturing the underlying patterns present in the dataset and are able to predict solar radiation with a high degree of accuracy. Furthermore, the solid linear correlation suggests that the models are not only accurate but also consistent in their predictions across different instances of solar radiation data. To further validate the reliability and robustness of the forecasting models, 95% confidence intervals were calculated for the key performance metrics MAE, RMSE, R^2, and ME for both BiLSTM (Table 3) and GRU (Table 4).

The confidence intervals were estimated using a bootstrapping approach with 1,000 iterations, providing valuable insight into the variability and stability of the forecasting models. These confidence intervals provide a deeper insight into the models' precision, complementing the results presented in Table 2. The narrow ranges of the intervals indicate that both models consistently maintain a high level of predictive accuracy across various conditions, further reinforcing their effectiveness in forecasting solar radiation.

The visual representations in Figures 1, 2, and 3 further support the findings presented in Table 2 regarding the performance of the Deep Neural Network (DNN) models in predicting solar radiation. In particular, the scatter plots shown in Figures 2 and 3 illustrate the correlation between the predicted and actual solar radiation values, providing a visual assessment of model accuracy and consistency.

Figure 2 shows predicted versus measured solar radiation values during the testing phase for both BiLSTM and GRU models.

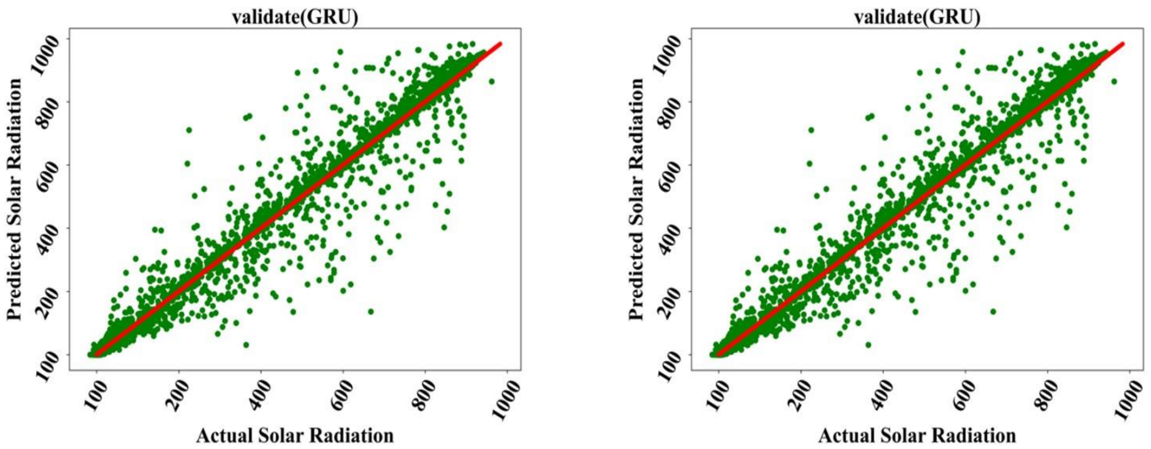

Figure 2. Measured versus forecasted solar radiation during validating phase.

While most of the data points are closely aligned with the diagonal line, indicating strong agreement between predicted and actual values, some points deviate further from the line. These outliers suggest that both models face difficulties accurately forecasting certain samples in the dataset, likely due to irregular weather conditions like partial cloud cover. These deviations help explain the higher Max Error values observed in Table 2, highlighting areas where model performance could be further improved.

Figure 3 present predicted versus measured solar radiation values during the validation phase for both BiLSTM and GRU models. The majority of points are near the diagonal line, demonstrating the models' ability to generalize well. However, the presence of a few outliers indicates that the models struggle to handle certain complex or unpredictable scenarios in the data. This difficulty is reflected in the higher Max Error values shown in Table 2, emphasizing the need for potential adjustments or enhancements to improve performance in such cases.

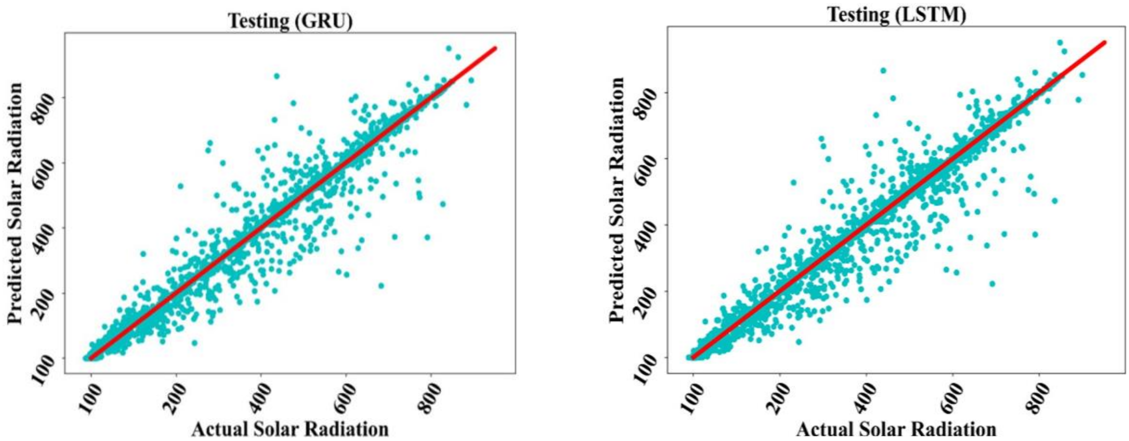

Figure 3. Measured versus forecasted solar radiation during testing phase.

To gain deeper insight into where the models struggle to accurately predict solar radiation, we present the measured and predicted values during a sunny day and a cloudy day in Figure 4. The comparison helps illustrate the models' performance under stable, predictable conditions versus more volatile, non-stationary scenarios. While both models show accurate predictions on sunny days, discrepancies become more evident on cloudy days, where sudden fluctuations in solar radiation pose a challenge. These discrepancies indicate the limitations of the models in handling rapid, irregular variations, helping to explain the higher Max Error values observed in Table 2. Understanding these challenges provides valuable insight for further model refinement.

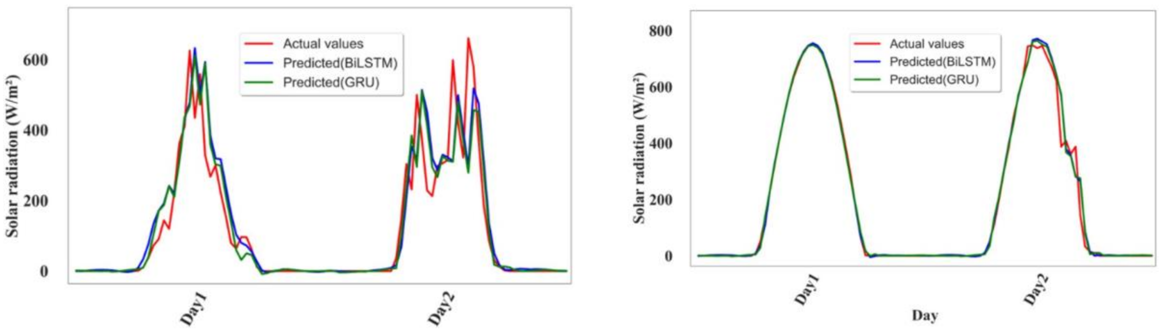

Figure 4. Measured and forecasted solar radiation under partial cloud cover and sunny days.

Figures 5 and 6 illustrate the absolute errors of the two models during partial cloud cover and sunny days, respectively, providing valuable insights into the challenges faced by the deep neural network (DNN) models when forecasting solar radiation under varying weather conditions.

The higher absolute errors observed during partial cloud cover compared to sunny days highlight the challenges the models face in accurately predicting solar radiation under less predictable weather conditions. The non-stationarity of the dataset, driven by the chaotic nature of weather phenomena, introduces significant unpredictability and variability, complicating the forecasting task. This underscores the need for continued research and model refinement to better capture and address the effects of such complex weather conditions.

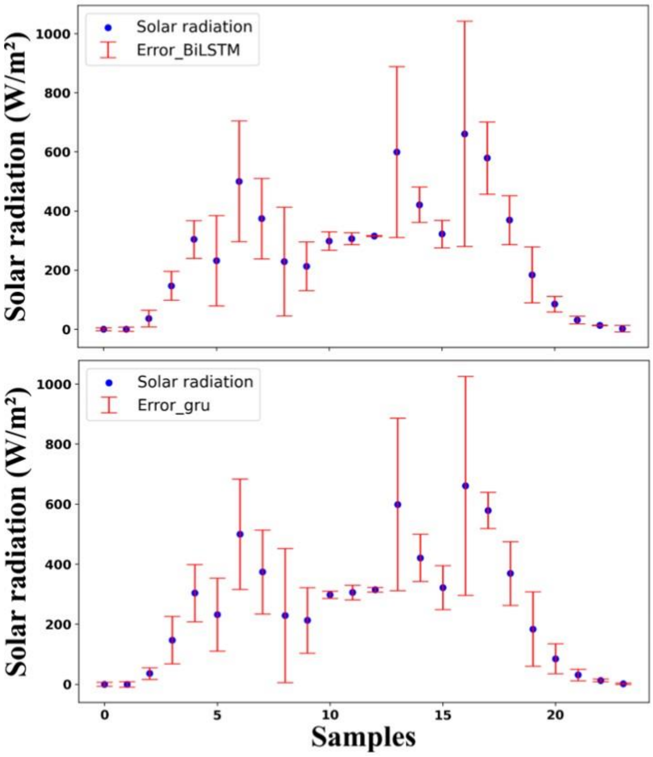

Figure 5. Actual solar radiation scatter plot and the absolute error of the two models during a cloudy day.

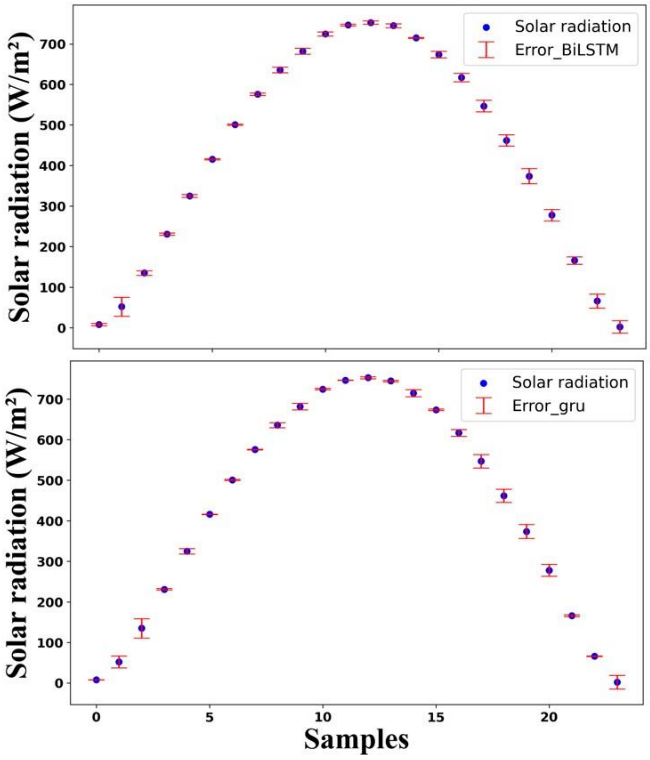

Figure 6. Actual solar radiation scatter plot and the absolute error of the two models during a sunny day.

To offer context and compare the performance of our models, Table 5 presents the forecasting errors obtained from a previous study conducted in the same semi-desert region using data from 2016 to 2018. This earlier work employed traditional machine learning techniques such as Random Forest (RF), Artificial Neural Networks (ANN), Linear Regression (LR), and Support Vector Regression (SVR), selecting relevant meteorological inputs through the Pearson correlation coefficient. While RF and ANN achieved relatively higher accuracy than LR and SVR, their performance still falls short compared to the Bi-LSTM and GRU models explored in our study, as demonstrated in Table 2. This comparison underscores the enhanced capacity of deep learning models to handle complex, non-linear, and temporal dependencies in solar radiation forecasting.

Table 5: Statistical errors metrics for a previous study [16].

Model	ME	MAE	RMSE	R^2 (%)
ANN	245.7	30.3	44.49	93
RF	483.5	67.33	96.94	58
SVR	551.13	77.4	109.17	44
LR	1345.74	79.2	155.86	31

5. ONCLUSION

This paper presents the development of GRU and BiLSTM models for one-step ahead forecasting of solar radiation. The dataset used for training and evaluation was collected in the east-central region of Morocco. The study findings indicate that both the Bidirectional Long Short-Term Memory and Gated Recurrent Unit (GRU)-based forecasters effectively avoided overfitting. The study also demonstrates the capability of these forecasting models to provide highly accurate predictions, achieving correlation coefficients within the range of 97.9% to 98.2%.

These results underscore the strong potential of BiLSTM and GRU models as forecasting tools for optimizing solar energy production, improving system efficiency, and contributing to more effective grid management. In addition to the strong performance demonstrated by these models, a comparison with previous studies conducted in the same region further highlights their effectiveness. Traditional machine learning approaches like RF and ANN, while achieving satisfactory results, showed limitations compared to the deep learning models explored in this study. This emphasizes the capability of BiLSTM and GRU to better capture complex temporal dependencies and non-linear patterns in solar radiation forecasting.

However, the study identifies challenges faced by these two forecasters when forecasting under partial cloud cover—mainly due to non-stationarity in the dataset. This underscores the importance of ongoing model development and refinement to effectively address such weather conditions.

In our future work, we aim to enhance the predictive performance of the models by incorporating additional meteorological variables, such as cloud cover, temperature, and wind speed, which are known to influence solar radiation. Moreover, we plan to explore hybrid modelling techniques, combining BiLSTM and GRU with advanced approaches like ensemble learning, transfer learning, or attention mechanisms, to more effectively capture non-linear patterns and manage the complexities associated with variable weather conditions. These improvements could not only address the identified limitations but also provide a more robust forecasting framework applicable in diverse semi-desert climates.

Authors contribution: Abdellatif Ait Mansour: Conceptualization, Model Development, Methodology, Simulation, Writing – Original Draft.

Youssef Boutahri: Visualization, Data Analysis, Review & Editing.

Amine Tilioua: Validation, Supervision, Data Analysis, Review & Editing.

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Conflicts of Interest: The authors declare no conflict of interest.

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