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Deep learning based photovoltaic generation on time series load forecasting

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ABSTRACT

In recent years, solar irradiance forecasting has become essential to managing, developing, and effectively integrating photovoltaic (PV) systems properly into the smart grid. The foundation of a conventional variational autoencoder (VAE) is an entirely coupled layer that includes both decoder and encoder components. In this study, a novel deep attention-driven model for forecasting named bidirectional long short-term memory (BiLSTM) which is combined with the VAE model is introduced as an enhanced version of the VAE. BiLSTM is integrated at the encoder side of VAE to effectively extract and learn temporal dependencies that are embedded in the panel irradiance data. Additionally, a self-attention mechanism (SAM) is added to bilateral variational autoencoder (BiVAE) which is known as BiVAE-SAM that highlights the important characteristics. The proposed BiVAE-SAM permits the VAE's capacity to design the temporal dependency. The examined models are assessed using sun irradiance measurements from New York City, Turkey, Canopy, Los Angeles, California, and Florida. The outcomes exhibit that the proposed BiVAE-SAM model performs better mean absolute percentage error (MAPE) with values of 1.7935, 0.7828, 1.3491 and 2.8346 respectively for California, Los Angeles, New York City, and Florida, over existing stacked denoising auto-encoders (SDA) model at projecting solar irradiance.

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1. INTRODUCTION

Nowadays, solar energy is a well-known renewable source since it is plentiful and environmentally beneficial [1]. As a result, photovoltaic (PV) has become increasingly important in the generation of power in recent years. The increasing number of PV power systems being installed globally necessitates a precise assessment of the energy to be obtained before projects are implemented [2]. In fact, it takes knowledge of certain parameters, including solar radiation, ambient temperature, module temperature, and physical properties of every component developing the PV module, to forecast the energy generated by any PV system [3]. Being highly dependent on erratic and uncontrollable weather variables such as ambient temperature, wind, pressure and humidity present a difficulty to the solar PV [4]. The hazards brought on by PV power's unpredictable nature enhance as the solar PV generation rises [5]. Energy storage reduces these hazards, but there are also disadvantages such as high set-up and maintenance costs. Solar radiation forecasting, on the other hand, is a cheaper and quick-fix that works well for microgrid operation optimization issues including peak shaving, reducing the impact of uncertainty and solving financial issues in the power system [6]. Ramp occurrences which are abrupt changes in solar irradiance, are of interest for an extremely short-term and short-term forecast timeframe. Solar irradiation fluctuaations that are abrupt and severe reduce the reliability and standard of PV power [7]. The greatest PV power ramp rate is therefore estimated using forecasting findings for the short-term timeframe. Time series data which are produced in the solar power generation domain are defined by the collection of data points at predetermined intervals. Nevertheless, the variability brought on by moving clouds that are influenced by atmospheric and local weather conditions has stochastic characteristics, making it exceedingly difficult to forecast [8]. Therefore, solar irradiance forecasting is a quick, low-cost fix that works well for microgrid operation optimization issues like peak shaving, reducing the impact of uncertainty, and solving the power system's economic dispatch problem. In this regard, forecasting for the long-term and medium-term horizons supports market participation and function optimization [9].

A sequence of time-ordered data is called a time series, and it is typically used to show how a phenomenon changes over time. The application of decision-making strategies is made possible by time series forecasting which estimates the future values of time series. When applied to time series forecasting, deep learning (DL), the most advanced area of machine learning (ML) at the moment, handles complex, high-dimensional time series that are typically too complex for other ML techniques to handle [10]. Because of their accuracy, DL models are currently a challenging approach for forecasting solar energy. In order to forecast solar irradiance and PV power, the current study examines DL models for handling time-series data [11]. A suitable forecasting approach must therefore be chosen and solar power forecasting must be tailored for a particular application. Forecasting solar irradiance is becoming popular these days. A challenging task involving plenty of data is solved using the DL model, a component of ML framework [12]. To find meaningful depictions, the DL structure's numerous layers dynamically acquire abstract features from the raw data [13]. Since they excel as the input data scale rises, DL models set themselves apart from other learning methods [14]. The outcome demonstrates that typical ML models obtained better results after a certain quantity of training data, while DL models continue to enhance their precision as the number of training data rises [15]. Successful models are established for managing time-series data such as speech, text and image [16]. Learning models selected as newly established models, and their comparisons are discussed in the present work as suitable models for continuous data and are used for solar forecasting [17]. Creating hybrid models that overcome these drawbacks and outperform ML models in a range of applications has become a recent trend in DL. Hybrid approaches generate model parameters at each time step by combining DL with well-studied quantitative time-series models. Hybrid models, on the one hand, enable domain experts to use past data to inform network training, reducing the network's hypothesis space and enhancing generalization.

Guariso *et al.* [18] proposed two forms of neural networks such as feed-forward (FF) and long short-term memory (LSTM), both applied for solar forecasting. The results were rigorously evaluated using appropriate indices and comparable measurable benchmarks, with the clear sky serving as two persistent predictors. As a result, every network design was roughly consistent with the global sun irradiance and assured to have a slow forecasting accuracy in the next few hours. The LSTM and FF results are strong and have developed a distinctive regional prediction.

Brahma and Wadhvani [19] presented the LSTM model to forecast solar irradiance. The main goal was to estimate the regular solar radiation in two places every day using data obtained from the NASA POWER project. The model for the forecast of solar irradiance information was achieved by ML models utilized for discovering the data patterns and relationships as well as for predicting feature solar data. It suggests that the bidirectional long short-term memory (BiLSTM) was employed to improve the effectiveness in a single area by daily forecasting the solar irradiance data and discovering previous data. But, because of the nature of ML models, it is challenging to identify the models.

By combining the best features of either the chicken swarm optimisation (CSO) or grey wolf optimisation (GWO) algorithms, Jayalakshmi *et al.* [20] proposed an LSTM model that forecasts solar irradiance and uses a multi-tasking method for multi-time scale models. The sharing method was a successful way to divide up the tasks. The performance of the newly presented multitasking technique was investigated for predicting various time scales using a lengthy LSTM model.

The CSO-GWO received training to forecast on an hourly, daily, and weekly basis. ResNet, recurrent neural network (RNN) and coupled gated recurrent units (GRU) have been proved by Yan *et al.* [21] to forecast the load modeling. ResNet initially developed the capability to remove the original dataset. This RNN excluded the training feature from the input. A hybrid DL model neural network and a gated current unit forecasted changes in sun irradiance throughout the four seasons. Short-term fluctuations in solar irradiance were accurately predicted by the newly implemented DL model. Additionally, the forecasting model advanced beyond the DL model. The standard network width development methods had unintended consequences like gradient model overfitting, among others.

An effective deep model for day-ahead power load forecasting using stacked denoising auto-encoders (SDA) was presented by Tong *et al.* [22]. Initially, SDA improves the features of historical data according to temperature factors and electricity load; and then, the model is trained to predict an entire electricity demand for the next day. This contribution demonstrated the theoretical features that SDA was retrieved from the initial power load data and more precisely anticipated the load tendency with reduced errors.

Convolutional neural network and multilayer perceptron model (CNN-MLP) were introduced by Alani *et al.* [23] for predicting global irradiance. For this model, a hemispherical sky imager was used. Time series for the GHI and other variables were additionally collected from a ground meteorology location in Morocco. The short-term forecasting of solar irradiance added a crucial answer to ensure the best usage of produced energy. The electrical power generated by the two PV cells were aggressively achieved by the CNN model's root mean square error (RMSE), which also forecasts under foggy conditions. Oliveira and Borges [24] showed how the temporal resolution and PV generation model affected the dependability assessment of distribution networks. The major goal was to look into how PV generation models affected the distribution system reliability research. To measure how PV production disturbs the reliability indexes, solar energy production was put into a method for evaluating reliability using Monte Carlo simulation after the relevant models were created. Additionally, the effects of spatial smoothing brought on by the scale of the plant were examined for several PV arrays, and the temporal precision of irradiance readings in power produced an estimated sequence.

Despite many benefits of solar PV power generation, the extremely fluctuating sun's irradiance in various geopolitical areas/regions and at various times of the year, have a substantial impact on the predicted energy yield. It is impossible to ignore how this diversity affects the system's economic viability and profitability. Different methods are used to forecast the energy produced by solar PV to tackle this difficulty. With an emphasis on data-driven methodologies, this paper provides an in-depth and systematic evaluation of current developments in solar PV power forecasting techniques. A major aim is to improve the forecasting precision of solar intensity by using a powerful hybrid data-driven model. The hybrid model that is proposed combines the advantageous aspects of the self-attention process, BiLSTM, and VAE. The Bi-LSTM layer gathers data from previous and subsequent time steps by processing the input sequences both, forward and backward. It returns the sequences for the following layer and has 128 units. The attention layer assists the model to concentrate on most relevant parts of the input sequence. In essence, the extension of the conventional VAE is the primary contribution of this article. The major contribution of this research is mentioned as follows: i) the effectiveness of the encoder is increased by integrating a BiLSTM at the encoder side which is successfully included in solar irradiance concentration tests; ii) second, after BiLSTM, a self-attention method is incorporated to highlight the necessary elements on the encoder side. An objective of these actions is to improve the input utilized in the variance inference procedure; and iii) in terms of mean absolute error (MAE), mean absolute percentage error (MAPE), and RMSE, the suggested bilateral variational autoencoder-self-attention mechanism (BiVAE-SAM) is compared to the existing technique's performance. The structure of this study is as follows; section 2 explains the information about dataset description, PV generation module and power and energy at standard reporting conditions (PESRC) model. Section 3 provides the mathematical equation of BiVAE-SAM model, while section 4 demonstrates the result analysis and its comparison, and at the end, the conclusion of this research is given in section 5.

2. PROPOSED METHOD

The aim is to examine how PV power generation changes the assessment of the reliability of distribution networks. Data on sun irradiance acquired from New York city, Turkey, Canopy, Los Angeles, California, and Florida to evaluate the efficacy of the proposed BiVAE-SAM model. By calculating weights for each time step's output, the SAM efficiently makes use of the BiLSTM's cell memory information to identify global features and raise prediction accuracy. An inverter model and a few degradation factors are each utilized in this paper. As performing designs, PV module displays a PV system's power output under environmental conditions. The literature often distinguishes between two types: a circuit equivalent model and straightforward semi-empirical expressions. To circumvent a lengthy and iterative numerical procedure, simple semi-empirical formulations are used in this paper's modeling. Additionally, the suggested flexible approach, BiVAE-SAM permits focusing on the key attributes via an attention system and utilizing the BiLSTM benefits in time-series modeling. To capture long-term dependencies of time series data, a bi-LSTM with an attention mechanism selects the most relevant input features from all historical time-series data.

2.1. Dataset description

The validation of the suggested model requires six distinct kinds of data sets; here, every set of data relates to 1, 2, 3, 4, 5 and 6 distinct areas. Predicting the day-ahead total electrical load is crucial for energy efficiency and logically scheduling the electric generating units which are addressed in this study. The electricity load conditions in Los Angeles, Florida, California, and New York City between 15 July 2015 to 10 September 2016 are shown in Figures 1(a) to (d). Thus, there are 366 tuples for training from the data between 15 August 2015 and 15 August 2016 to train the model and project a daily total load for these four areas between 16 August 2016 and 31 August 2016. The vertical axis represents the relevant electric load level, while the horizontal axis represents all hours of the above dates. The Figures 1(e) and (f) shows the data collected from turkey and canopy datasets. In this dataset, 70% was used for training, the remaining 15% for testing, and another 15% for validation.

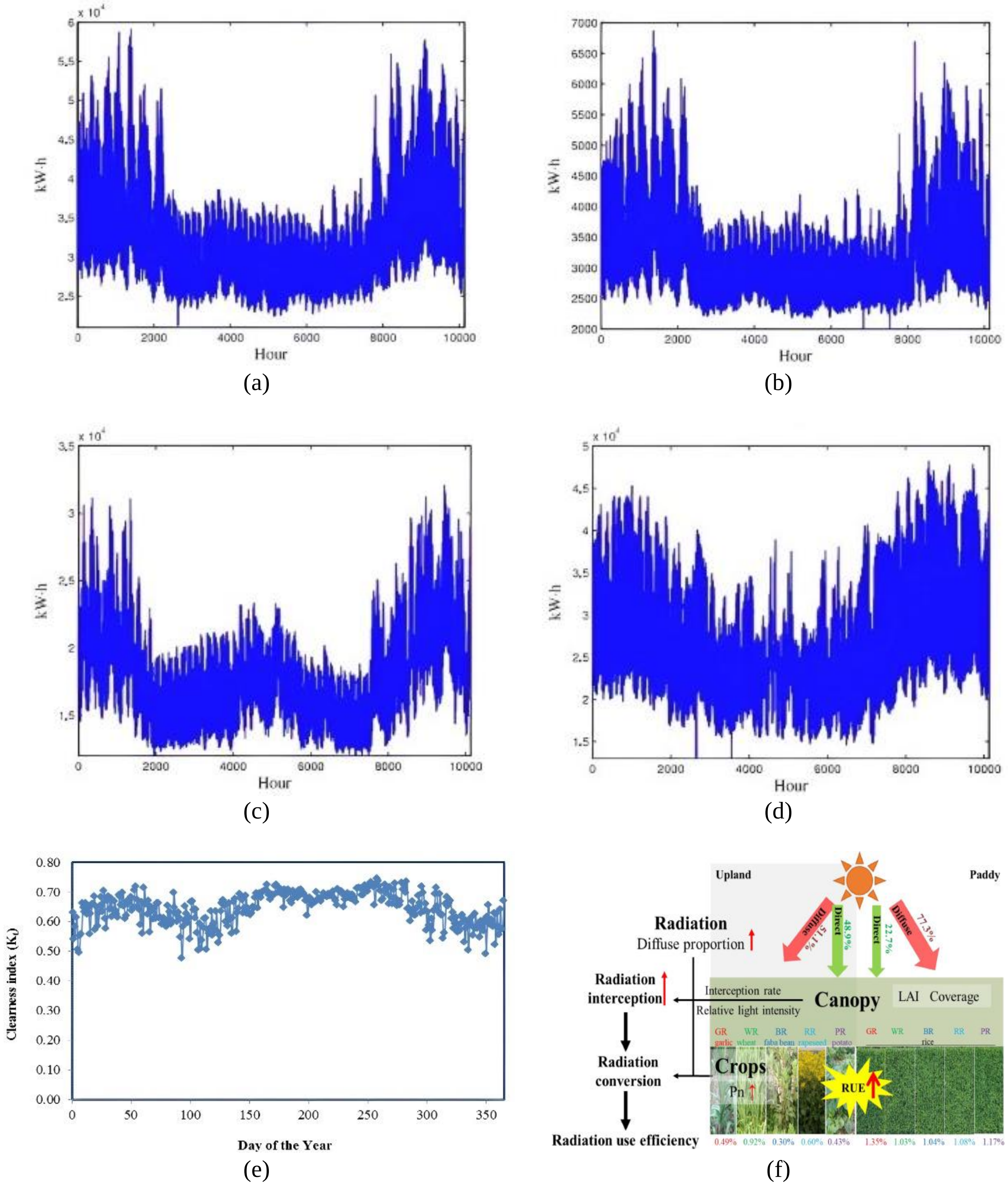

Figure 1. Load distributions from; (a) California, (b) Los Angeles, (c) New York City, (d) Florida, (e) Turkey, and (f) Canopy

2.2. PV generation models

The most relevant environmental factors, irradiance and ambient temperature are taken into account by PV-generating models to anticipate the power of output delivered into a grid. It is taken into account that some factors have a direct influence on the output, like the spatial smoothing consequence caused by plant size and the effect of temperature and radiation monitoring period. Figure 2 illustrates the modeling and simulation method and displays the models used to calculate the output power of the PV plant, and the parameters are specified in the module (irradiance and ambient air temperature).

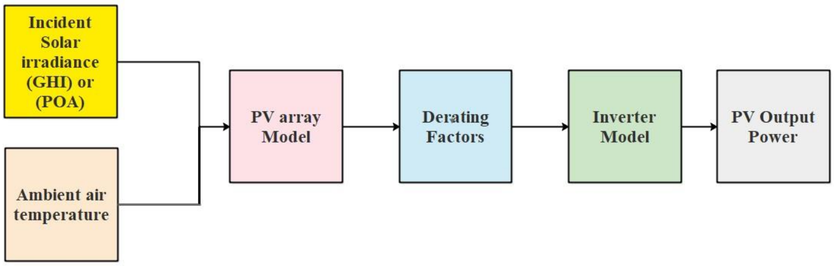

Figure 2. Modelling of PV system formation

A PV module is developed with the ability to capture a solar resource quality at various time scales, is important to evaluate the PV generation effect on the electrical system. A set of DC-AC inverters and PV modules is taken into account by PV generating models for the process of energy conversion. The objective of the PV panel is to calculate the effective radiation, which, takes into consideration and reflects the average lighting supplied for the plant. The output factor which is delivered into the electrical system after raising the voltage level is referred to in the AC-produced power.

2.3. PESRC

The PESRC model was considered as the simplest one that offers the general estimation of the power generated from a solar power module. In standard test conditions (STC), the power module is assumed to be a function that differs linearly from the ratio of incident to reference radiation. This linear function is presented in (1):

$$P_{mod} = f\,(G_i) = \frac{P_{STC}}{G_{STC}} \times G_i \leftrightarrow P_{mod} = \frac{G_i}{G_{STC}} \times P_{STC} \tag{1}$$

Where, G_{STC} refers to incident irradiance under STC circumstances which is 1.000 W/m^2, G_i refers to the incident solar irradiance in W/m^2, P_{mod} refers to the output power of PV module in Watts, while P_{STC} describes PV module's maximum output of power under STC circumstances. Thus, (2) offers the PV array's power.

$$P_{array} = N_m \times P_{STC} \times \frac{G_I}{G_{STC}} \tag{2}$$

In (2) gives an estimate of the array's maximum power for a particular irradiance situation and period. The model does not take the fluctuation in cell temperature into account. This model is frequently used to determine the output power offered by PV modules and is regarded as a classic in the literature because it combines simplicity and accuracy. Depending on the cell material and manufacturer, it ranges from 0.5% to 0.3%/°C. Although it is advised to utilize the coefficient stated by the manufacturer, the typical value is 0.35%/°C. The PV array's maximum output power is estimated by using (3).

$$P_{array} = N_m \times P_{STC} \frac{G_I}{G_{STC}} \times \left[1 + \gamma \times (T_c^{amp} - T_c^{STC})\right] \tag{3}$$

Here, γ is referred to as the maximum power temperature coefficient of a cell, T_c^{STC} refers to cell temperature at STC which is equivalent to 25 °C and T_c^{amp} refers to cell temperature at ambient conditions. From (3), once T_c^{amp} is superior over the reference temperature (25 °C), in the case of γ contains a negative symbol, a factor <1 that characterizes the decrement of output power is attained.

3. BIDIRECTIONAL VARIATIONAL AUTOENCODER WITH SELF-ATTENTION MODULE

In this research, Bi-LSTM process is incorporated with SAM to enhance the effectiveness of load forecasting. Significant constraints are specified with superior weights with the help of attention mechanism for enlightening the model to accessible information. The suggested BiVAE-SAM model utilizes the benefits of BiLSTM and attention unit's concentration of key features in the time-series modeling. In this section, the self-attention system is integrated on the encoder side immediately once the BiLSTM emphasizes the relevant features. These actions are intended to improve the input utilized in the procedure of variational analysis. Figure 3 provides a summary of the suggested approach's framework.

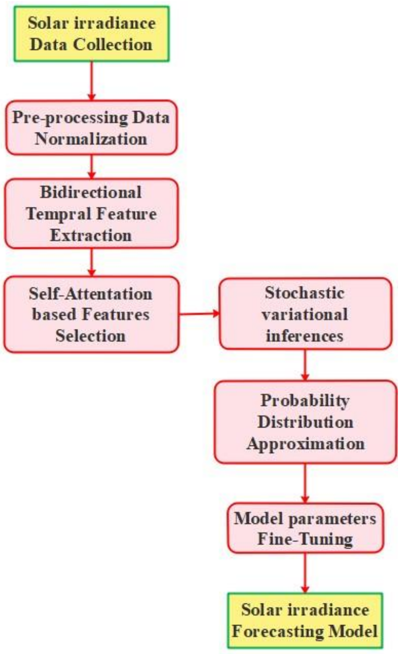

Figure 3. Flowchart of proposed BiVAE-SAM

This research proposes an efficient unsupervised learning-based solar irradiance magnitude forecasting method named variational autoencoder (VAE), a generative model extension. The suggested hybrid generative model depends on bidirectional data processing of time-series and strives for enhanced accuracy in forecasting solar irradiance magnitude through robust time-dependencies modeling. The suggested model's schematic diagram is shown in Figure 4. Later, a normalization technique is utilized to rescale the data to uniformly distribute a range of data (0, 1) and increase the stability of the model.

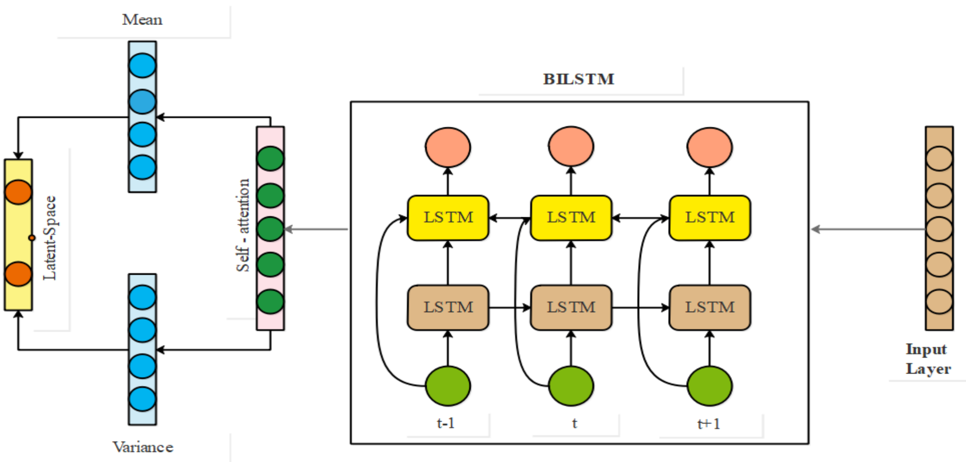

Figure 4. Schematic representation of the proposed BiVAE-SAM module

An effective DL model for emotion classification tasks is named Bi-LSTM [25]. Bi-LSTM optimizes the weights during training in order to reduce classification error and generalize emotional expressions that are not visible. Bi-LSTM provides better temporal dependency modeling in language than both conventional ML techniques and some single-directional LSTM models. Figure 5 shows the structure of a Bi-LSTM.

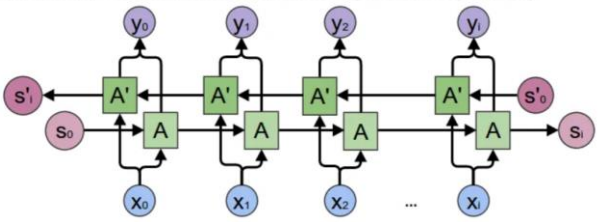

Figure 5. Depiction of a Bi-LSTM design

A forward RNN referred as $A_1 \rightarrow A_2$ ...$\rightarrow A_t$ is included in the forward computation. At time t, the input contains sequential data x_t, and output A_{t-1} from the earlier stage. Meanwhile, a backward RNN, referred as $A_1 \rightarrow A_2$ ...$\rightarrow A_t$ contributes to inverse computation. At time t, output is A_{t+1} from next stage, and the information about learning parameters is described in Table 1.

Table 1. Specifications of learning parameters

Parameter	Range
Gradient decay factor	0.5
Initial learn rate	0.009
Max-epochs	50
L2Regularization	0.06
minibatch size	27
optimizer	Adam
Execution environment	auto
Gradient threshold	1

In order to deal with lengthy data sequences, the attention is intended to be focused on a particular region containing the characteristics of a data sequence. The SAM produces a context vector based on a weighted sum of extracted characteristics, despite the fact that it is the extension of initial attention that allows interaction among input elements. xi refers to precise radiation and $P(xi)$ refers to a prediction which is expressed in (4):

$$P(xi) = W_i + b \tag{4}$$

The arithmetic formula for SAM is expressed in (5):

$$r_{ij} = P(xi)P^T(xi) \tag{5}$$

r_{ij} refers to the relation between the *ith* and *jth* value of the specified input, and (6) is employed to estimate the context vector ω.

$$\omega = softmax(r_{ij}) = \frac{e^{rij}}{\sum_j e^{rij}} \tag{6}$$

The Bi-LSTM network cannot address every issue. The path from the previous unit to the current unit is still sequential. Now that it has appendages and disregards its own branches, this path is more complicated. Without a doubt, Bi-LSTM and it is derivatives are capable of memorizing a large amount of long-term data. They are unable to recall longer series, such as 1,000 orders of magnitude, and only recall a sequence of 100 orders of magnitude. As a result, this paper suggests a technique that combines LSTM with a SAM. It is discovered that this technique successfully predicts the time-series data and aids in resolving the aforementioned issues. In order to improve the quality of irradiance prediction, the SAM uses a regulation strategy that is predicted by combining the strong dissimilarity inference with an effective regularization. As a result, stochastic variational predictions which aim to represent irradiance probability densities are more effectively executed in the enhanced feature space. The SAM's continuous description (context vector ω) is fed into the covariance matrix σ and regularized data mean μ distributions. Utilizing a vector of latent variables characterized by high-dimensional latent space z, VAE attempts to compute $P(x)$, probability distribution of the recorded panel irradiance, graphically by learning to generate samples that are comparable to a data point. VAE is a probabilistic method that depicts a joint density $P(z, x)$, where z denotes the hidden factor and x denotes the experimental factors in this case. Throughout training, the latent space is calculated using (7):

$$z = \mu + \sigma \odot \delta \tag{7}$$

δ refers to random variable: $\delta \sim \mathcal{N}(1,0)$, thus (8) is specified as:

$$z \sim \mathcal{N}(\mu, \sigma) \tag{8}$$

In reality, VAE contains 2 portions, the encoder $q\Theta$ and decoder $p\theta$ with (Θ, θ) their constraints. $\mathcal{O}_{VAE}$ is signified in (9):

$$\mathcal{O}_{VAE} = E_{q(z)}[log\, p(x|z)] - K\, L(q(z)\, ||p(z)) \tag{9}$$

log $p(x|z)$ denotes the log-likelihood of detected information x which defines a specific hidden parameter z. log $p(x|z)$ provides the similarity between $q(z)$ and x. Additionally, it calculates reconstruction error of x from z that efficiently denotes the decoder. Additionally, Kullback–Leibler of $q(z)$ and $p(z)$ refers to the regularization factor and estimates divergence among (p; q), which is the encoder portion with a sample of Z: $z{\sim}q(z|x)$. The pre-trained suggested model's parameters (weights) are adjusted and optimized to achieve the greatest performance utilizing the back-propagated method with supervised learning, which also aids in achieving the global minima. In this phase, the learning of how to map a given data series to its next response is enforced.

4. RESULTS AND DISCUSSION

4.1. Performance measures

The findings show that the model is effective and performs better than four widely utilized DL models namely, RNN, BiLSTM, LSTM, and GRU. These tests use various performance metrics which are briefly discussed below. The measures for example, coefficient of determination (R2), RMSE, mean absolute error (MAE), explained variance (EV) and median absolute error (MDAE) used to measure forecasting accuracy which are defined in (10) to (14):

$$R^2 = \frac{\sum_{i=1}^{n}[\left(\mathcal{Y}_{i,-}\ \bar{\mathcal{Y}}\right)\cdot(\hat{\mathcal{Y}}_i - \hat{\mathcal{Y}})]^2}{\sqrt{\sum_{i=1}^{n}[\left(\mathcal{Y}_{i,-}\ \bar{\mathcal{Y}}\right)^2}\cdot\sqrt{\sum_{i=1}^{n}(\hat{\mathcal{Y}}_i - \hat{\mathcal{Y}})^2}} \tag{10}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{t=i}^{n}(\hat{\mathcal{Y}}_i - \hat{\mathcal{Y}})^2} \tag{11}$$

$$MAE = \frac{\sum_{t=1}^{n}|\mathcal{Y}_t - \hat{\mathcal{Y}}|}{n} \tag{12}$$

$$EV = 1 - \frac{Var(\hat{y} - y)}{Var\ (y)} \tag{13}$$

$$MDAE(\mathcal{Y}, \widehat{\mathcal{Y}}) = median(\mathcal{Y} - \widehat{\mathcal{Y}}) \tag{14}$$

Where, $\mathcal{Y}$ refers to original irradiance, $\hat{\mathcal{Y}}$ refers to the corresponding forecasted standards. Then, the MAPE is employed to show the mean forecasting error among the actual and predicted load. The predicted load e'_k for kth day is considered, MAPE is demarcated in (15):

$$MAPE\ (e, e') = \frac{1}{16}\sum_{k=1}^{16}\frac{|e_k - e'_k|}{e_k} \tag{15}$$

4.2. Forecasting solar irradiance

In this section, sun irradiance measurements from six datasets are used to assess the effectiveness of proposed BiVAE-SAM prediction model. Additionally, when the BiVAE-SAM approach's performance contrasted with that of the RNN, GRU, LSTM, and BiLSTM models, four widely used models. Using training data, DL models are designed and employed to project the trajectory of solar irradiation. Based on evaluating solar irradiation from Turkey and Canopy, the outcomes of the five models are under consideration. The predicted outcomes using data from Turkey are summarised in Table 2 to statistically assess the performance of the suggested technique.

Table 2. Forecasting outcomes on Turkey

Approach	RMSE	MAE	R2	EV
RNN	17.92	8.649	0.987	0.988
GRU	15.834	6.877	0.990	0.990
LSTM	12.807	5.842	0.991	0.991
BiLSTM	15.671	6.017	0.991	0.992
Proposed BiVAE-SAM	8.302	4.077	0.995	0.995

The BiVAE-SAM achieves the best R2 and EV, as is observed, demonstrating that the proposed technique successfully captures more than 99.7% of irradiance variance. Furthermore, BiVAE-SAM has the smallest modeling error, with RMSE=8.302 and MAE=4.077, when compared to the other models that are taken into consideration, which show the efficacy of the suggested strategy with RMSE values between [12:807, 17:92] and MAE within [8:649, 5:842]. As a result, the BiVAE-SAM outperforms the other model in terms of forecasting accuracy. This is explained by the BiVAE-SAM excellent capacity to model nonlinear dynamics and collects the time-dependent data from solar irradiance. Figures 6 and 7 shows the graphical illustration of RMSE, MAE, R2, and EV on turkey irradiance data with the proposed model.

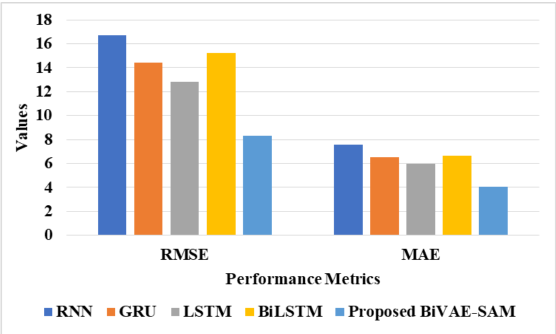

Figure 6. Performance analysis of Turkey dataset in terms of RMSE and MAE

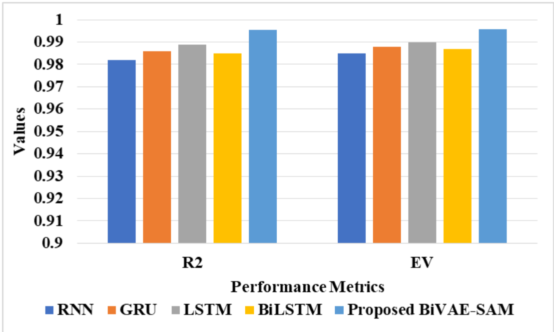

Figure 7. Performance analysis of Turkey dataset in terms of R2 and EV

In a similar way, Table 3 lists the statistical parameters according to Canopy testing results' by the models. The findings demonstrate the suggested BiVAE-SAM model's enhanced predicting abilities. Note that the suggested method beats other approaches used in this series by recording minimal error of RMSE (11:503), MAE (4.938), and R2 (99:60%) in contrast to different methods, which reported RMSE among [16:931, 14:391] and MAE in [12:584, 6:476].

Table 3. Forecasting outcomes on Canopy

Approach	RMSE	MAE	R2	EV
RNN	14.391	6.476	0.991	0.991
GRU	15.847	8.158	0.994	0.992
LSTM	14.999	9.481	0.995	0.994
BiLSTM	16.931	12.584	0.993	0.994
BiVAE-SAM	11.503	4.938	0.996	0.996

Figures 8 and 9 make it obvious that the predicted observation resulting from the suggested BiVAE-SAM strategy generates a rather obvious diagonal on the Canopy and Turkey data, demonstrating the hybrid model's continued success. Overall, the findings clearly evidence that the suggested strategy surpasses all of the models that are taken into consideration. Table 4 shows the performance analysis of MAPE with various classifiers for California, Los Angeles, New York City, and Florida to evaluate the efficiency of the proposed BiVAE-SAM forecasting model.

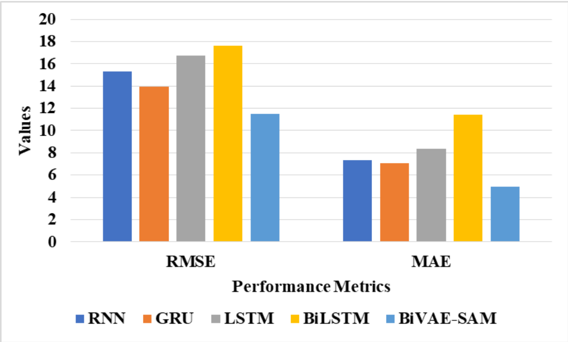

Figure 8. Graphical illustration of Canopy dataset in terms of RMSE and MAE

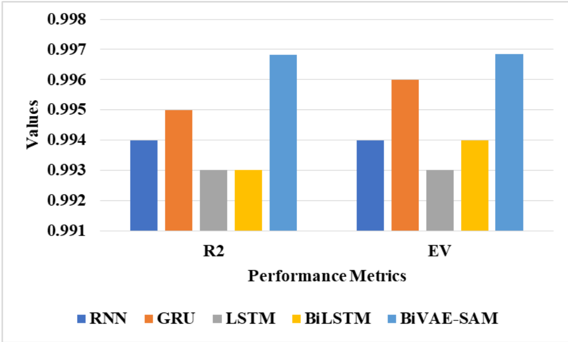

Figure 9. Graphical illustration of Canopy dataset in terms of R2 and EV

Table 4. Performance of various classifiers in terms of MAPE

Datasets	MAPE	
	Existing SDA [22]	Proposed BiVAE-SAM
California	RNN	3.4671
	GRU	3.0137
	LSTM	2.3975
	Bi-LSTM	2.0769
	BiVAE-SAM	1.7935
Los Angeles	RNN	1.9824
	GRU	1.6816
	LSTM	1.3425
	Bi-LSTM	1.0237
	BiVAE-SAM	0.7828
New York City	RNN	2.1768
	GRU	1.9631
	LSTM	1.7528
	Bi-LSTM	1.5843
	BiVAE-SAM	1.3491
Florida	RNN	4.1843
	GRU	3.7826
	LSTM	3.3179
	Bi-LSTM	3.1428
	BiVAE-SAM	2.8346

The results from the Turkey and Canopy datasets are used to calculate the MAPE metric. Furthermore, the proposed BiVAE-SAM technique effectively records the less error in forecasting all datasets. At this point, it should be noted that on both datasets, GRU and LSTM outperform other models under consideration. A dense diagonal is building in the points cloud, which is a sign of successful prediction. In this regard, the predicted values match the magnitude of sun irradiation as it is measured.

4.3. Comparative analysis

Four different types of datasets are required to validate the suggested BiVAE-SAM model. A series of tests on the above data sets of four regions are run and compared with the suggested approach with the current SDA to validate the efficacy and performance enhancements of the existing SDA framework [22]. Tong *et al.* [22] employed three different types of crucial data: season parameters, date-related meteorological parameters, and historical power load data. A two-module deep feature extraction and electrical load prediction architecture is proposed based on DL. There are three deep sub-networks in the feature extraction module. The 24-component electrical load vector from the previous day, which reflects the hourly power loads, is delivered to the first sub-network. Then, it is built using DL to analyze low-level input and extract certain latent higher-level qualities that describes more intricate patterns. The improved attributes are then concatenated with a season parameter before being entered into the electrical demand forecasting module. The comparative examination of the proposed BiVAE-SAM and the existing SDA [22] in terms of MAPE is shown in Table 5 and Figure 10, respectively. From Table 5, it is evident that the proposed BiVAE-SAM attains superior outcomes in terms of MAPE performance metrics on all the stated datasets.

Table 5. Comparative analysis for existing SDA with proposed BiVAE-SAM in terms of MAPE

Datasets	MAPE	
	Existing SDA [22]	Proposed BiVAE-SAM
California	2.6706	1.7935
Los Angeles	0.9552	0.7828
New York City	1.7261	1.3491
Florida	3.7631	2.8346

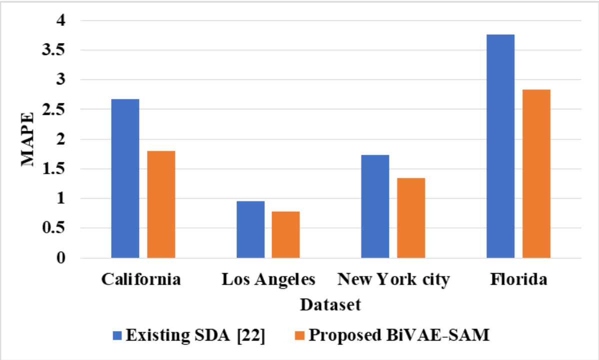

Figure 10. Graphical representation of MAPE performance

4.4. Discussion

This paper presents BiVAE-SAM, a novel deep attention-driven solar irradiance forecasting model. Furthermore, BiVAE is enhanced with a SAM called BiVAE-SAM which draws attention to significant features. Using sun irradiance measurements from New York City, Turkey, Canopy, Los Angeles, California, and Florida, the proposed model is evaluated using the existing SDA [22], which uses weather for the most recent day and the load vector from the previous day as input for overall load forecasting. The outcomes prove that proposed BiVAE-SAM overcomes the current SDA [22] model, which has 2.6706, 0.9552, 1.7261, and 3.7631 MAPE performance at projecting solar irradiance, respectively for California, Los Angeles, New York CITY, and Florida, with 1.7935, 0.7828, 1.3491, and 2.8346. These results demonstrate that, on all data sets, the suggested BiVAE-SAM model outperforms the existing SDA. First off, the findings demonstrate that the proposed BiVAE-SAM model has fewer MAPE errors and performs better than SDA [22]. When the outcomes from the proposed technique are contrasted with the results produced by the existing SDA [22], the feature extraction module in the suggested model helps to achieve greater accuracy than the existing SDA [22]. These outcomes validate the success of proposed BiVAE-SAM when compared to the BiLSTM to LSTM; it is important to note that the former is significantly slower and takes longer to train. The primary disadvantage of VAEs is the propensity to produce hazy, unrealistic results. This is related to the manner in which VAEs recover data distributions and calculate loss functions. Therefore, an improvisation is required to overcome the above-stated drawbacks which is clearly mentioned as a future works in the subsequent section.

5. CONCLUSION

This study introduces the BiVAE-SAM hybrid model, an efficient hybrid model for forecasting solar irradiance. The suggested method takes advantage of the BiLSTM's strong time-dependencies modeling capability in conjunction with SAM to enhance the presentation of features extracted in conventional VAE. Self-attention and BiLSTM are built into the VAE model's encoder portion. With the help of two datasets gathered from California, New York City, the US, Florida, Turkey, and Los Angeles, the suggested hybrid model's performance is evaluated. The analyzed DL models' predicting accuracy is evaluated using five metrics of effectiveness: R2, EV, MAPE, MAE, and RMSE. The outcomes display that proposed BiVAE-SAM outperforms existing SDA model in terms of MAPE by achieving 1.7935, 0.7828, 1.3491 and 2.8346 for California, Los Angeles, New York City and Florida, respectively. Naturally, this study exhibits the potential of DL for predicting solar irradiance without the use of external inputs. In the future, this research will be further expanded by evaluating several DL models to enhance the efficiency of the load forecasting models.

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