

Predictive Modeling For Solar-Thermal Power Plant Output: Leveraging Machine And Deep Learning Techniques

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ABSTRACT:

It is vital to correctly forecast the output of a solar power plant to manage the energy efficiency and stability of the grid. The current study examines multiple machine and deep learning ideas for forecasting the power output of a plant using data already available to us. Key aspects such as temporal variables, solar irradiance, etc. that are important for setting up the relation between climate conditions and power output are non-negotiable parts of the available data set. The study considers 5 models currently: Linear Regression, Decision Tree Regression, Random Forest, Support Vector Regressor (SVR), convolutional neural networks (CNN), and bidirectional long short-term memory (BiLSTM). Highest accuracy was shown by the random forest model, that of around 72.39% with a standard deviation of 4.36%, over and above other methods. 53.42% accuracy was displayed by the Decision Tree Regressor, but high variance limited its usage. At 27.87%, the linear regression method could not handle the non-linear factors in the data. The least useful was the SVR with an accuracy of 0.79%. Supposedly, the BiLSTM method shows promising results while using temporal dependencies – a R^2 score of 0.6793, a mean absolute error (MAE) of 28,519.93, and a mean squared error (MSE) of 1,594,774,513.30, thus properly utilizing the sequential data available. It performed better than the CNN model, which showed a test loss of 2,618,489,344.0 and an MAE of 39,056.19. To summarize the findings, we can confidently state that while BiLSTM is useful for sequential dependencies for time-series forecasting, the random forest method is appropriate for non-linear forecasting. Thus, it becomes vital to select the right predictive model based on pre-available data to get the desired result for output forecasting.

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1. Introduction

As solar power generation continues to grow and becoming a substantial part of every nation's energy portfolio, the need for robust and reliable predictive models for solar power plants becomes increasingly important.

Power grids owners need a high degree of predictability to meet their planned loads at every point of time. In this respect, traditional power generation units like coal based thermal plants are ideal for power grid managers. On the other extreme end, solar power plants come with an extremely high degree of unpredictability owing to factors like cloud patterns, varying weather conditions, diurnal and seasonal variations of solar radiation, and atmospheric issues like rain, snow, dust, haze and fog. Therefore, as solar power continues to become a larger part of our energy portfolio, there is a rising and urgent need to develop robust predictive models to help in power grid planning and management.

There is a need to perform an extensive comparative study a large variety of predictive models in the context of solar power plants. We can start with traditional methods like Linear Regression as a baseline even though we know that it will not perform well due to the highly nonlinear nature of solar power. Models like Random Forest and support vector regression (SVR) are known to be good in predicting non-linear relationships. Methods like CNN and long short-term memory (LSTM) use advanced hierarchical data extraction are good in capturing sequential correlations better.

The current research paper performs a comparative study of a large set of predictive models to forecast solar power plant parameters like direct normal irradiance (DNI) and real-time power generation values.

This paper considers the following learning models:

- Decision Tree Regressor,
- Linear Regression,
- Bidirectional Long Short-Term Memory (BiLSTM),
- Convolutional Neural Networks (CNN),

- Random Forest, and
- Support Vector Regressor (SVR).

All the forecasting methods are evaluated on the following parameters:

- accuracy,
- mean absolute error (MAE),
- mean squared error (MSE), and
- R^2 score

2. Related Work

Through photovoltaic production uncertainty, Feng et al. [1] (2024) showed a path for maximizing the complimentary working of solar plants and hydropower reservoirs. Solar power output was created by principal component analysis and pattern clustering, while load variance was decreased using a cooperation search algorithm. This model reduced the problems of photovoltaic integration and enhanced scheduling.

Larson et al. [2] (2016) used the model of numerical weather prediction (NWP) least-squares optimization to create a forecasting system for photovoltaic (PV) power output for one day ahead. The method resulted in a forecast skill gain of 13%–23% over a persistence model with comparative RMSEs of 10.3%–14.0% upon evaluation at two non-tracking PV facilities in the USA. The model successfully reduced high over-prediction events and corrected systemic irradiance forecast errors by the results.

Using LSTM and BPNN, Dhaked et al. [3] (2023) created an intelligent weather-based model for predicting solar PV power output, which emphasized how temperature and irradiance affect PV output, focusing on the significance of error-free prediction for the stability of the grid and energy management. The result showed that LSTM provided had a more accurate seasonal forecast than BPNN, taking factors such as MAE, MAPE, and R^2 score into consideration.

Direct normal irradiance (DNI) prediction models and their application to concentrated

solar thermal plants were researched by Law et al. [4] (2014). They showed the importance of correct DNI forecasting in maximizing the productivity and economic feasibility of concentrated solar thermal plants. By examining methods such as cloud motion vectors, numerical weather prediction models, time series analysis, and hybrid approaches, we focus on the necessity of stable error measurements and a reliable DNI dataset for equitable analysis. Although it was observed that the DNI forecast for two days ahead helped improve revenues and decrease errors, further study is recommended for short-term forecasts and their effects on various energy economies.

To overcome the difficulties of weather fluctuations, Nguyen et al. [5] (2021) suggested an improved LSTM model for short-term forecasting of solar power plant output in Vietnam, where to maximize output, multiple LSTM setups and traditional forecasting techniques were compared. It demonstrated good accuracy when applied to the Thanh Thanh Cong No 1 (TTC) SPP using actual pre-available weather data, with a MAPE of 3.491% as opposed to 10.857% when utilizing anticipated data. Further, the model could properly manage weather-related prediction errors, lowering the MAPE from 10.857% to 9.881%.

Again, using an advanced LSTM model, Bui et al. [6] (2022) improved the short-term forecasting of solar power plant output under restricted conditions. In case of errors and missing data, the research presented new methods such as the P/GHI coefficient and the global horizontal irradiance (GHI) interval division. With a RMSE reduced value of 6.710% and MAPE reduced value at 6.059%, the improvised training algorithm resulted in fewer forecasting errors. We can clearly establish that this method can handle solar power utilities at a practically feasible industrial scale where real life operational limitations are also applicable.

Singh and Garg [7] in 2023 displayed a machine learning method for output of a solar PV plant in Madurai. It studied multiple models based out of machine learning and how correctly each one of them solved the issues of widely varying output energy strange. What the results actually showed was how the various methods helped in improving

the accuracy and other important data outputs in PV facilities that are grid connected. Thus, showing how the models could improve the overall energy management when the output forecasting is concerned.

At the Phong Dien power plant in Vietnam, Quang et al. [8] (2021), for short term predictions, took the help of a LSTM model that reconfigured the overall framework so as to adapt to the available features of the plant at Phong Dien, even taking the available weather data as input. This put the much-needed emphasis on using meteorological dataset from the commercial data providers to improvise on forecasting ability, along with better model performance.

In a grid-connected 20-kWp solar plant in Tiruchirappalli, India, Ehsan et al. (2017) [9] proposed a method to predict the solar output one day in advance through an artificial neural network (ANN) that was perceptron-based. It gave approximately 11200 patterns to the neural network over a span of seventy days based on air temperature and solar plant power output. The forecasting method was trained to improvise and optimize on multiple learning pathways. When eventually the output gave a mean absolute percentage error (MAPE) in preferred range, it was concluded that the forecasting can possibly be used for industrial level load management.

In Russia, a forecasting model based on short term output was proposed by Snegirev et al. [10] (2017) that focused on decreasing the large-scale power generation uncertainty usually associated with output at industry level. It aimed at decrease in reserve capacity so as to increase the overall feasibility of the traditional plant. It proposed to address the issues of energy management in market by a math-based approach which focused on hourly output average of such plants, crosschecked by real time operational data.

Using data from the Zagatouli PV power plant in Burkina Faso, Palm et al. [11] (2024) studied solar PV production output forecasting using LSTM, GRU, and a hybrid LSTM-GRU model.

The top values of RMSE (10.629), MAE (2.0), and R2 (0.999) were obtained using the hybrid LSTM-GRU model, which performed better than the other ones. It recommended the hybrid model's use for error-free solar PV forecasting in energy management usages, highlighting its superiority over others.

Another detailed study of the solar PV power forecasting method was done by Sobri et al. [12] (2018), who showed the importance of these techniques in controlling power production uncertainty and fluctuations. It divided prediction methods into three types: ensemble approaches, time-series statistical methods, and physical methods. It focused on how AI techniques are currently being applied nowadays because of their superior skill to consider complex and non-linear data. The study also mentioned how efficiently these ensemble approaches combine the major qualities of several models to enhance forecasting precision. For anyone interested in working on the optimal design of solar PV systems, this study is indispensable. A seasonal multi-step forecasting model based on the model of random forest was suggested by Jogunuri et al. [13] (2024) for short-term solar PV power output. The model was used for the prediction range of 15 and 30 minutes using on-site weather data and power output from a 20 kW on-grid setup. The results showed notable accuracy of 49% and 50% above reference models as support vector regression, artificial neural networks, and deep neural networks. For grid stability and optimizing energy balance in solar-integrated networks, the study showed the importance of accurate forecasting. Pedro and Coimbra [14] (2012) used a range of models to a 1 MWp single-axis tracking PV facility in Merced, California, to anticipate solar power output without the need for exogenous input data. Metrics such as MAE, MBE, and R2 were used to compare varied models as Persistence, ARIMA, kNN, ANN, and GA-optimized ANN for forecasts that were one and two hours in advance. It showed that ANN-based methods performed better, with GA optimization leading to notable accuracy gains. Their work showed how seasonal solar fluctuation affects model performance and highlighted the importance of choosing the correct model based on

the solar power plant parameters.

Inman et al. [15] (2013) studied various solar forecasting methods. They showed the importance of precise prediction at different time scales - minute-wise, hourly, daily, etc. - to maintain grid balance, lower reserve costs, and improve reliability. Their study explored the theory and applications of solar prediction techniques for industry-scale power output and solar resource prediction for effective power grid management.

Khan et al. [16] (2022) used data from Pakistan's Quaid-e-Azam Solar Park to analyze statistical and AI-model methods for solar PV power forecasts on an hourly basis. It was found that the recurrent neural network (RNN) was better than other models, but specifically, the bidirectional long-short-term memory (BiLSTM) method was the best that achieved optimized accuracy in all meteorological conditions. With an RMSE of 0.0025, R2 of 0.99, and a coefficient of variation of RMSE (Cv) of 0.0095%, the BiLSTM algorithm showed promising results, strengthening its dependability for predicting PV output power.

In order to calculate the thermal output of concentrating solar power plants, Wang et al. [17] (2020) implemented a hybrid approach that combined deep learning with mechanism modeling. Convolutional neural networks (CNNs) and long short-term memory (LSTM) networks recalibrated the input data to capture spatial-temporal coupling, even as mechanism modeling accurately pinpointed climatic elements without any dependence on subjective input selection. With mean RMSE of 5.061 MWt and MAE of 2.871 MWt, it was successfully operated on a Solar Two-like system in Zhangbei, establishing its solid effectiveness in forecasting thermal power output for strong, reliable, and effective grid utilization.

Eroshenko et al. [18] (2018) also applied a hybrid method that blends both deep learning and mechanism modeling to create a short-term forecasting model. CNN and LSTM models recreated input information, using spatial-temporal correlations. On the other hand

mechanism modeling found vital climatic factors, which showcased its reliability in handling the challenges of non-schedulable thermal output for grid and plant management when it was used to a Solar Two-like concentrating solar power plant in Zhangbei, achieving mean RMSE of 5.061 MWt and MAE of 2.871 MWt. Further, by applying the actual data from South Korean solar power plants, Kim and Hur [19] (2019) created an ensemble model to increase the accuracy of short-term solar output forecasts. It combined the results of hourly regression, support vector regression (SVR) and naïve Bayes classifier (NBC), along with weighting factors depending on the reciprocal of the standard deviation of the forecast error. Normalized mean absolute error (NMAE), which shows forecasting errors, was successfully reduced by this new ensemble method, indicating its reliability in increasing power system stability and solar power output predictions. For solar power generation prediction, Zhang et al. [20] (2024) showed a Dynamic Bayesian Network (DBN) method that uses data from multiple sources, for example sensor inputs, weather data, operational metrics, and lagged output information. It accounts for temporal variations caused by system failures or deterioration using an error compensation method. For forecasting horizons spanning from one hour to one week, the DBN showed even better accuracy (92%–95%) than techniques such as SVR, ANN, kNN, and LSTM. They concluded that DBN based methods are more efficient, robust, and have lesser dependence on the data in comparison to neural

network-based models.

3. Proposed Work

Described below are the various important stages or layers of the process—data collection and preprocessing, model selection, training, and the resulting evaluation.

Data Collection and Preprocessing:

For the current proposed research paper, previously available data records of an actual solar power plant were considered.

The major emphasis was on pre-available historical data – taking the factors such as year, month or day into consideration. Direct Normal Irradiance (DNI) and other climatic factors were also included, along with the real solar power plant, power output values. To make the data fit for machine learning and deep learning models, the data cleaning was done and missing values were replaced with the mean value. Figure 1 shows the monthly average data for DNI SUM (Direct Normal Irradiance) and the actual generation of power output across the given range of data. This visualization allows us to focus on how the output is affected by variations in solar irradiance in different seasons. This is important for a clear analytical modelling of the output performance of solar power plants. These kinds of insights can be applied to further improvise the output accuracy of forecasting models for solar power plants.

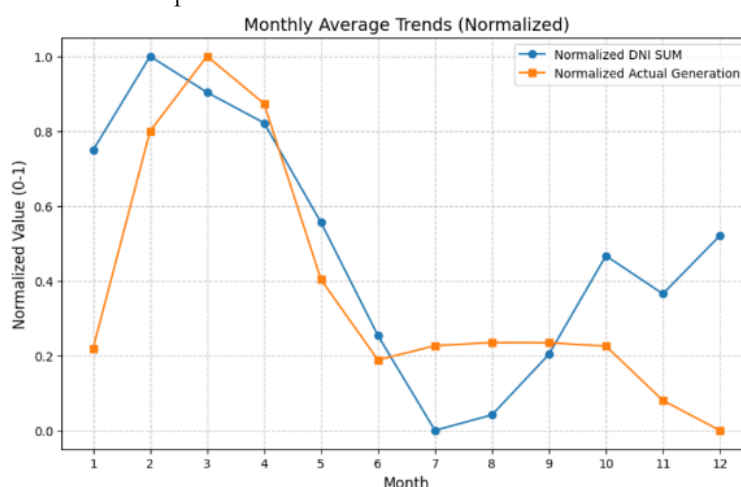


Figure 1. Monthly Average Trends for Direct Normal Irradiance (DNI) SUM and Actual Power Generation.

Feature Separation:

The categorization of the data is divided into two parts: input features and target variables. Here, the input features included DNI, day, month, and year, representing the input features that affect solar power generation. The target variable was the actual power output that the model aims to forecast.

Data Scaling:

The Standard Scaler was employed to standardize the input data for the simple purpose of uniformizing the input aspects across the input range and reducing the dominance of larger value sets. This scaling technique thus transformed the features to have a mean of 0 and a standard deviation of 1, resulting in the improvement of the models' convergence during training.

Train-Test Split:

The pre-processed data were split into training and testing sets, where 75% of the data was used for training and 25% for testing. The training set was used to fit the models, whereas the testing set was reserved for evaluating the models' generalization performance on unseen data. This data split ensured that the models' performance was not influenced by overfitting to the training data.

3.1 Model Selection and Implementation

To accurately predict the power output, a total of six models were selected based on machine learning and deep learning, each customized uniquely to capture different aspects of the dataset's features. They were selected to provide a detailed and extensive comparison of ensemble-based methods, traditional statistical approaches, and advanced neural networks. You can find the detailed elaboration of the methods below:

Random Forest Regressor:

It is an ensemble learning algorithm that creates multiple decision trees during training and then creates an average of their predictions to improve accuracy and reliability. Because it can handle non-linear relationships and resists overfitting, it is an ideal choice for datasets with complex patterns. Random Forest takes good advantage of its ensemble nature to handle variance and improve generalization, particularly in regression tasks like

solar power forecasting.

Decision Tree Regressor:

This method creates a single tree to map the relationship between features and the target variable. Though it is quite good in capturing non-linear relationships, its major limitation lies in its vulnerability to overfitting, especially compared to Random Forest's ensemble approach. We can consider decision tree regressor model as a benchmark to estimate the benefits of ensemble learning, using it for forecasting.

Linear Regression:

Even though it is well known that this classical statistical method will be unable to predict the highly nonlinear solar data, we include it in our study as a baseline model to compare other models against it. This model assumes a linear relationship between input features and the target variable.

Support Vector Regressor:

SVR uses kernel functions to transform input features into higher-dimensional spaces in order to create maps for non-linear relationships. Though it is quite effective for complex datasets in moderation, SVR has problems with larger datasets or those that require extensive hyperparameter tuning.

Bidirectional Long Short-Term Memory:

BiLSTM is a kind of recurrent neural network (RNN) capable of processing sequential data in both forward and backward directions. This model is designed to handle temporal dependencies in time-series data. Owing to its strengths, we expect BiLSTM to excel in modeling the temporal relationships in solar power predictions.

CNN Model:

This model for solar power output forecasting is a totally connected deep neural network (DNN). Such models are good for nonlinear predictive modeling striking a balance between complexity and regularization. It begins with an input layer that accepts feature vectors of temporal and

environmental variables, followed by three hidden layers with 128, 64, and 32 neurons, all using the ReLU activation function to capture non-linear relationships. Dropout layers with a 30% dropout rate are applied after each of the hidden layers to prevent overfitting. The output layer contains a single neuron with a linear activation function to forecast the continuous target variable. The model is coupled with the Adam optimizer for efficient learning and uses mean squared error (MSE) as the loss function, along with mean absolute error (MAE) for evaluation. Enhancement of regularization is achieved with an early stopping mechanism and monitoring validation loss to prevent overtraining. Trained over a maximum of 100 epochs with batch normalization, the model achieves a test loss of 2,618,489,344 and a MAE of 39,056.19. As this model demonstrates effective convergence without making any significant overfitting, we can clearly establish that, this proposed model gives robust and reliable solutions for solar power plant power output forecasting.

3.2 Model Training

All the machine and deep learning models were trained on the pre-processed training dataset, with customized configurations and optimization pathways to ensure optimal performance. Each training model is elaborated below in detail:

Random Forest and Decision Tree Regressor: These algorithms were initially tested using default hyperparameters to establish baseline performance. Further, hyperparameter fine-tuning was applied to optimize vital factors, such as the number of estimators, minimum samples, maximum depth, and per split for the random forest, and the splitting criteria and depth for the decision tree. This iterative fine-tuning method improvised the models' ability to generalize the unseen data, variance, and balancing bias effectively, as shown in Figure 2.

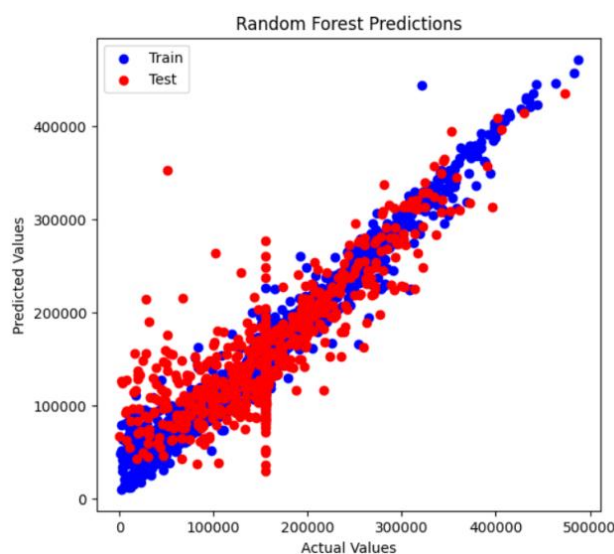


Figure 2. Random forest predictions vs. actual values.

Linear regression and SVR: Owing to their simplicity and interpretability, the models of linear regression and SVR were tested with standard configurations. Linear regression used a straightforward fitting process, and SVR used a radial basis function kernel to process non-linear

relationships. The SVR's training involved setting regularization and kernel parameters to their default values, with limited hyperparameter tuning to maintain output efficiency, as shown in Figure 3.

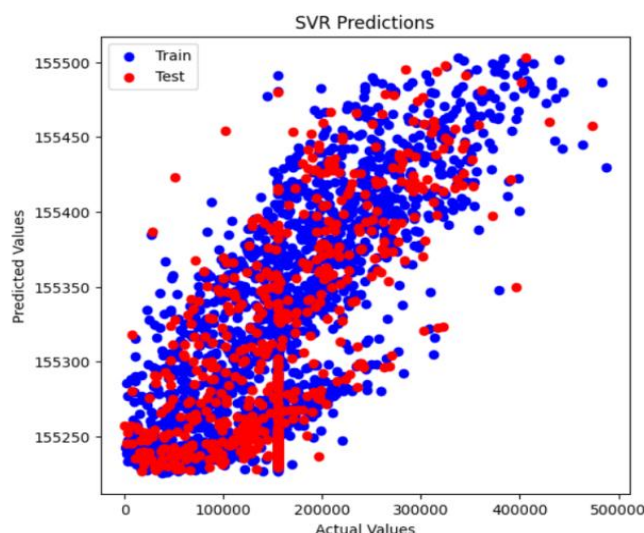


Figure 3. SVR predictions vs. actual values.

Bidirectional Long Short-Term Memory: The algorithm of BiLSTM was created with a deep learning architecture with multiple LSTM layers to handle the sequential dependencies in the dataset. It was optimized using the Adam optimizer, a preferable choice for its adaptive learning rate skills, and the mean squared error (MSE) loss

function that penalizes large prediction errors. The training was conducted over multiple epochs, with a batch size of 32, and the training process was closely monitored using validation loss to ensure convergence of the output data, as shown in Figure 4.

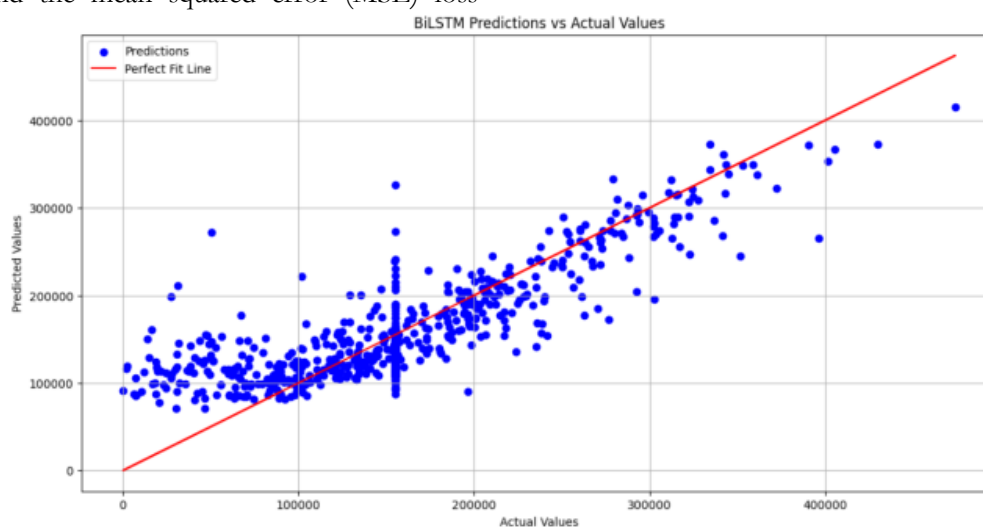


Figure 4. BiLSTM predictions vs. actual values.

CNN: This model was designed with three dense layers coupled in between with dropout layers to decrease overfitting by randomly deactivating neurons while testing. CNN employed the Adam optimizer for gradient-based optimization and the mean squared error (MSE) for the loss function.

An initial stopping method was integrated to abort the model training when validation loss failed to show improvement with consecutive epochs, thus preventing inconsequential and unnecessary training and proper mitigation of overfitting, as shown in Figure 5.

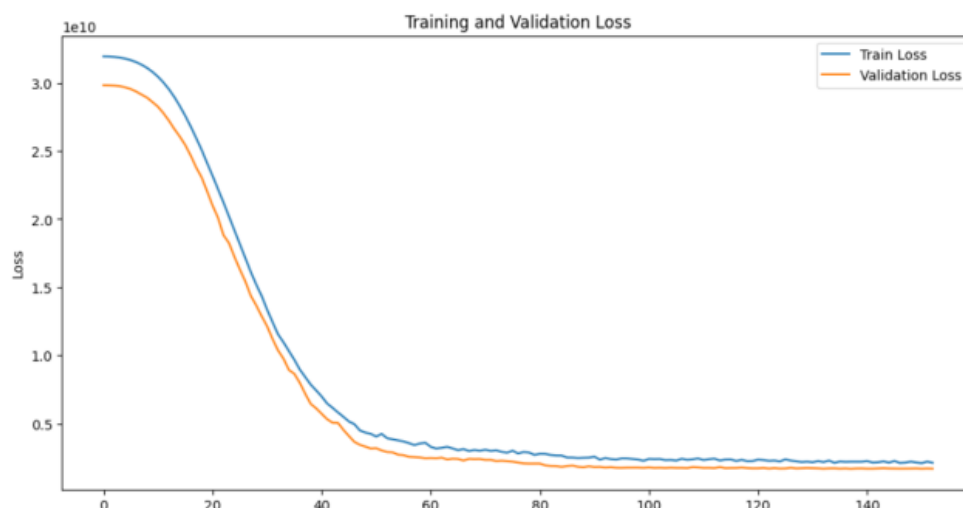


Figure 5. CNN Training and Validation Loss.

3.3. Model Evaluation

For a complete comparative analysis of the performance of each model, all models were evaluated on the training/testing dataset using a combination of statistical metrics, which provided vital insights into the precision, accuracy, and reliability of the forecasts, ensuring an unbiased and reliable comparison across all models. The following metrics were applied for the aforementioned evaluation of the models:

Accuracy:

It evaluates overall the quality of prediction of machine learning algorithms by conducting a comparative mapping of predicted values to the actual observed values.

Mean Absolute Error:

MAE gives the value for the average magnitude of errors between the actual and predicted values, making it an efficiently readable measure of performance.

Mean Squared Error:

This metric focuses on larger prediction errors by squaring the difference between actual and predicted values. As compared to the MAE, the MSQ penalizes higher deviations to a greater degree.

R² Score:

The R² metric gives the proportion of variance in the target variable that the algorithm can work out. R² value of 1 indicates perfect prediction.

This multi-metric evaluation approach helped to create a well-informed comparative analysis, focusing on the strengths and limitations of each model in the relevant context of solar power output forecasting.

4. Results and Discussion

The performance of each of the predictive models was critically analyzed with respect to their strong and weak points.

Amongst all models in our range of consideration, the RFR model gave the best output performance with an impressive accuracy of 72.39%.

In close comparison, The BiLSTM model showcased good ability while dealing with sequential data, achieving the lowest mean absolute error (MAE) of 28,519.93 and a high R² score of 0.6793. Thus, BiLSTM could efficiently handle temporal factors in given dataset, making it specifically efficient for time-series data.

On the other hand, models such as the CNN, gave comparatively moderate performance even while showcasing its ability to handle non-linear patterns in the data. But CNN's overall applications are limited by its handicap in dealing with temporally dependent datasets when compared to BiLSTM model. Traditional methods like linear regression and support vector regression didn't fare any better as they struggled to capture the complexity and non-

linearities in the dataset. Linear regression, due to its simple linear assumptions, and SVR, due to problems in hyperparameter tuning for high-dimensional data, delivered less than optimal results, conclusively showcasing their limitations in the current context.

5. Visualization and Performance of All Models

In order to comprehensively see, understand, and compare the output performance of all concerned models, it is imperative to study the visualization aspect of each one. Plots were graphed for each of them to compare the predicted and actual solar power output, giving a ready-to-view and analyze the efficiency of each algorithm in terms of alignment with true values.

To support the process and to study their respective convergence behavior, the curves for training as well as validation losses were also created for the deep learning algorithms, such as BiLSTM and CNN, that offered valuable insights into the models' learning skills and performances, and showcasing for both of them whether they achieved stable training or encountered overfitting issues.

Various types of data visualizations highlighted the forecasting accuracy of algorithms and provided comparisons between the methods. By combining quantitative metrics with visual data, we obtained a deeper understanding of the comparative strengths and weaknesses of the different predictive methods studied.

Random Forest Regressor:

The model shown in Figure 6 emerged for the most part as the best in this study, with an accuracy of 72.39% and a standard deviation of 4.36%. Random Forest is an ensemble learning technique that creates multiple decision trees and then averages their predictions to increase accuracy and reduce overfitting at the same time. It successfully handled the non-linear relationships in the data, tactically handling the range of the dataset in its ensemble structure to generalize well across training and testing data. The high precision and relatively low standard deviation make Random Forest the best model compared to others, particularly for datasets with noteworthy variability and non-linear dependency.

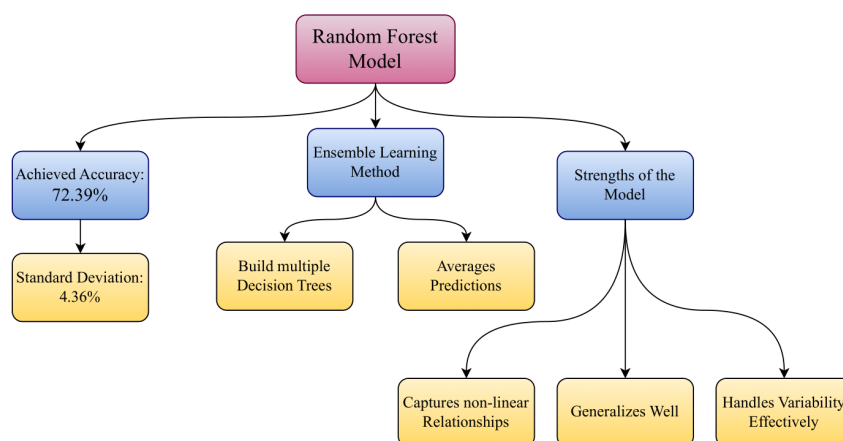


Figure 6. Performance Analysis of the Random Forest Model.

Decision Tree Regressor:

Figure 7 illustrates a single-tree model of the Decision Tree Regressor, which is achieved with a reduced accuracy rate of 53.42% and a standard deviation of 10.21%. Though it can effectively model non-linear data, its major limitation lies in its tendency to overfit, as we can see in this study.

Without the obvious advantage of the ensemble averaging technique of the random forest, the Decision Tree failed in comparison to generalize properly regarding the test data, resulting in comparatively inferior performance. Though it still performed better than some other models, overall, it is less reliable for forecasting due to its high variance and susceptibility to overfitting.

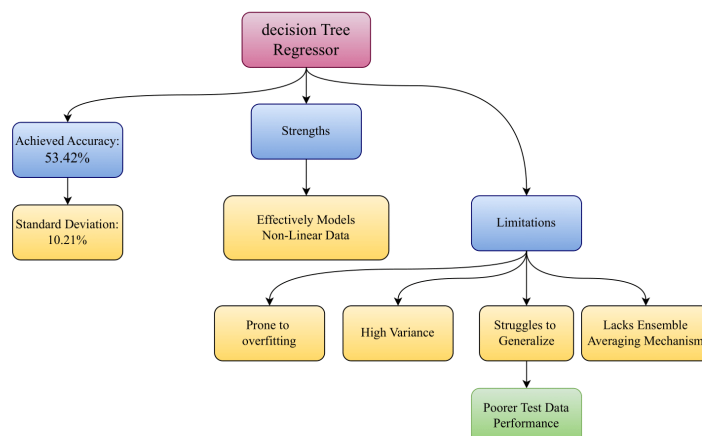


Figure 7. Performance Analysis of the Decision Tree Regressor Model.

Linear Regression:

Figure 8 shows the method of linear regression, a traditional statistical model, which also performed substandard in this study, achieving an accuracy of 27.87% and a standard deviation of 2.82%. Linear regression struggled to handle the non-linear relationships inherent in the dataset because it

assumes a linear relationship between input features and the target variable. As the linear regression technique is quite straightforward to implement and interpret, its lack of complexity and flexibility makes it unsuitable for modeling complex solar power generation patterns. Thus, linear regression ranked as one of the worst performers in the current comparative analysis.

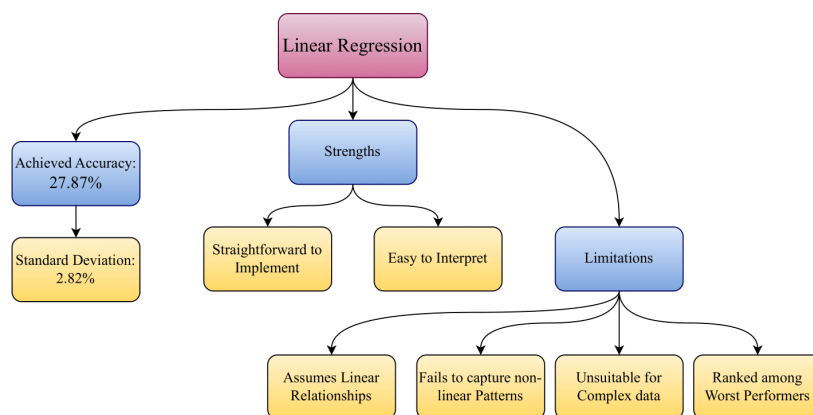


Figure 8. Performance analysis of the linear regression model.

Support Vector Regressor:

The SVR technique, as shown in Figure 9, achieved an accuracy of 0.79% and a standard deviation of 0.89%, indicating its limited utility for this dataset. SVR usually works better for small and moderately complex datasets, but it struggles

with larger datasets with higher dimensions, where the factor of hyperparameter tuning becomes a challenging limitation for the overall results. The achieved output suggests that SVR could not sufficiently model the non-linear and temporal characteristics of solar power output, making it one of the least suitable models for this job.

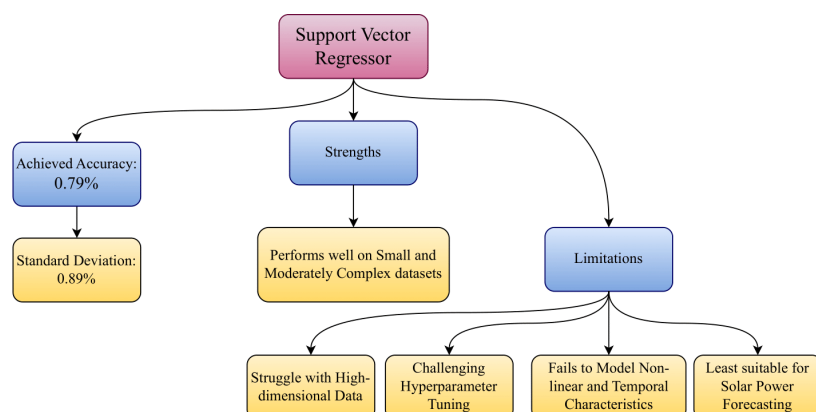


Figure 9. Performance Analysis of the SVR Model.

Bidirectional long-term memory:

The BiLSTM model is shown in Figure 10. achieved a strong result, achieving an R^2 score of 0.6793, a mean absolute error (MAE) of 28,519.93, and a mean squared error (MSE) of 1,594,774,513.30. BiLSTM effectively leveraged the temporal features in the dataset as it is designed to capture sequential dependencies in time-series data, performing better than all other

models in terms of MAE. BiLSTM's ability to effectively handle both past and future temporal data made it specifically suitable for this forecasting work. Although its accuracy was slightly lower than Random Forest, its low MAE and MSE highlight its superior forecasting precision, making it the best model for practical application with regard to time-series data in this study.

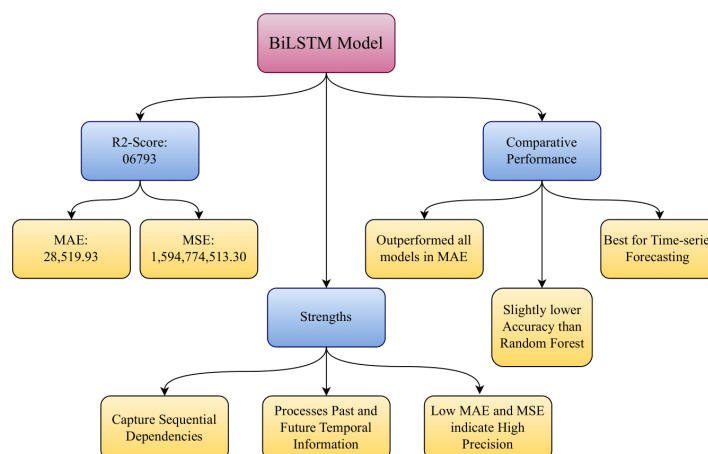


Figure 10. Performance Analysis of the BiLSTM Model.

Convolutional neural network:

As shown in Figure 11, the CNN model achieved a test loss of 2,618,489,344.0 and a mean absolute error (MAE) of 39,056.19, placing it behind both the BiLSTM and Random Forest methods. While CNNs excel at processing complex non-linear patterns, they are limited by their ability to handle temporal dependencies directly. This is what we

found in our studies. As compared to BiLSTM, the CNN model had higher errors and less precision in its predictions, underlining the need to focus on temporal modeling in solar power prediction. Although the CNN performed slightly better than some models, regarding time-dependent tasks, it performed worse than the BiLSTM model.

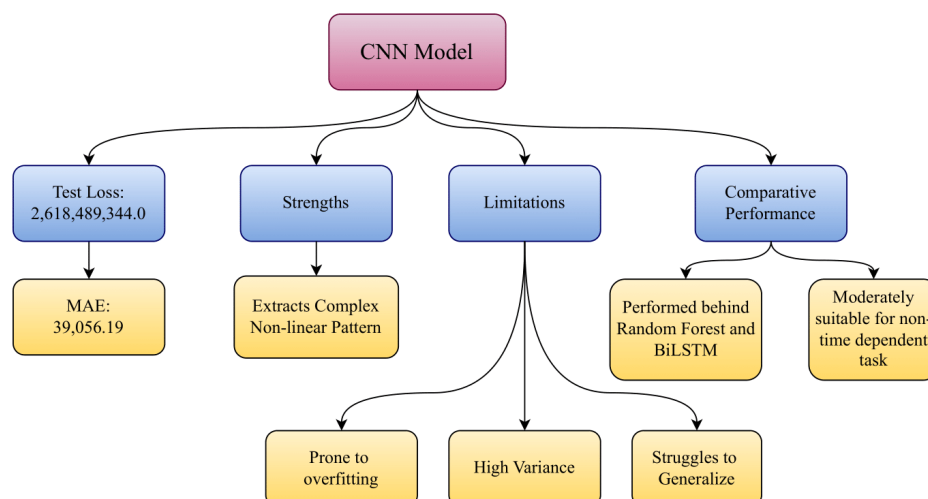


Figure 11. Performance Analysis of the CNN Model

6. Discussion

Out of all the models under our current consideration, the Random Forest method emerged as the best overall for the objective, with the highest accuracy of 72.39% and was found to be effective in capturing non-linear relationships in given input dataset, indicating its robust nature for general regression jobs. In comparison, BiLSTM performed well in time series data, achieving a lowest MAE (28,519.93), and R^2 score of 0.6793, showing its inherent superior skills while handling sequential dependencies. Hence BiLSTM can be said to work well with datasets having temporal patterns. CNN's performance was better only while dealing with non-linear data but when compared with BiLSTM its inherent limitations of handling temporal dependencies were exposed. Older orthodox techniques such as linear regression, achieving accuracy value of 27.87% and SVR, achieving accuracy value of 0.79% could not cope up to the required standards, majorly due to their limitations in capturing both complex non-linear data and temporal relationships within the datasets. On the other hand, the method of decision tree regressor, while achieving a reasonable accuracy of 53.42%, displayed a high variance along with overfitting challenges, restricting its practical application for the task. Overall, we can deduce the basic fact that any method chosen must be done so keeping the unique features of the dataset in mind. For example, BiLSTM is good for time series tasks, while random forest is well equipped for general forecasting. So,

we can say that novel machine learning and deep learning models carry promising potential for predicting solar power output, even bringing into focus newer hybrid models for future improvisations in forecasting accuracy and more data generalization sense.

7. Conclusion and Future Work

We compared the predictive performance of various machine learning and deep learning models in accurately forecasting the output for solar power using historical data. We found that the random forest model was an effective and reliable choice for predicting solar data with the highest accuracy of 72.39%.

The BiLSTM algorithm was a close second, with the lowest mean absolute error (MAE) of 28,519.93. It illustrated its superior performance ability with datasets with strong temporal dependencies, highlighting its dominance in time-series predictions. Models such as CNN performed moderately, and the traditional ones like SVR and linear regression were not quite effective in handling the non-linear nature of the dataset. Overall, the summarized results show the utmost importance of choosing the correct forecasting method based on the unique character of the dataset to obtain optimized accuracy and robust reliability in the desired prediction.

In conclusion, we feel that there is still a lot of room and possibility to tackle the challenges of

solar power forecasting with specialized predictive and forecasting methods. We recommend the study of hybrid models that can combine the strengths of multiple algorithms—for example, BiLSTM may be coupled with the random forest model so that the combined method can handle both non-linear pattern acknowledgment and temporal dependency of the dataset. We also recommend incorporation of transfer learning techniques to improve forecasting by the models, specifically with limited sample data. The input data can be further improved by including weather forecasts, humidity levels, temperature levels, and cloud cover predicted by weather agencies to enhance the output power prediction accuracy. We feel that a wider input data set can improve the performance of the predictive and forecasting models.

Future research must aim at better models, better input datasets and better forecasting quality metrics to improve the accuracy, scalability, robustness, and reliability of forecasting models suitable for solar power predictions which can guide power grids across the globe.

8. Limitations of the Work

Here we outline the major limitations of this work. The feature dataset was minimal in nature as it included only temporal variables and direct normal

irradiance (DNI), while leaving out important environmental aspects such as humidity, temperature, cloud cover, wind speed, atmospheric pressure, etc.

Another limitation is that the dataset came from a single geographical location. Without more data from different global locations, we cannot validate the application of the results of our study to other locations.

Additionally, the study used a basic 25-41% train-test split without cross-validation, potentially introducing evaluation bias during the process. There was not sufficient description of the optimization of the hyperparameter for deep learning algorithms, even as the CNN was applied on fully connected layers, rather than on actual convolutional operations.

Also, the study did not consider the following: statistical significance testing, domain-specific baseline comparisons, prediction time horizons, practical feasibility in real-world deployment, scaling issues (our data was from a 50 MW plant), applicability across diverse solar power plant technologies (our data came from a concentrated solar power plant) and compatibility across varying geographic locations.

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Abbreviations

AI-Artificial intelligence

ANN: Artificial neural network

ARIMA-Autoregressive Integrated Moving Average

BiLSTM-Bidirectional Long Short-Term Memory

BPNN-Back Propagation Neural Network

CNN: Convolutional Neural Network

CST: Concentrated solar thermal

DBN: Dynamic Bayesian Network

DL: Deep Learning

DNN: Deep Neural Network

DNI-Direct Normal Irradiance

GA: Genetic algorithm

GHI-Global Horizontal Irradiance

GRU: Gated Recurrent Unit

kNN - k-Nearest Neighbors

LSTM-Long Short-Term Memory

MAE-Mean Absolute Error

MAPE-Mean Absolute Percentage Error

MBE: Mean Bias Error

ML: Machine Learning

MSE-Mean Squared Error

NBC: Naive Bayes Classifier

NMAE-Normalized Mean Absolute Error

NWP-Numerical Weather Prediction

PV: Photovoltaic.

RBF-Radial Basis Function

ReLU-Rectified Linear Unit

RMSE-Root Mean Squared Error

RNN: Recurrent neural network

SPP: solar power plant

SVR: Support Vector Regressor

TTC-Thanh Thanh Cong

UPS: United Power System

Statement and Declaration

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