Leveraging AI and Data-Driven Techniques for Solar Power Prediction

Anjali
Department of Electronics and Communication Engineering
Indira Gandhi Delhi Technical University for Women
New Delhi, India
Email: anjaliikashyap.25@gmail.com

Himanshi Kataria
Department of Electronics and Communication Engineering
Indira Gandhi Delhi Technical University for Women
New Delhi, India
Email: himanshikataria58@gmail.com

Livya Jajoria
Department of Electronics and Communication Engineering
Indira Gandhi Delhi Technical University for Women
New Delhi, India
Email: livyajajoria6@gmail.com

Nirma Peter
Department of Electronics and Communication Engineering
Indira Gandhi Delhi Technical University for Women
New Delhi, India
Email: nirmapeters@gmail.com

Isha Malhotra
Department of Electronics Engineering
School of Engineering and Technology, Vivekananda Institute of Professional Studies - Technical Campus (VIPS-TC)
New Delhi, India
Email: isha.malhotra2691@gmail.com

Nidhi Goel
Department of Electronics and Communication Engineering
Indira Gandhi Delhi Technical University for Women
New Delhi, India
Email: nidhi.iitr1@gmail.com

***Abstract*—The demand for accurate short-term solar power forecasting has increased rapidly as India continues to expand its renewable energy capacity, especially in fast-growing metropolitan regions like Delhi. The widespread deployment of photovoltaic (PV) systems, combined with rising electricity consumption, places additional stress on the power grid. Moreover, Delhi experiences highly variable weather conditions such as sudden cloud cover, pollution, humidity, and haze which can quickly alter solar irradiance and cause significant fluctuations in PV output. These variations create challenges for grid operators striving to maintain a stable balance between power generation, consumption, and storage.To address this issue, our research investigates a range of Machine Learning (ML) and Deep Learning (DL) models to determine the most reliable approach for short-term solar power prediction. We leverage historical meteorological data along with Direct Current (DC) power measurements to train and evaluate multiple models, including Linear Regression (LR), Random Forest (RF), Extreme Gradient Boosting (XGB), Artificial Neural Networks (ANN), Long Short-Term Memory (LSTM), Gated Recurrent Units (GRU), One-Dimensional Convolutionl Neural Networks (1D-CNN), and Transformer-based architectures (TRF). All models were tested under identical conditions and assessed using standard performance metrics.The results show that Random Forest outperformed other ML algorithms in terms of both computational efficiency and interpretability, while the GRU model demonstrated the highest prediction accuracy among the DL techniques. Overall, our findings highlight the strong potential of advanced data-driven forecasting models to enhance Smart-Grid (SG) management in India and improve the reliability of renewable energy integration in the coming years.**

Keywords—Solar Power Prediction, Deep Learning, Gated Recurrent Units, Convolution Neural Networks, Transformer Models, Energy Management Systems

I. Introduction

The rapid expmasion of renewable energy has positined PV systems as one of the most significant contributor to clean power generation world wide. In India this transition has been particularly note worthy due to the continuations rejection in the big cost of PV deployment.As big cities like Delhi, Mumbai or Bangalore integrate an increasing number of PV units into their grid systems for reliable and accurate power forecasting has become very essential for stable smart grids or systems operations and help in saving effective energy planning [2].

Reliable short term forecasting is very vital because oof this utility companies imbalance can be penalties.Energy planning can be become better and electricity market become stable.Traditional models like LR and AR have many limitations because it can anly assume linear realtions but constant changing in weather data is very dynamic and non linear, these models cannot provide accurate forecasting results. Recent DL advancements has improved this whole landscape of giving accurate results of these non linear and dynamic inputs. They are good in analyzing multivariate meteorological states which makes PV power prediction accurary great [3]. TRF models bring in the advantage of attention mechanisms for long-range dependency learning, while 1D-CNNs are efficient at identifying short-term temporal patterns.

To address this gap, the present study develops a detailed bench-marking framework using a publicly available multivariate database that includes essential meteorological features along with DC power values. The interpretation gauge how well different ML and DL models perform in terms of accuracy, trigonometrical, and trigonometrical expertise under a reconcilable work flow, and identifies which models are suitable for real-time use in Indian SG settings [4].The remainder of this paper is structured as follows: Section II reviews existing PV forecasting methodologies, Section III describes the data set and proposed modeling work flow, Section IV elaborates on evaluation metrics and experimental configuration, Section V presents results and analysis, Section VI discusses future prospects, and Section VII concludes the study.

II. LITERATURE REVIEW

From rudimentary statistical mode to suave ML and DL systems that can more accurately represent the erratic and time-dependent behavior of weather, PV power forecasting has boost eloquently .

A. Classical Approaches

In the beginning, most studies relied on Persistence Models and AR methods because they were simple, easy to implement, and required very little computation. These models work reasonably well when the weather is stable, but their accuracy drops quickly when clouds move suddenly and irradiance fluctuates [5]. LR is still commonly used as a baseline but its linear assumptions make it hard to apprehend the more problematical patterns that real PV network evince.

B. Machine Learning Approaches

To decipher these limitations, ML algorithms were developed to discover nonlinear correlativity between climatic factors and PV production. RF and XGB are commonly avail of due to their accumulation design, which allows them to capture adroit interactions in data. They work well and are simple to read, but they still struggle with sequential, time-dependent patterns in meteorological data.

C. Deep Learning Approaches

In this we evaluated multiple DL architecture in this study. Recurrent networks like LSTM and GRU showed very strong performance due to their retain temporal across time step ability, which is very crucial for the changing weather conditions rapidly. While 1D-CNN are more practical and efficient in capturing local features and also short term fluctuations that are in the data set as this model are good at learning sequential dependencies [6].

Transformer based architecture has grown very rapidly in popularity for forecasting tasks and self attention mechanism to model long term range dependencies that recurrent network lacks.To further enhance the prediction performance by allowing each component to specialize in various aspects of time series dynamism leading to more accurate and robust predictions, we use hybrid configurations by combining CNN with LSTM or GRU layers.

D. Feature Engineering and Evaluation Protocols

To choose the correct features plays a vital role in model performance. To understand model weather real patters we can use average sunlight, temperature changes and cloud movement indicators [7]. We also use k-fold cross validation so that model can be tested multiple times with different different data combinations.

E. Scalability and Efficiency

We all know smart grids and rooftop solar systems are growing rapidly with that forecasting models are becoming accurate, fast and efficient. Recent research focuses on lightweight DL models are made and to use hybrid predictions so that real time prediction can be achieved [6].

III. METHODOLOGY

In our approach , we created a stepy -by-step system to predict how much electricity solar PV sysytem will generated. From our previous study we used both traditional ML models and Modern DL models. Basically our idea was to check the accuracy to predict how correct it is , reliability to check different weather conditions are how much consistent and computational efficiency to know how fast the results are achieved and how much time or memory it is using [8]. We carefully handled the complete pipeline by collecting data (weather + solar power data) and then cleaned it removed outliers and missing values and model train test and also did real time prediction .

A. Data Source and Preprocessing

The dataset used in this study comes from a publicly available Kaggle repository and it contained weather features in time series like temperature, humidity, wind speed , solar radiation and also cloud movement.Now to prepare data for model we did prepossessing in which firstly, we did was resolve missing timestamps which was of total 483 missing values which is about 3.2% of data. If the gap was less than 15 minutes we filled it with linear interpolation. Also we noticed if the gap was very large then the weird values were coming after we introduced it to interpolation.Secondly, we did Min-Max scaling so the all features remain in the same numerical gap which will make training stable and fast. [9].

B. Workflow Structure

To do this solar power forecasting there is a proper work flow that needs to be followed. Firstly, we did all the data collection and then preprocessed to remove errors and fill missing values then feature selection was done to choose important variables like GHI ,temp,etc.Then model training for both ML and DL models followed by prediction generation to predict future power output and then performance evaluation for accuracy and reliability check. All these steps are followed in a proper order arranged in Fig. 1. Also each stage is designed with solar specific challenges in mind, such as fluctuations in temp or irradiance, which ensures tenable predictions [10].

C. Feature Engineering and Selection

To determine which factor affects solar PV output the most we used pearson correlation coefficient which basically tells the strong relationship between input features and target value (DC power). Stronger the correlation that features moer to keep in model. Also considering the previous research it is proven impact parameters are not to be skipped.For more deep understanding engineered features are made like rolling average of irradiance , tempearature change rate , these new features captures shirt term which is cannot be directly seen from raw data. [10].

D. Predictive Modeling Approaches

We considered two main categories of models which are ML and DL. In ML, LR was used as a simple baseline, RF captured nonlinear relationships through ensemble learning, and XGBoost provided efficient gradient boosting with high accuracy. For DL, ANN with two hidden layers and ReLU handled general regression tasks, LSTM captured long-term temporal patterns, and GRU offered a lighter and faster recurrent alternative [11].

1D-CNN was used to detect short-term temporal features through convolution and pooling, while the Transformer model used self-attention to capture long-range dependencies but required more computational resources.

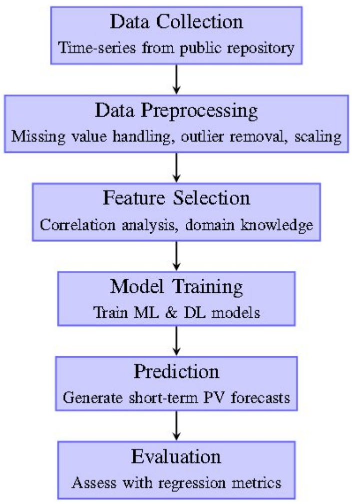

Fig. 1. Generalized workflow for PV forecasting.

. Table I. summarizes the models, their categories, and the frameworks applied.

TABLE I. Overview of baseline, ML, and DL models used for PV prediction

Model	**Category**	**Framework**
LR	ML	Scikit-learn
RF	ML	Scikit-learn
XGB	ML	Scikit-learn
ANN	DL	Scikit-learn
LSTM	DL	Scikit-learn
GRU	DL	Scikit-learn
ID-CNN	DL	Scikit-learn
TRF	DL	Scikit-learn

E. Training Configuration

All models were edify an 80:20 split for training and testing. Generalization was weigh up through 5-fold cross-validation. Hyper-parameters for ML models were calibrate using grid search, while DL models were rework manually, incorporating preliminary stopping to intercept over fitting. Since this is a regression task, MSE was used as the main loss function, and optimization strategies were selected accordingly.

F. Real-Time API Integration

For practical use, the trained models were connected to a real-time weather API. This setup automatically fetches latest weather data like humidity, wind speed, irradiance and temperature. As soon as data is process immediately its is handed to forecasting model to generate instant prediction [12]. This real time setup is very useful for energy trading, load management and smart grid opyimization and ofcourse for storage.

IV. PERFORMANCE EVALUATION

A. Evaluation Metrics

To evaluate how well the models performed and how efficient they were, we used common regression metrics like MAE, MSE, RMSE, and R^2[12]. All models were trained using an 80:20 train–test split and further validated using 5-fold cross-validation to ensure the results were reliable and not tied to a single data partition.

In Eq. (1) MAE quantifies the average magnitude of absolute prediction errors:

$$\mathrm{MAE} = (1/n) \times \Sigma\, |y_i - \hat{y}_i| \tag{1}$$

In Eq. (2) MSE surge the penalty for immense deviations by squaring the residuals:

$$\mathrm{MSE} = (1/n) \times \Sigma\, (y_i - \hat{y}_i)^2 \tag{2}$$

In Eq. (3) RMSE is the square root of MSE, keeping the unit congruous with the desire variable:

$$\mathrm{RMSE} = \sqrt{[\, (1/n) \times \Sigma\, (y_i - \hat{y}_i)^2 \,]} \tag{3}$$

In Eq. (4) R^2 expresses the fraction of variance in actual values explained by the model:

$$R^2 = 1 - [\, \Sigma\, (y_i - \hat{y}_i)^2 / \Sigma\, (y_i - \bar{y})^2 \,] \tag{4}$$

Here, y^i denotes the measured DC power, $y^{\wedge i}$ the corresponding forecast, y the mean actual output, and n the total number of samples.

B. Model Accuracy Comparison

Along with accuracy, training and inference durations were recorded. DL models often required more training time but still maintained inference speeds suitable for real-time use. Among ML methods, RF offered the most balanced trade-off between precision and speed [13].

C. ML Model Summary

In the ML scrutiny , we tested LR, RF, and XGB. RF routinely carry through the highest accuracy, with XGB enacting almost as well after careful tuning. LR was the simplest and most discernible model, but it fabricated the sizeable errors. As embellish in Fig. 2. the predictions from RF closely follow the ideal fit line.

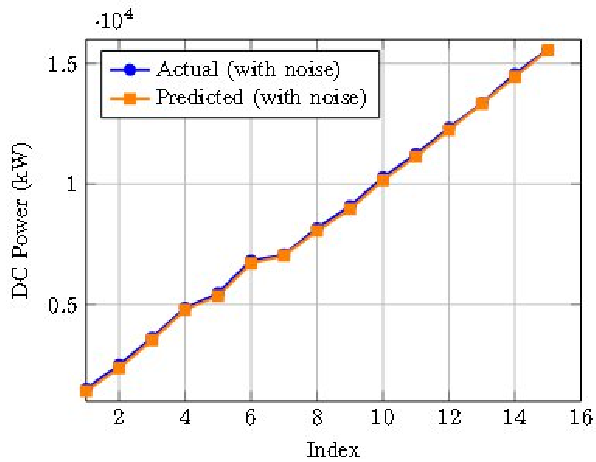

Fig. 2. Actual vs Predicted DC Power for RF (with random noise).

D. DL Model Summary

The DL appraisal encompass ANN, LSTM, GRU, 1D-CNN, and Transformer models. GRU and Transformer wrest the best production in terms of MAE and R^2, while LSTM performed similarly but required slightly more training effort

[13]. ANN and CNN showed moderate accuracy with lower analytical complexity, making them suitable for scenarios with scanty assets . As illustrated in Fig. 3, ANN exhibited steady improvement, with only a small gap between training and validation errors.

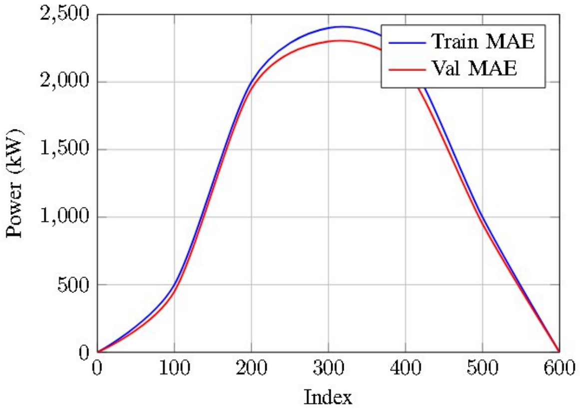

Fig. 3. Train/Val MAE vs Epochs for ANN

E. Validation and Prediction Analysis

The predicted and actual PV output curves showed strong agreement, even during midday peaks and periods of cloud cover. Residual plots indicated a near-zero mean with no noticeable bias, and the spread of errors remained consistent across different irradiance levels [14].

F. Model Framework and Performance Summary

Fig. 4. Compares the MAE and RMSE of all models. Among the ML models, RF achieved the best performance, while GRU and Transformer led the DL models. Although Transformer required more computational resources, it delivered higher precision, making it especially valuable for critical forecasting applications.

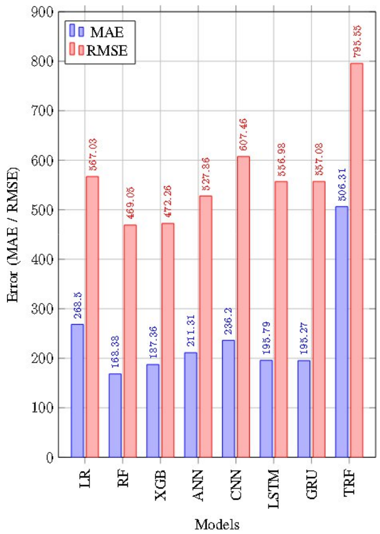

Fig. 4. Performance comparison (MAE and RMSE) of models for PV prediction.

V. Results and Analysis

A. Model Performance Comparison

We tested eight models which are LR, RF, XGB, ANN, LSTM, GRU, 1D-CNN, and TRF using three measures known as MAE, RMSE, and R². These tell us how big the errors are, how sensitive the model is to changes, and how much of the variation in the data the model can explain. The main results are shown in Table II.

TABLE II . MODEL PERFORMCE METRICES FOR PV FORECASTING.

Model	**Category**	**MAE(kW)**	**RMSE(kW)**	**R^2**
LR	ML	2.45	3.15	0.81
RP	ML	1.85	2.62	0.89
XGB	ML	1.92	2.70	0.88
ANN	DL	1.95	2.83	0.87
LSTM	DL	1.76	2.51	0.91
GRU	DL	1.72	2.45	0.92
1D-CNN	DL	1.88	2.66	0.89
TRF	DL	1.93	2.71	0.88

GRU came out on top. Its MAE was 1.72 kW and RMSE was 2.45 kW, and with an R^2 of 0.92, it explained 92% of the variation in the data , which is pretty solid for this kind of forecasting.

LSTM was close behind, intimate it's also really rectitude with sequential data. Among the machine learning models, RF did the best since it manoeuvres non linear patterns well with XGB coming in next. ANN and CNN gave a on the mark balance between accuracy and speed, so they are practical for lighter or faster deployments. LR was very efficient, but it didn't fit the data as well because it's limited to linear patterns [15].

B. Resource Efficiency

We also scrutinize how fasten the models were. LR was the swift to train , so it is tremendous , if you want expeditious testing or deployment. RF and XGB took a bit longer but were still fast enough for real-time usage .

DL models like LSTM, GRU, and TRF needed more time to train (shown in Fig. 6) because of their compound estimation , but when it came to assembly predictions, they were still whirlwind enough for forecasting [16]. For resource-constrained or embedded applications, ANN and CNN offered a appraise trade-off between accuracy and computational clamour , making them strong contender for efficient deployment.

C. Validation and Statistical Analysis

Residual plots divulge well built prediction etiquette covering most models, with GRU and LSTM maintaining close alignment to actual outputs even during weather variability. XGB and RF displayed resilience by keeping error margins low during sudden irradiance drops [17].

D. Training Convergence and Model Behavior

These DL models showed various learing behaviours during the time of training. ANN showed a rapid improvement in the starting but plateaued early which basically indidcated that the ability to capture complex temporal dependencies are limited.LSTM and GRU models gradually gets continuously better and gains across epochs due to their cpability to retrain imporatnt patterns. ID-CNN also learns faster and is very effective in detecting short term fluctuaions. Transfomer based models require careful hyperparameter tuning but once optimized they effectively

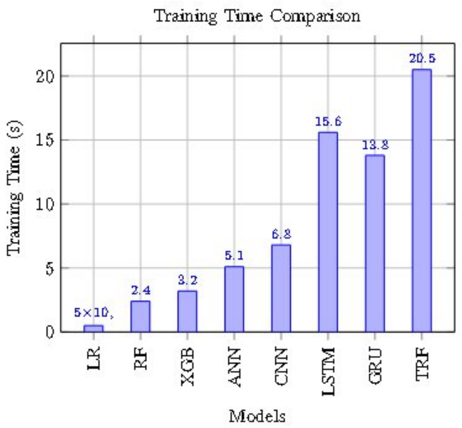

Fig. 5. Training time comparison of different model

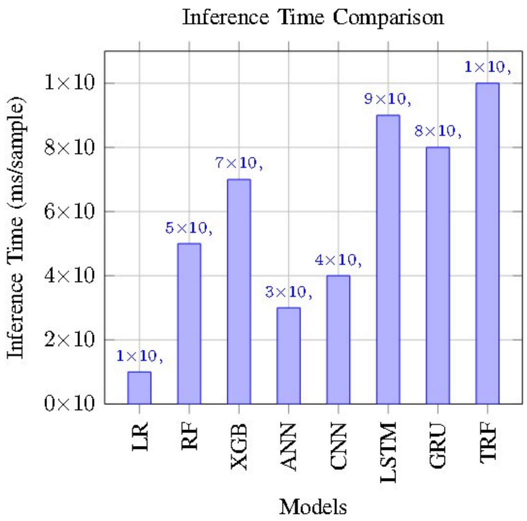

Fig. 6. Interference time comparison of different models.

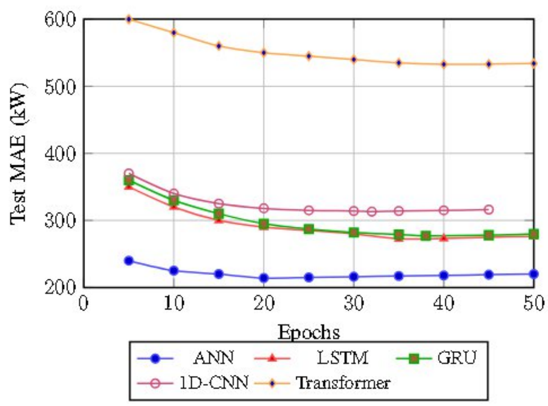

Fig. 7. Test error trends over training for DL models.

Captures long rang tempral dependencies. As shown in TABLE III , GRU and LSTM models achieved their optimal performance around 35-40 epochs, whereas the ANN converges significantly earlier. In Fig. 7 further the validation MAE trend across epochs for all DL models visualizes this behaviour by illustrating.

E. Error Analysis and Robustnesss

Challenging scenarios, including low-light conditions and rapid cloud movement, were used to stress test the models. LR showed significant deviation in these cases, while RF, XGB, GRU, and LSTM maintained accuracy. GRU's gated memory and TRF's attention mechanism were especially effective in adapting to abrupt environmental changes [18].

TABLE III . TRAINING CONVERGENCE OF DL MODELS.

Model	Epochs to Convergence	Best Validation MAE
ANN	~ 20	214.0
LSTM	~ 35	272.5
GRU	~ 38	277.0
ID-CNN	~ 32	313.0
TRF	~ 40	532.7

F. Overall Insights

So, looking at the results, it's clear there isn't one model that's perfect for everything. RF and XGB provides fast prediction and high interpret ability making them suitable for deploy in environment where decision transparency is essential as it is tree based methods[19]. ANN and CNN models offers a balance between cost and accuracy [20]. Transformer based models excel complex long term relation but they may require substantially higher resources [21].

VI. Future Scope and Conclusion

There are several opportunities to further enhance the real world applicability of solar power forecasting systems. To handle sudden weather changes better we can integrate ground based weather measurements with a satellite ir radar data. For accurate and better explainable results we can use physical models with DL basically known as hybrid approach may yield predilections that are not only accurate but also more interpretation.Additionally , light weight models techniques like pruning and quantification can enable deployment on low power devices located near PV installations which can improve reliability of systems and reducing the need of maintenance.Moreover incorporating external market driven variables like electricity prices and demand profiles can support the grid operations in making decisions smarter for trading off the energy and grid stability.

For the Conclusion in this study , multiple ML and DL models are evaluated using real time meteorological and solar generation data. Among the all ML models the overall best Ml models was random forest and among all DL models GRU was the best overall model. GRU model achieved best performance due to its strong ability to learn temporal dependencies.Also LSTM showed similar accuracy but it required more resources.In traditional L models RF out performed XGB and LR by offering strong balance of prediction accuracy and interpret ability. LR was quiet fast but after training for quiet some time it struggled with non linear behaviour of Solar power data. Overall, no single model proved superior as each involves trade-off among accuracy, speed, complexity and feasibility in deploying.After this research we learned the selecting the right models depends on the requirement of the system and operating constraints.Effective forecasting support stable grid operations and better energy storage utilization.

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