

PV ENERGY FORECASTING USING DEEP LEARNING ALGORITHM

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Abstract

Solar energy has vast potential in India which is a rapidly growing economy with diverse geographical features. Solar energy has intermittent behaviour and depends on geographical and weather conditions. Therefore, the reliability of the solar depends on the seamless operation of solar plants with the latest technologies. The main objective of power operator is to facilitate the renewable power sources intergeration for maintaining an uninterrupted power supply. To achieve this objective, researchers have employed various Deep Learning methods of machine learning, such as RNN, LSTM, CNN and SVM for accurate solar power forecasting with higher relibaility. In this paper, a GA-CNN deep learning algorithm is employed with an optimized hyperparameters technique for PV energy forecasting. This technique outperforms when compared with the other methods such as LSTM, KNN-SVM, and CNN-RNN techniques in terms of RMSE, MAE, MSE and R-Square performance indices. This method provides a better and more robust method of deep learning for solar PV energy forecasting.

Keywords: CNNRNN; DL; GACNN; KNNSVM; LSTM; Solar Power Forecasting

Introduction

Even though solar energy is sporadic, there are several ways it may be applied to assist developing countries in solving their energy issues. India's reliance on long-lasting energy sources like air currents, sunlight, and heat from the earth's crust, load in the vast natural reservoirs present on 75 % of the earth's surface. India is a rapidly developing and economically astute country surrounded by oceans and mountains. To reduce the technology gap in this rapidly growing financial sector, this area needs trustworthy sources that can provide almost four times the quantity of energy now consumed.

(Vaswani *et al.*, 2017; Zhang *et al.*, 2021).

The number of PV power-generating devices utilizing accessible sun beams is steadily increasing. Since human needs are constant despite fluctuations in PV plant production, projecting plant output has received a lot of attention. Another argument for demand forecasting is the possibility of using alternate grid-based energy-producing techniques when PV electricity is in short supply (Yang *et al.*, 2018). It also supplies the grid with surplus electricity. This precise estimate will result in a balanced application of force in both internal and

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exterior directions. (Chung *et al.*, 2014; Wang *et al.*, 2018)

Grid operators synchronized the production of both renewable and nonrenewable energy by grid integration. If it is feasible to predict the output changes in any way, dispatching control will be able to provide the load with steady power. Thus, PV output estimation becomes a crucial general application (Tosun *et al.*, 2020). A few researchers have developed technologies which are used to calculate PV power. Solar panel performance is degraded by the ambient light which is unpredictable. The panels must be protected from solar damage by unpredictable cloud cover. Therefore the inclusion of the weather factors prediction opens a new dimension in solar energy prediction. (Trigo-González *et al.*, 2019). There are a variety of DL techniques available to anticipate accurate PV energy forecasting. The CNN-RNN regularly beats the SVM, LSTM, and many other techniques in every case (Obiora and Ali, 2021). K-nearest neighbour, Convolution Neural Network (CNN), Long Short-Term Memory (LSTM), (De *et al.*, 2020) Recurrent Neural Network (RNN), Support Vector Machine (SVM), and Hybrid of CNN-RNN are a few examples of Deep Learning models. In this paper, a GA-CNN deep-learning algorithm is employed with an optimized h-parameters technique for PV energy forecasting. The proposed methodology is implemented on the Bhadla, Rajasthan real-time dataset series. (Jnr *et al.*, 2021). The proposed methodology covers the following research gaps listed below,

1. GA-CNN deep-learning model is more accurate than the other deep-learning methods.
2. This methodology covers the weather variables such as ambient light variability and cloud cover which increases the reliability of the PV system.
3. Improved the Grid operation by the prior intimation of the power fluctuation in PV.
4. It improves the energy management of the Grid and addresses the energy shortage of the Grid in developing nations like India.

Deep Learning Techniques

Deep-Learning is a subclass of machine learning algorithms which is dominated by CNNs. The goal is to learn a difficult job by applying a series of convolution filters to the input data and then classifying the resulting data. At the beginning of the 21st century, computers equipped with CNN have shown remarkable proficiency in areas like as reading handwritten numbers, locating objects, and recognizing human voices (Mustaqeem *et al.*, 2022). Further to develop a efficient model with the robust predictors, several authors have deployed

different artificial intelligence (AI) algorithms to anticipate the hourly Maximum Daily Electricity Price (MDEP) and Average Daily Electricity Price (ADEP) from 2020 and 2021. Cho *et al.* (2014) The top predictors in the majority of models for predicting the day-ahead MDEP, with reference to the sensitivity analysis; with inputs as Pt1max, Pt7max, and Pt30max. Additionally, CNN-LSTM outperformed in forecasting the MDEP and ADEP both in the power market of Iran.

Time series methods are utilized to examine the data characteristics and patterns of past information. The aforementioned techniques offer the advantage of being immune to exogenous variables, thereby presenting a unique benefit. However, in instances where the input is inconsistent, the magnitude of forecast inaccuracy increases. The exponential smoothing technique can be conceptualized as an approach that considers the incorporation of weighted means. This methodology prioritizes statistical data that is closely linked to the projected data, assigning it greater significance. The assigned weights to the proximate data are higher than the distant data sets which shows an exponential rise in the weights. These techniques are used for the future prediction of the state variables of solar plants. (Mahmud *et al.*, 2021; Cheng *et al.*, 2021; Li *et al.*, 2020).

Another method for spatial-temporal forecasting of solar irradiation with a one-day lead time aims to ensure the reliable and sustainable operation of power system. The approach involved applying discrete Fourier transform (DFT) to a solar irradiance time series to extract frequency characteristics. PCA is used to determine important frequency features and is used in Elman-based NN for making 24-hour solar irradiance projections. The technique rules over other models such as ARIMA, PCA-BPNN, and the persistence method, achieving the highest accuracy in day-ahead forecasting using spatiotemporal data. (Liu *et al.*, 2021c). As the unpredictability of photovoltaic (PV) power generation lowers the dependence of the national grid on distributed energy sources such as solar and wind energy generation. Because of the significance of these types of systems, prediction models need to be built for them. Therefore, a detailed investigation is required to forecast solar power for national Grid convenience to maintain the stability of the system. (Ahmad *et al.*, 2018) The learning approaches, data analysis, forecasting methodology and the significance variables have an impact on forecasting accuracy. The supervised learning strategies are utilized extensively for more accurate predictions. To extract features of the variables, many researchers have used wavelet

transformations and Empirical Mode Decomposition (EMD) decomposition. In recent years, projecting solar photovoltaic power output with Deep Learning has surpassed physical models of PV models. There are other methods which are gaining popularity for optimal estimation of PV energy by the use of Deep Learning in PSO, GA, and WOA. Fonseca, (da Silva Fonseca *et al.*, 2012; Wang *et al.*, 2020a; Ahmed *et al.*, 2020; Liu *et al.*, 2021b). These are evolutionary algorithms which use GHI intensity, wind speed, and ambient temperature as the three most prevalent inputs for solar PV power prediction. These variables have been demonstrated a crucial impact on the ability to predict the output. Probabilistic predictions for the system operations that consider many sources of uncertainty are of tremendous assistance, even though reliable forecasts are still the industry standard. A study shows that Deep Learning models are utilized to predict renewable energy including techniques for data pre-processing, algorithms for parameter selection, and measures for evaluating prediction performance. (Liu *et al.*, 2021a; Abdel-Nasser and Mahmoud, 2017; Harrou and Sun, 2020). The latest research on renewable energy sources included the presentation of percentage error values, coefficient of determination values, survey findings and potential future employment opportunities. Artificial neural networks ANN, LSTM, KNN, SVR, and other well-liked ML forecasting models are frequently employed in solar power applications. (Liu *et al.*, 2021c; Li *et al.*, 2023) The most fundamental Deep Learning architecture is an ANN (de Paiva *et al.*, 2019). Similar to the neurons in the real brain, a group of linked artificial neurons forms the foundation of an ANN, and each connection can send messages to neighbouring neurons. Input, hidden, and output layers make up the fundamental ANN structure, also referred to as a Multi-Layer Perceptron Neural Network (MLP-NN). (Mahmud *et al.*, 2021)

This paper is organized into five sections. In section I, a literature survey has been done on recent trends in deep-learning techniques. It also includes the major contributions of the paper compared with the previous techniques. The second section is dedicated to the proposed methodology. In the third section the elaborated explanation of important steps used in the deep-learning techniques is given. In the fourth section, the results of the implanted GA-CNN deep learning algorithm are compared with the LSTM, KNN-SVM, and CNN-RNN techniques in terms different performance indices. The fifth section is dedicated to the conclusion of the study carried out in the solar PV energy forecasting.

Proposed methodology

Inspired by the concepts of biology, a genetic algorithm (GA) is a strong search and optimization method. By using genetic operators, the program creates new people with higher fitness via generations of evolution. Genetic algorithms (GA) are well-suited for solving high-dimensional, non-convex optimization problems (AlKandari and Ahmad, 2019). Any given solution's fitness function provides a direct assessment of its quality. A genetic algorithm, or GA, is a kind of computational optimization that draws inspiration from the principles of evolution and natural selection. (AlSkaif *et al.*, 2020; Wang *et al.*, 2020b).

Hyper Parameter (h-parameters)

It is crucial to remember that optimizing hyperparameters (h-parameters), is an iterative process that calls for thorough trial and error, assessment, and fine-tuning in order to determine the ideal h-parameters for a given deep-learning task. The optimization of h-parameter requires expertise in the subject and hands on the technique to identify the abnormalities. (El Alani *et al.*, 2021; Abbaskhah *et al.*, 2023).

Dropout Rate: There are several types of regularization in the deep learning algorithm, Drop rate is one of the among which reduced the overfilling of the algorithm outcomes and improves the performance. It is also a probability of disabling of the neuron in a ANN network layer during the training process. (Mishra *et al.*, 2020; Wang, *et al.*, 2019b; Jalali *et al.*, 2022). Randomly generates input units are set to zero using this dropout rate. The research work describes the output of the unit which is momentarily ignored. In order to achieve this, NN become reliant on certain traits forcing them to develop more dependable universal structure. (Singh *et al.*, 2013; Gao *et al.*, 2020). This h-parameter also defined the likeliness of each neuron raging from 00 to 1 where 0 and 1 defines no drop out and complete dropout respectively. Keeping the drop out of 0.5 is considered which is problem specific.

Batch Size: It is the no. of training samples that are passed through the network in a forward and backward both once. (Tovar *et al.*, 2020; Wang *et al.*, 2019a). It displays the total number of data points processed by the training algorithm for every update step or iteration. Throughout the training process, the entire training dataset is divided into batches, and the network's weights are adjusted for each batch using the computed gradients. The batch size selection may affect the CNN's compute

performance and training dynamics. The number of samples processed in a single forward/backward run of the network is referred to as the batch size of CNN. It's a hyperparameter that can be changed during CNN training. Training dynamics and memory use are both influenced by the batch size. (Abuella and Chowdhury, 2015; Elsaraiti and Merabet, 2022).

H-parameters Optimization

The GA assesses the fitness of solutions after a randomly initialized start. Then, a subset of solutions is picked, with better solutions more likely to be picked. To increase their effectiveness, these solutions are reconfigured. To further explore the

parameter space, some of the new solutions are then randomly modified. The newly “created” solutions are then assessed for fitness, and the process is continued until a suitable solution is identified, the quality of the solutions stops improving which show that threshold is reached. (Zha *et al.*, 2022). The procedure is visualized in Figure 1. The GA runs three times. using the same input data because it has certain stochastic components as shown in Figure 2.

To generate statistically meaningful data, the training procedure should preferably be performed numerous times for each configuration of the h-parameters because the random weight initialization of a CNN also introduces stochastic aspects. However, because it would significantly lengthen the optimization process, this is not realistic. Some CNNs are chosen to act as “parents” once each CNN’s suitability has been assessed. The “children” of these parents are recombined to form the current generation, which also includes the top three CNNs from the previous generation. The variation of h-parameter values can also rise as a result of particular h-parameter mutations. A total of 30 generations are completed for each optimization cycle. (Hong *et al.*, 2022b). There are several parameters used in the GA optimization technique which are given in Table 1.

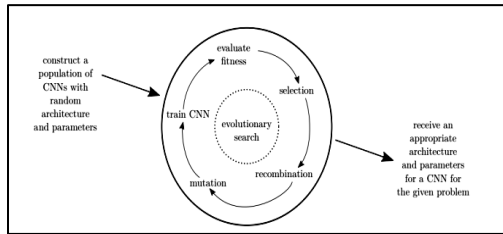


Figure 1. GA-CNN Cycle

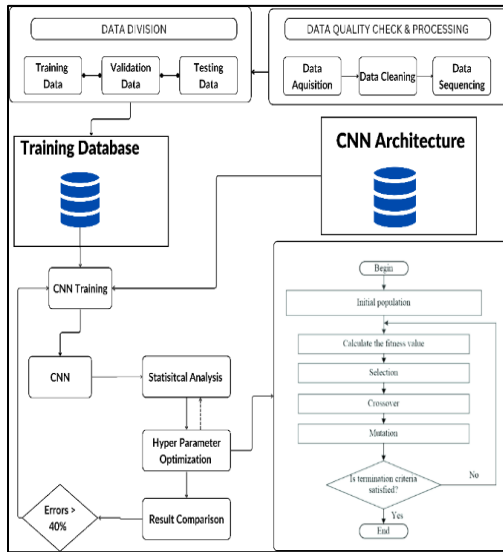


Figure 2. Flowchart of GA-CNN Methodology

Table 1. Genetic Algorithm Parameters

Parameter	Type / Value
Population size	50
Initialization	Random
Selection Mechanism	Tournament
Crossover Function	Crossover Heuristic
Mutation Operator	Gaussian
Pareto Set Fraction	0.35
Parallel Evaluation of Function	Yes
Creation	Nonlinear
Population Data Type	Double Vector

Data Analysis and Site Selection

In this section, the important steps are formulated for the model establishment of the deep-learning network used in solar PV energy estimation. The important steps include the regression model analysis, dataset segregation and site selection.

Correlation and Regression Analysis

The Regression analysis is performed to explore the relationship between the evaluation indices of CNN and its two selected hyperparameters. The findings of this analysis are presented in Table 2 and Table 3, which display the results for sMAPE and nRMSE respectively. (Makridakis *et al.*, 2018).

It is evident that the obtained P values are expected to be below 0.5. Specifically, for the sMAPE evaluation index, the dropout rate and Batch size exhibit P values of 0.006 and 0.268, respectively. These values indicate a significant relationship between the evaluated h-parameters and the sMAPE index. (Jnr *et al.*, 2021). Equation (1) representing the regression relationship. (1) serves as a mathematical representation of the identified relationship between the h-parameters and the evaluation indices. It encapsulates the

insights gained from the analysis, providing a quantitative understanding of how the h-parameters impact the performance of the CNN model.

$$\text{SMAPE} = 0.29525 - 0.00835 \text{ DROPOUT RATE} - 0.000018 \text{ BATCH SIZE} \quad (1)$$

The analysis further culminated in the derivation of a regression equation that accurately represents the relationship between nRMSE and the aforementioned h-parameters. Equation (2) serves as a mathematical model capturing the dependencies uncovered through the analysis. It produces the possible quantitative assess the effect of the h-parameters on the nRMSE metric. A comprehensive analysis is conducted in this study to find the relationship between the h-parameters, Dropout Rate, Batch Size, and the nRMSE evaluation index. The findings underscore the importance of these h-parameters in influencing the model's performance. Armed with this knowledge, researchers and practitioners can make informed decisions regarding h-parameters optimization to enhance the model's accuracy and effectiveness. (Chen *et al.*, 2018; Zha *et al.*, 2022; Heidarpanah *et al.*, 2023).

$$\text{nRMSE} = 0.1633 - 0.0401 \text{ DropOut Rate} - 0.000231 \text{ Batch Size} \quad (2)$$

Dataset and Site Selection

India possesses a vast expanse of land characterized by a multitude of climatic conditions across its many regions. The annual solar energy received is approximately 5.6 kWh/m². (Abbaskhah *et al.*, 2023) conducted a study. It has investigated the geographical locations inside India for solar Global Horizontal Irradiance (GHI) forecasting. This study focuses on the dataset obtained from the Bhadla region in Rajasthan, which is known for its arid and semi-arid environment. This climate is characterized by elevated temperatures and limited precipitation. During the summer months (April to

Table 2. Correlation Analysis for sMAPE v/s H-parameters

Term	Coefficient	Standard Error Coef
Constant	0.29525	0.00149
Dropout Rate	-0.00835	0.00185
Batch Size	-0.000018	0.000015

Table 3. Correlation Analysis of RMSE V/S H-parameters

Term	Coefficient	Standard Error Coef
Constant	0.1633	0.0238
DropOut Rate	-0.0401	0.0297
Batch Size	-0.000231	0.000233

June), temperatures in Bhadla exceeding 40°C or even higher. Monsoon season in Bhadla typically occurs from July to September, when the area receives the majority of its annual rainfall. However, the amount of rainfall in Rajasthan is relatively low compared to other regions of India, and the monsoon can be unpredictable, leading to periods of drought. In the winter months (November to February), Bhadla experiences cooler temperatures, with average highs ranging from 20-25 °C. Overall, the site has a hot and dry climate with limited rainfall. It is important to note that weather patterns can vary from year to year, and specific weather conditions may be influenced by factors such as El Niño and other climate phenomena. The dataset has been collected from NASA Predictions of Worldwide Energy Resources (NASA POWER), the following hourly data set was utilized for the calculating PV panel (Moserbear FS 390 W) power generation and features of predictors in ML models; MERRA-2 Temperature above 2 Meters from gorund in (°C), CERES SYN1deg All Sky Surface Shortwave Downward Irradiance (Wh/m²), CERES SYN1deg Clear Sky Surface Shortwave Downward Irradiance (Wh/m²), CERES SYN1deg All Sky Insolation Clearness Index (dimensionless), and MERRA-2 Relative Humidity at 2 Meters (%). Solar PV power calculation is given

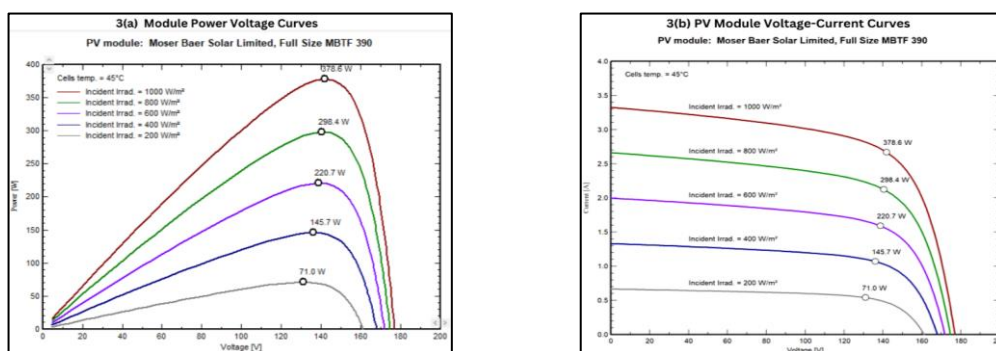


Figure 3. (a) shows the Power-Voltage Curves and (b) Voltage-Current of the PV-Module

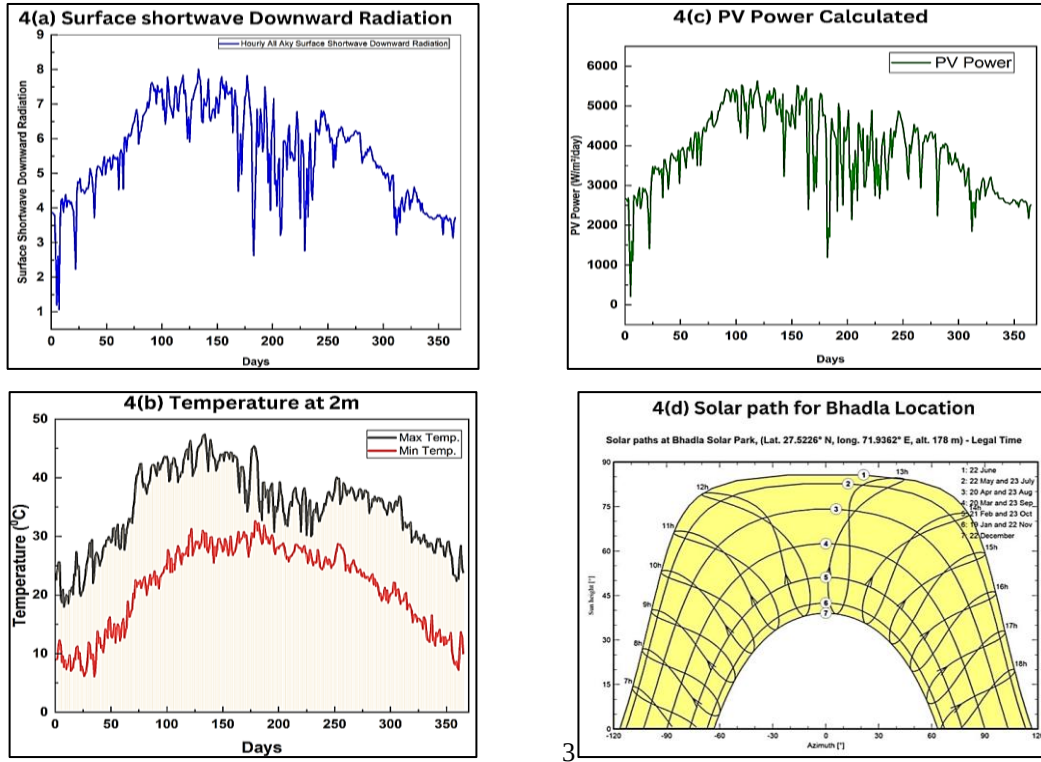


Figure 4. (a) Surface shortwave Downward Radiation (b) Temperature at 2 m (c) PV power Calculated (d) Solar path for Bhadla Location

by (3). where A and B are the respective temperature coefficients. Figure 3 describes the Moser-bear PV Panel Current, Voltage and Power Curves at different incident irradiances ranging from 200 W/m²-1000 W/m². The ΔT is the operating temperature increased from previous record. For a single-crystal silicon cell, A is considered as approx. 20 $\mu\text{W}/^\circ\text{C}$ and B as 5 $\mu\text{W}/^\circ\text{C}$ approx., where u defines the unit. (Kim and Cho, 2019; Guo, 2022; Sekhar and Dahiya, 2023)

$$P = P_o [1 + (\alpha - \beta) \Delta T] \quad (3)$$

Using the shortwave and longwave downward radiations the PV energy generation has been calculated as shown in Figure 4.

The total PV power has been calculated on the per panel basis working at 15% efficiency. The dataset used for solar power forecasting is segregated into training, testing and validation are 70%, 15% and 15% of the total available dataset. The complete dataset is segregated into four seasons Summer, Monsoon, Autumn and Winter of the Bhadla region. The summer duration is considered from March - June, Monsoon has been considered from July - September, Autumn is

considered from October - November and Winter is considered from November - February. These four seasons datasets are named W1, W2, W3 and W4 respectively.

Results and Discussion

In this section the implemented technique GA-CNN is compared with the DL techniques implemented in the work viz. CNN-RNN, KNN-SVM and LSTM. Such techniques are compared on the basis of the performance evaluators listed in Table 4 as discussed below:

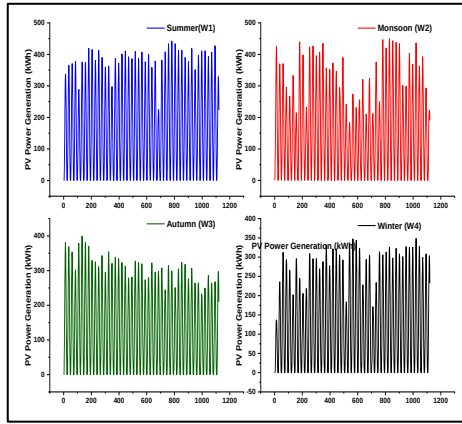
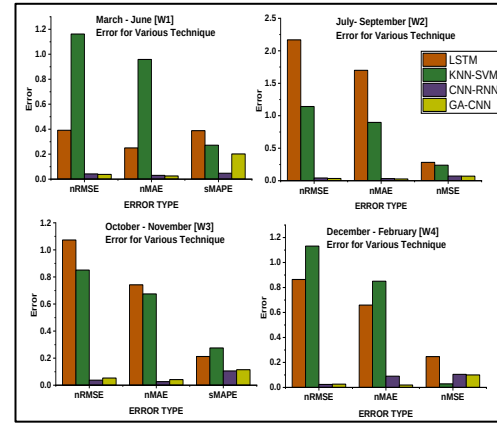
Evaluators and Estimators

Several indicators are selected and employed as estimators in the research and analysis to evaluate methodologies and the accuracy of predictions provided.

These parameters serve as reliable indicators for assessing the accuracy and effectiveness of the implemented methods and predictions. Initially, CNN-RNN, LSTM, and KNN-SVM techniques are implemented on the available dataset. These techniques are compared with the GA-CNN algorithm in terms of performance evaluator as

Table 4. Evaluation Parameters

Evaluator Indices	Formulae
Mean Absolute Error	$MAE_k = \frac{1}{N} \sum_{t=1}^N \epsilon_{t+k} $
Mean Squared Error	$MSE_k = \frac{1}{N} \sum_{t=1}^N \epsilon_{t+k}^2 $
Root Mean Square Error	$RMSE_k = \left(\frac{1}{N} \sum_{t=1}^N \epsilon_{t+k}^2 \right)^{1/2}$
Symmetric Mean Absolute Percentage Error (sMAPE)	$sMAPE = \frac{1}{N} \sum_{n=1}^t \frac{ Y_{Pred,n} - Y_{Test,n} }{(Y_{Pred,n} + Y_{Test,n})/2}$
Percentage Improvements	$\delta_{rmse/mae} = \frac{\rho_{1,rmse/mae} - \rho_{2,rmse/mae}}{\rho_{1,rmse/mae}}$

**Figure 5. Seasonal Hourly Data for Bhadla Location****Figure 6. Comparative Results of Evaluation Parameters**

given in Table 4. In Table 4, $Y(Pred,n)$ and $Y(Test,n)$ are the predicted actual values of the testing dataset. $\delta_{rmse/mae}$ is the percentage improvement, $\rho_{1,rmse/mae}$ and $\rho_{2,rmse/mae}$ are the RMSE/ MAE values for the various models implemented. (Li *et al.*, 2022; Li *et al.*, 2012; Hong *et al.*, 2022a). ϵ_{t+k} is the error at the t+kth instant.

Figure 5 shows the reference data for the comparison of the estimated data. It shows the plot of the segregated data at different seasons W1, W2, W3 and W4. In Figure 6, it has been observed that the validation of all the implemented and proposed techniques has validated the results of the technique as forecasted values with 30% of testing and validation dataset giving more accurate results in terms of various performance indices. Figure 6 shows the graphical comparison of the different methods in terms of performance evaluator which is later compared in Table 5. It compares the implemented methods with other machine learning

techniques on seasons W1, W2, W3 and W4. It is observed that KNN-SVM has the highest error compared to the other methods which is followed by the LSTM, and CNN-RNN methods.

These methods have a high error compared to the GA-CNN. The second important observation i.e., the average RMSE error of the CNN-RNN is 0.0362 which is slightly less than the GA-CNN 0.0379. But in the case of MAE, MSE and MAPE. GA-CNN outperforms the CNN-RNN method. Figure 7 to Figure 10 represent the energy forecasting of Solar PV using the CNN-RNN method for all case studies and Figure 11 to Figure 14 represent the GA-CNN technique outcomes graphically. The GA-CNN method and CNN-RNN methods are compared with the reference data as shown previously in Figure 5 for different seasons. A more elaborate comparison is given in the tabular form as given below in Table 5.

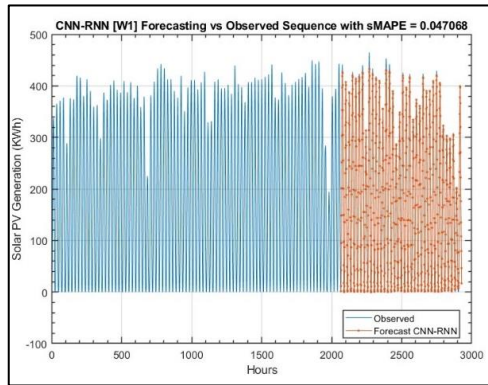


Figure 7. CNN-RNN forecasted and observed sequence for W1 season

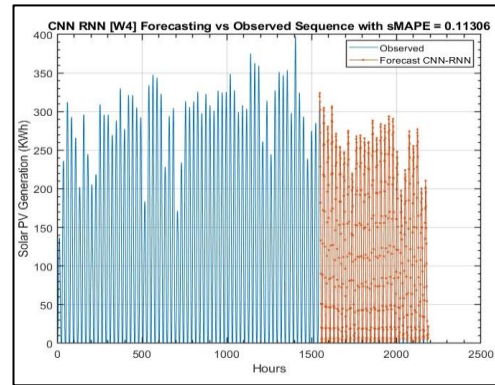


Figure 10. CNN-RNN forecasted and observed sequence for W4 season

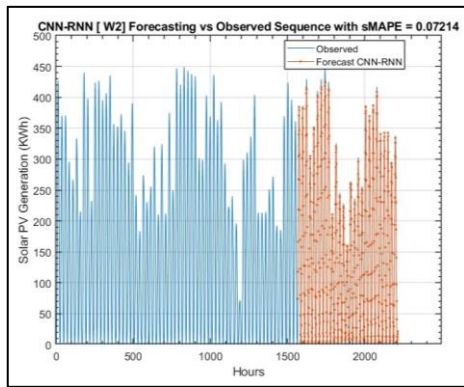


Figure 8. CNN-RNN forecasted and observed sequence for W2 season

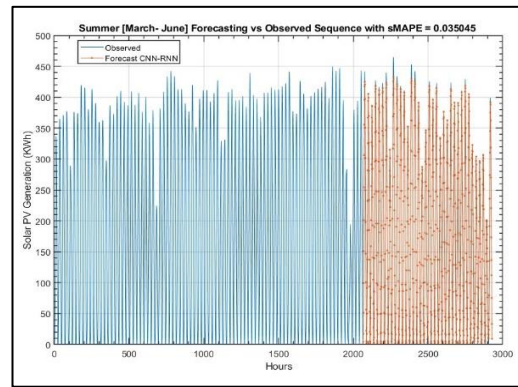


Figure 11. GA-CNN forecasted and observed sequence for W1 season

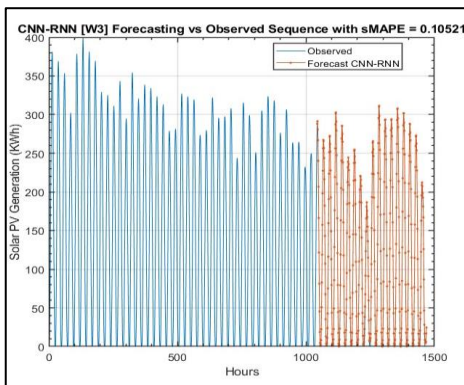


Figure 9. CNN-RNN forecasted and observed sequence for W3 season

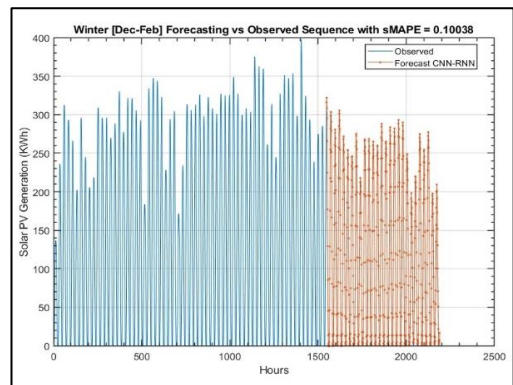


Figure 12. GA-CNN forecasted and observed sequence for W4 season

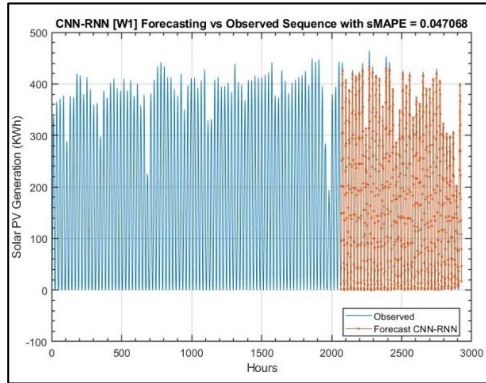


Figure 13. GA-CNN forecasted and observed sequence for W3 season

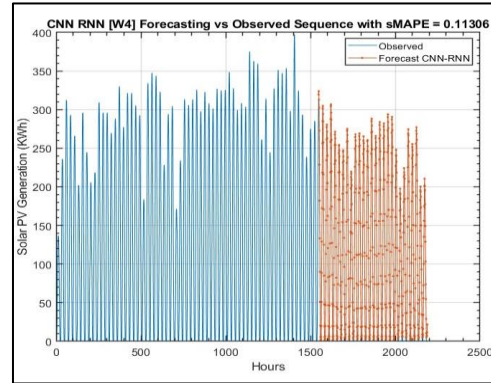


Figure 14. GA-CNN forecasted and observed sequence for W2 season

Table 5. Comparative Results of All Implemented Techniques for Different Cases

Method	Error type	Summer	Monsoon	Autumn	Winter
		W1	W2	W3	W4
LSTM	nRMSE	0.3914	2.1683	1.0728	0.8646
	nMAE	0.2498	1.6991	0.7419	0.659
	nMSE	21.548	591.454	135.1735	85.7417
	sMAPE	0.38806	0.2829	0.2121	0.2472
KNN-SVM	nRMSE	1.1621	1.1423	0.8507	1.1317
	nMAE	0.9581	0.897	0.6748	0.8502
	nMSE	189.950	164.1564	84.9868	146.917
	sMAPE	0.2721	0.239	0.2753	0.0287
CNN-RNN	nRMSE	0.0419	0.0414	0.0376	0.0241
	nMAE	0.0306	0.0331	0.0267	0.0897
	nMSE	0.2473	0.2151	0.1658	0.2198
	sMAPE	0.0471	0.0721	0.1052	0.1052
GA-CNN	nRMSE	0.0379	0.0349	0.0529	0.0262
	nMAE	0.0259	0.0265	0.0413	0.0196
	nMSE	0.2017	0.1532	0.3284	0.0786
	sMAPE	0.035	0.0706	0.1149	0.1004

From the Table 5, it is observed that the GA-CNN performs better in Summer and monsoon but CNN-RNN performs better in Autumn and winter slightly in terms of RMSE error. In terms of MAE GA-CNN performs better than the CNN-RNN in W1, W2 and W3 seasons. In the comparison of MSE and MAPE the GA-CNN performs better in seasons W1, W2, and W4 when compared to CNN-RNN. Therefore, the GA-CNN has the sufficient advantage to take over the CNN-RNN Deep Learning method in solar PV energy estimation. In this study, the CNN-RNN method is better than the LSTM and KNN-SVM methods.

Furthermore, it is observed that the implementation of lower batch sizes and higher dropout rates in the previous techniques resulted in an increased number of iterations per epoch, consequently extending the execution time for forecasting. However, with the implementation of the proposed GA-CNN technique, the iterations per epoch has significantly reduced from 19,000 to 1,200 leading to improved results within a shorter time frame.

Furthermore, the implementation of optimization techniques enables the improvement of

forecasting speed and efficiency, hence boosting the overall efficacy of the algorithm in terms of correctness and computational speed.

Conclusions

The results of this study show that the batch size and rate of dropout may be adjusted using the GA-CNN technique with improved h-parameters. This method primarily improves the prediction of solar PV energy's accuracy and robustness under varying weather conditions. The second noteworthy finding is that predicting times are shorter as a result of h-parameter optimization. When forecasting solar PV energy, this technique can be used instead of CNN-RNN. Precise energy forecasting keeps the system stable and gets ready for the appropriate actions. Therefore, in contrast to other deep-learning techniques that are less precise and demand significant computer power, GA-CNN can operate as a brute force to decrease the computational time and raise the accuracy and robustness.

References

- Abbaskhah, A., Sedighi, H., Akbarzadeh, P., and Salavatipour, A. (2023). Optimization of horizontal axis wind turbine performance with the dimpled blades by using CNN and MLP models. *Ocean Engineering*, 276:114185. <https://doi.org/10.1016/j.oceaneng.2023.114185>
- Abdel-Nasser, M. and Mahmoud, K. (2017). Accurate photovoltaic power forecasting models using deep LSTM-RNN. *Neural Computing and Applications*, 31(7):2727-2740. <https://doi.org/10.1007/s00521-017-3225-z>
- Abuella, M. and Chowdhury, B. (2015). Solar power forecasting using artificial neural networks. 2015 North American Power Symposium (NAPS), Charlotte, NC, USA, 2015, pp. 1-5. <https://doi.org/10.1109/NAPS.2015.7335176>
- Ahmad, M.W., Mourshed, M., and Rezgui, Y. (2018). Tree-based ensemble methods for predicting PV power generation and their comparison with support vector regression. *Energy*, 164:465-474. <https://doi.org/10.1016/j.energy.2018.08.207>
- Ahmed, R., Sreeram, V., Mishra, Y., and Arif, M.D. (2020). A review and evaluation of the state-of-the-art in PV solar power forecasting: Techniques and optimization. *Renewable and Sustainable Energy Reviews*, 124:109792. <https://doi.org/10.1016/j.rser.2020.109792>
- AlKandari, M. and Ahmad, I. (2019). Solar power generation forecasting using ensemble approach based on deep learning and statistical methods. *Applied Computing and Informatics*, ahead-of-print. <https://doi.org/10.1016/j.aci.2019.11.002>
- AlSkaif, T., Dev, S., Visser, L., Hossari, M., and Sark, Wilfried van. (2020). A systematic analysis of meteorological variables for PV output power estimation. *Renewable Energy*, 153:12-22. <https://doi.org/10.1016/j.renene.2020.01.150>
- Chen, T., Lehr, J.M., Lavrova, O., and Martínez-Ramón, M. (2018). Distribution feeder-level day-ahead peak load forecasting methods and comparative study. *Iet Generation Transmission and Distribution*, 12(13):3270-3278. <https://doi.org/10.1049/iet-gtd.2017.1745>
- Cheng, L., Zang, H., Ding, T., Wei, Z., and Sun, G. (2021). Multi-Meteorological-Factor-Based Graph Modeling for Photovoltaic Power Forecasting. in *IEEE Transactions on Sustainable Energy*, 12(3):1593-1603. <https://doi.org/10.1109/TSTE.2021.3057521>
- Cho, K., van Merriënboer, B., Gulcehre, C., Bahdanau, D., Bougares, F., Schwenk, H., and Bengio, Yo. (2014). Learning Phrase Representations using RNN Encoder-Decoder for Statistical Machine Translation. *EMNLP 2014 - 2014 Conference on Empirical Methods in Natural Language Processing*, Proceedings of the Conference, p. 1724-1734. <https://doi.org/10.3115/v1/D14-1179>
- Chung, J., Gulcehre, C., Cho, K., and Bengio, Y. (2014). Empirical Evaluation of Gated Recurrent Neural Networks on Sequence Modeling. *Neural and Evolutionary Computing*, <https://doi.org/10.48550/arXiv.1412.3555>
- da Silva Fonseca, J.G., Jr., Oozeki, T., Takashima, T., Koshimizu, G., Uchida, Y., and Ogimoto, K. (2012). Use of support vector regression and numerically predicted cloudiness to forecast power output of a photovoltaic power plant in Kitakyushu. *Japan. Prog. Photovolt: Res. Appl.*, 20(7):874-882. <https://doi.org/10.1002/pip.1152>
- de Paiva, G.M., Pimentel, S.P., Marra, E.G., de Alvarenga, B.P., Mussetta, M., and Leva, S. (2019). Intra-day forecasting of building-integrated PV systems for power systems operation using ANN ensemble. 2019 IEEE Milan PowerTech, Milan, Italy, pp. 1-5 <https://doi.org/10.1109/PTC.2019.8810480>
- De, V., Teo, T.T., Woo, W.L., and Logenthiran, T. (2018). Photovoltaic Power Forecasting using LSTM on Limited Dataset. 2018 IEEE Innovative Smart Grid Technologies - Asia (ISGT Asia), Singapore, 2018, pp. 710-715. <https://doi.org/10.1109/ISGT-Asia.2018.8467934>
- El Alani, O., Abraim, M., Ghennioui, H., Ghennioui, A., Ikenbi, I., and Dahr, F.E. (2021). Short term solar irradiance forecasting using sky images based on a hybrid CNN-MLP model. *Energy Reports*, 7:888-900. <https://doi.org/10.1016/j.egy.2021.07.053>
- Elsaraiti, M. and Merabet, A. (2022). Solar Power Forecasting Using Deep Learning Techniques. in *IEEE Access*, 10:31692-31698. <https://doi.org/10.1109/ACCESS.2022.3160484>
- Gao, B., Huang, X., Shi, J., Tai, Y., and Zhang, J. (2020). Hourly forecasting of solar irradiance based on CEEMDAN and multi-strategy CNN-LSTM neural networks. *Renewable Energy*, 162:1665-1683. <https://doi.org/10.1016/j.renene.2020.09.141>
- Guo, L. (2022). SAR image classification based on multi-feature fusion decision convolutional neural network. *IET Image Processing*, 16(1):1-10. <https://doi.org/10.1049/ipr2.12323>
- Harrou, F. and Sun, Y. (2020). Advanced Statistical Modeling, Forecasting and Fault Detection in Renewable Energy Systems. *IntechOpen*, London, 210p.
- Heidarpanah, M., Hooshyaripor, F., and Fazeli, M. (2023). Daily electricity price forecasting using artificial intelligence models in the Iranian electricity market. *Energy*, 263(Part E):126011. <https://doi.org/10.1016/j.energy.2022.126011>
- Hong, Y.-Y., Chan, Y.-H., Cheng, Y.-H., Lee, Y.-D., Jiang, J.-L., Wang, S.-S. (2022a). Week-ahead daily peak load forecasting using genetic algorithm-based hybrid convolutional neural network. *IET Generation, Transmission and Distribution*, 16(12):2416-2424. <https://doi.org/10.1049/gtd2.12460>
- Hong, Y.-Y., Taylar, J.V., and Fajardo, A.C. (2022b). Locational Marginal Price Forecasting Using Deep Learning Network Optimized by Mapping-Based Genetic Algorithm. in *IEEE Access*, 8:91975-91988. <https://doi.org/10.1109/ACCESS.2020.2994444>
- Jalali, S.M.J., Ahmadian, S., Kavousi-Fard, A., Khosravi, A., and Nahavandi, S. (2022). Automated Deep CNN-LSTM Architecture Design for Solar Irradiance Forecasting. in *IEEE Transactions on Systems, Man, and Cybernetics: Systems*, 52(1):54-65. <https://doi.org/10.1109/TSMC.2021.3093519>
- Jnr, E.O.-N., Ziggah, Y.Y., and Relvas, S. (2021). Hybrid ensemble intelligent model based on wavelet transform, swarm intelligence and artificial neural network for electricity demand forecasting. *Sustainable Cities and Society*, 66:102679. <https://doi.org/10.1016/j.scs.2020.102679>
- Kim, T.Y. and Cho, S.B. (2019). Particle Swarm Optimization-based CNN-LSTM Networks for Forecasting Energy Consumption. 2019 IEEE Congress on Evolutionary Computation (CEC), Wellington, New Zealand, p. 1510-1516. <https://doi.org/10.1109/CEC.2019.8789968>
- Li, G., Guo, S., and Cheng, C. (2023). Short-term Forecasting Approach Based on bidirectional long short-term memory and convolutional neural network for Regional Photovoltaic Power Plants. *Sustainable Energy, Grids and Networks*, 34:101019. <https://doi.org/10.1016/j.segan.2023.101019>
- Li, G., Xie, S., Wang, B., Xin, J., Li, Y., and Du, S. (2020). Photovoltaic Power Forecasting With a Hybrid Deep Learning Approach. 2020, 8:175871-175880. <https://doi.org/10.1109/ACCESS.2020.3025860>
- Li, M.-W., Xu, D.-Y., Geng, J., and Hong, W.-C. (2022). A hybrid approach for forecasting ship motion using CNN-GRU-AM and GCWOA. *Applied Soft Computing*, 114:108084. <https://doi.org/10.1016/j.asoc.2021.108084>
- Li, Z.M., Xu, S. W., Cui, L.G., Li, G.Q., Dong, X.X., and Wu, J.Z. (2012). The Short-Term Forecast Model of Pork Price Based on CNN-GA. *Advanced Materials Research*, 628:350-358. <https://doi.org/10.4028/www.scientific.net/AMR.628.350>

- Liu, C.H., Gu, J.C., and Yang, M.T. (2021a). A Simplified LSTM Neural Networks for One Day-Ahead Solar Power Forecasting. in IEEE Access, 9:17174-17195. <https://doi.org/10.1109/ACCESS.2021.3053638>
- Liu, J., Shi, Q., Han, R., and Yang, J. (2021b). A Hybrid GA-PSO-CNN Model for Ultra-Short-Term Wind Power Forecasting. *Energies*, 14(20):6500. <https://doi.org/10.3390/en14206500>
- Liu, Z.-F., Luo, S.-F., Tseng, M.-L., Liu, H.-M., Li, L., and Md Mashud, A.H. (2021c). Short-term photovoltaic power prediction on modal reconstruction: A novel hybrid model approach. *Sustainable Energy Technologies and Assessments*, 45:101048. <https://doi.org/10.1016/j.seta.2021.101048>
- Mahmud, K., Azam, S., Karim, A., Zobaed, S., Shanmugam, B., and Mathur, D. (2021). Machine Learning Based PV Power Generation Forecasting in Alice Springs. in IEEE Access, 9:46117-46128. <https://doi.org/10.1109/ACCESS.2021.3066494>
- Makridakis, S., Spiliotis, E., and Assimakopoulos, V. (2018). Statistical and Machine Learning forecasting methods: Concerns and ways forward. *PLOS ONE*, 13(3):e0194889. <https://doi.org/10.1371/journal.pone.0194889>
- Mishra, M., Dash, P.B., Nayak, J., Naik, B., and Kumar Swain, S. (2020). Deep learning and wavelet transform integrated approach for short-term solar PV power prediction. *Measurement*, 166:108250. <https://doi.org/10.1016/j.measurement.2020.108250>
- Mustaqeem, Ishaq, M., and Kwon, S. (2022). A CNN-Assisted deep echo state network using multiple Time-Scale dynamic learning reservoirs for generating Short-Term solar energy forecasting. *Sustainable Energy Technologies and Assessments*, 52(Part C):102275. <https://doi.org/10.1016/j.seta.2022.102275>
- Obiora, C.N. and Ali, A. (2021). Hourly Photovoltaic Power Forecasting Using CNN-LSTM Hybrid Model. 2021 62nd International Scientific Conference on Information Technology and Management Science of Riga Technical University (ITMS), Riga, Latvia, 2021, pp. 1-6. <https://doi.org/10.1109/ITMS52826.2021.9615335>
- Sekhar, C. and Dahiya, R. (2023). Robust framework based on hybrid deep learning approach for short term load forecasting of building electricity demand. *Energy*, 268:126660. <https://doi.org/10.1016/j.energy.2023.126660>
- Singh, V.P., Vijay, V., Siddhartha Bhatt, M., and Chaturvedi, D.K. (2013). Generalized neural network methodology for short term solar power forecasting. 2013 13th International Conference on Environment and Electrical Engineering (EEEIC), Wroclaw, Poland, 2013, pp. 58-62. <https://doi.org/10.1109/EEEIC-2.2013.6737883>
- Tosun, N., Sert, E., Ayaz, E., Yilmaz, E., and Göl, M. (2020). Solar Power Generation Analysis and Forecasting Real-World Data Using LSTM and Autoregressive CNN. 2020 International Conference on Smart Energy Systems and Technologies (SEST), Istanbul, Turkey, 2020, pp. 1-6. <https://doi.org/10.1109/SEST48500.2020.9203124>
- Tovar, M., Robles, M., and Rashid, F. (2020). PV Power Prediction, Using CNN-LSTM Hybrid Neural Network Model. Case of Study: Temixco-Morelos, México. *Energies*, 13(24):6512. <https://doi.org/10.3390/en13246512>
- Trigo-González, M., Batlles, F.J., Alonso-Montesinos, J., Ferrada, P., del Sagrado, J., Martínez-Durbán, M., Cortés, M., Portillo, C., and Marzo, A. (2019). Hourly PV production estimation by means of an exportable multiple linear regression model. *Renewable Energy*, 135:303-312. <https://doi.org/10.1016/j.renene.2018.12.014>
- Vaswani, A., Shazeer, N., Parmar, N., Uszkoreit, J., Jones, L., Gomez, A.N., Kaiser, L., and Polosukhin, I. (2017). Attention Is All You Need. *Advances in Neural Information Processing Systems*, p. 5999-6009. <https://doi.org/10.48550/arXiv.1706.03762>
- Wang, F., Xuan, Z., Zhen, Z., Li, K., Wang, T., and Shi, M. (2020a). A day-ahead PV power forecasting method based on LSTM-RNN model and time correlation modification under partial daily pattern prediction framework. *Energy Conversion and Management*, 212:112766. <https://doi.org/10.1016/j.enconman.2020.112766>
- Wang, F., Zhang, Z., Chai, H., Yu, Y., Lu, X., Wang, T., and Lin, Y. (2019a). Deep Learning Based Irradiance Mapping Model for Solar PV Power Forecasting Using Sky Image. 2019 IEEE Industry Applications Society Annual Meeting, Baltimore, MD, USA, 2019, pp. 1-9. <https://doi.org/10.1109/IAS.2019.8912348>
- Wang, H., Liu, Y., Zhou, B., and Li, C. (2020b). Taxonomy research of artificial intelligence for deterministic solar power forecasting. *Energy Conversion and Management*, 214:112909. <https://doi.org/10.1016/j.enconman.2020.112909>
- Wang, K., Qi, X., and Liu, H. (2019b). Photovoltaic power forecasting based LSTM-Convolutional Network. *Energy*, 189:116225. <https://doi.org/10.1016/j.energy.2019.116225>
- Wang, Y., Liao, W., and Chang, Y. (2018). Gated Recurrent Unit Network-Based Short-Term Photovoltaic Forecasting. *Energies*, 11(8):2163. <https://doi.org/10.3390/en11082163>
- Yang, D., Kleissl, J., Gueymard, C.A., Pedro, H.T.C., and Coimbra, G.F.M. (2018). History and trends in solar irradiance and PV power forecasting: A preliminary assessment and review using text mining. *Solar Energy*, 168:60-101. <https://doi.org/10.1016/j.solener.2017.11.023>
- Zha, W., Liu, Y., Wan, Y., Luo, R., Li, D., Yang, S., and Xu, Y. (2022). Forecasting monthly gas field production based on the CNN-LSTM model. *Energy*, 260:124889. <https://doi.org/10.1016/j.energy.2022.124889>
- Zhang, H., Li, D., Tian, Z., and Guo, L. (2021). A Short-Term Photovoltaic Power Output Prediction for Virtual Plant Peak Regulation Based on K-means Clustering and Improved BP Neural Network. 2021 11th International Conference on Power, Energy and Electrical Engineering (CPEEE), Shiga, Japan, p. 241-244. <https://doi.org/10.1109/CPEEE51686.2021.9383350>