

SvedbergOpen
DISSEMINATION OF KNOWLEDGE

International Journal of Artificial Intelligence and Machine Learning

Publisher's Home Page: <https://www.svedbergopen.com/>

Research Paper

Open Access

Quantile Regression-Based Solar Power Prediction

Gargi Mishra¹, Nikita Kashyap², Ruchi Tripathi^{3*}¹PhD scholar, Department of Electronics and Communication Engineering, Guru Ghasidas. E-mail: Vishwavidyalaya, gargi623@gmail.com, ORCID iD: <https://orcid.org/0009-0007-6518-7223>²Assistant Professor, Department of Electronics and Communication Engineering, Guru Ghasidas Vishwavidyalaya, E-mail: nikita2010k@gmail.com, ORCID iD: <https://orcid.org/0009-0007-9070-5360>^{3*}Assistant Professor, Department of Electronics and Communication Engineering, Guru Ghasidas Vishwavidyalaya, ruchi.tri@ggu.ac.in, ORCID iD: <https://orcid.org/0000-0001-7368-8676>

ABSTRACT

Recent decades have seen an increase in the market for sustainable and green energy solutions. In all renewable resources, solar energy is one of the key sources because of its abundance. Integration of solar power into smart grids for meeting expanding energy demand relies on accurate predictions of solar power output. The efficiency of photovoltaic (PV) systems is highly influenced by climatic conditions, resulting in fluctuating power output that degrades the performance of smart grid systems. Hence, this work provides a probabilistic machine learning approach for solar power forecasting using reliable daily solar generation data. This work compares the effectiveness of predictive algorithms to forecast short-term solar power. The Normalized Mean Squared Error (NMSE) metric has been employed to assess the predicted accuracy of these models. The simulations and results highlight the effectiveness of probabilistic models, offering insights into enhancing grid stability and boosting the use of renewable energy sources.

Keywords: Solar power prediction, Kalman Filter, Quantile Regression, NMSE.

I. Introduction

Sustainability has emerged as a key global concern in overcoming environmental depletion, climate change, and the growing demand for energy. In this context, the "Affordable and Clean Energy" goal of the UN highlights the need to ensure universal access to sustainable energy by 2030. This goal necessitates a considerable shift to renewable energy sources, with solar energy emerging as a primary contributor. Solar energy enhances energy security and lowers reliance on combustible fuels. India's green energy sector is marked by the rapid adoption of advanced technologies and continuous innovation. Significant progress has been observed in areas of solar energy systems and smart grid infrastructure. The shift toward green energy in India is driving influential socioeconomic transformations that aids economic growth of the country. The generation of clean electricity in the power sector is contributing to increasing access to clean energy and promoting environmental sustainability.

Technological developments in the field of decentralized power stations contribute to enhancing the efficiency, reliability, and sustainability of the country's energy framework [1]. Reliable solar power planning and forecasting are crucial for power systems to optimize energy storage, grid control, and resource management. Accurate solar power forecasting ensures a steady power supply even during variable power output conditions [2]. Modern machine learning algorithms for PV power estimation have emerged drastically over the last decade. Some previously proven machine learning methods, like SVR and Gradient Boosting, provide means that can accurately predict the solar power output with a considerable value of RMSE [3].

The primary challenges with traditional forecasting methods employed for solar power prediction depend on the weather data, which makes it hard to evaluate a continuous and reliable output. An effective prediction model for the PV power sector that can compute past weather data is essential for the energy sector to optimize operational costs and ensure reliable power supply [4], [5], [6]. Machine Learning models can encounter challenges with non-linear datasets that are employed in earlier work [7], [8], [9]. Probabilistic machine learning models like Quantile Regression perform well on multi-feature datasets [10]. The research work here aims to predict the precise output of a regional solar power plant. The data collected from the local solar plant is analyzed to predict the next two hours' power generation. The work will contribute to encouraging the use of renewable energy sources, which is needed for meeting rapidly increasing energy demands, and help in achieving the goal of energy for all. Table I categorizes the types of solar power forecasting in different time horizons.

Major contributions of this research work are:

- Implementation of a probabilistic model for short-term solar power output forecasting.

- Evaluation of model performance using NMSE metrics.

II. Literature Review

In the past, deep learning-based methodologies have been proposed to predict PV power generation. MLP and LSTM emerged as the most applicable deep learning algorithms for the solar power prediction model [11]. Similarly, several machine learning methodologies for forecasting PV power and their performance have been evaluated using different metrics [12].

Recent advances in solar power forecasting pose challenges for integrating green energy into smart grid systems. Machine Learning methods use weather features like cloud cover, temperature, and solar irradiance to recognize historical patterns and learn from past data to test a new data set [13]. The evaluation metric NRMSE is used to evaluate forecasting models' performance, highlighting their significance for model optimization [14, 24]. Precise, reliable, and efficient prediction by these methods promotes the incorporation of renewable energy sources into smart grid operations and enhances energy sustainability [15, 25]. Existing machine learning models for PV power forecasting follow steps like data collection, data cleaning, handling time series, and then modeling complex algorithms [16]. The methodology implemented to build the predictive model includes data collection, which may be hourly, monthly, or yearly, pre-processing, feature Selection, ML model building, and error evaluation with NRMSE [17].

Statistical methods like the Kalman Filter used for PV power prediction boost the accuracy of the prediction output due to its recursive nature in the estimation and update process [18]. This enables the model to respond to real-time fluctuations in solar output, improving the accuracy for short term power estimations [19, 26,27].

Quantile Regression (QR) has emerged as a strong alternative to classical regression for prediction algorithms. Unlike standard least squares, which estimates the conditional mean, QR calculates conditional quantiles, allowing for prediction intervals rather than single-point forecasts. This feature is important for renewable energy integration into smart grid systems [20].

Table I: Types Of Solar Power Forecasting

Category	Time Horizon	Description	Applications
Short-term Forecasting	1–6 hours	Utilizes statistical methods for accurate near-term prediction	Scheduling, load-forecasting, energy management, improved grid balancing
Intra-day Forecasting	Within a day	Considers weather variations, cloud cover, and solar radiation changes throughout the day	Grid stability and energy resource optimization
Day-ahead Forecasting	24–48 hours	Provides forecasts for upcoming days using weather predictions	Energy market planning, maintenance scheduling, demand management
Medium to Long-term Forecasting	Days to 1 year	It estimates future solar energy output using weather trends, seasonal patterns, and historical data.	Scheduling, reserve planning, operational decisions
Week-ahead Forecasting	Up to 1 week	Extends beyond daily forecasting horizon	Energy purchase planning and resource management
Seasonal Forecasting	Weeks to months	Predicts solar generation patterns across different seasons	Demand variation planning and resource portfolio adjustment
Year-ahead Forecasting	1 year	Long-term prediction of solar generation trends	Policy planning, infrastructure development, capacity expansion decisions

III. Proposed Framework

This research work adopts a structured methodology that progresses through several well-defined stages to ensure a systematic analysis. The overall process initiates with the collection of suitable datasets, where both the quality and reliability of the acquired data play a significant role in evaluating the accuracy of models. Once the raw data is obtained, the next step involves comprehensive data preprocessing, which includes cleaning, normalization, and transformation procedures to eliminate inconsistencies and enhance the usability of the dataset for computational modeling. Following this stage, system modeling is carried out, wherein advanced forecasting and optimization techniques are applied to capture the dynamic characteristics of the system under study. Specifically, three distinct algorithms—Kalman filter and quantile regression are implemented due to their proven ability to handle time-series data, model uncertainty, and improve prediction accuracy. To assess the performance of these models, the Normalized Mean Squared Error (NMSE) metric is employed as a key evaluation criterion, thereby enabling a quantitative comparison of their predictive capabilities and robustness, as also suggested in prior studies [21,27].

The workflow, which is summarized in Fig.1, is represented in the form of a block diagram to provide a visual outline of the entire methodology. This diagrammatic representation highlights the logical flow of operations,

beginning from data collection to model evaluation, thereby offering a clear and concise overview of the research framework. Such a systematic approach not only ensures methodological consistency but also enhances the reliability of the results obtained.

A. Data Collection

The data is acquired from the nearby PV power plant located in the Bilaspur district of Chhattisgarh state. The solar power plant has a capacity of 3MWDC/2.2MW AC. It has 5544 solar panels, and the variables that are used in the dataset are date and time of power generation, module temperature, which is the temperature of the solar panel, ambient temperature, which is the temperature of the environment, solar radiation intensity value, and power generation output. For the research work, we have used a day-wise dataset recorded at an interval of every 5 minutes. The actual data is processed according to the requirements of the algorithm used. Fig.2 shows the image of the data collection site.

B. Data Visualization

The process of data visualization is used to simplify the complexity of datasets and make them easier to understand. It helps in recognizing patterns, trends, and relationships between variables. Additionally, the selection of input variables plays an important role in the performance of the model. This serves as a powerful tool for the analysis of datasets [22].

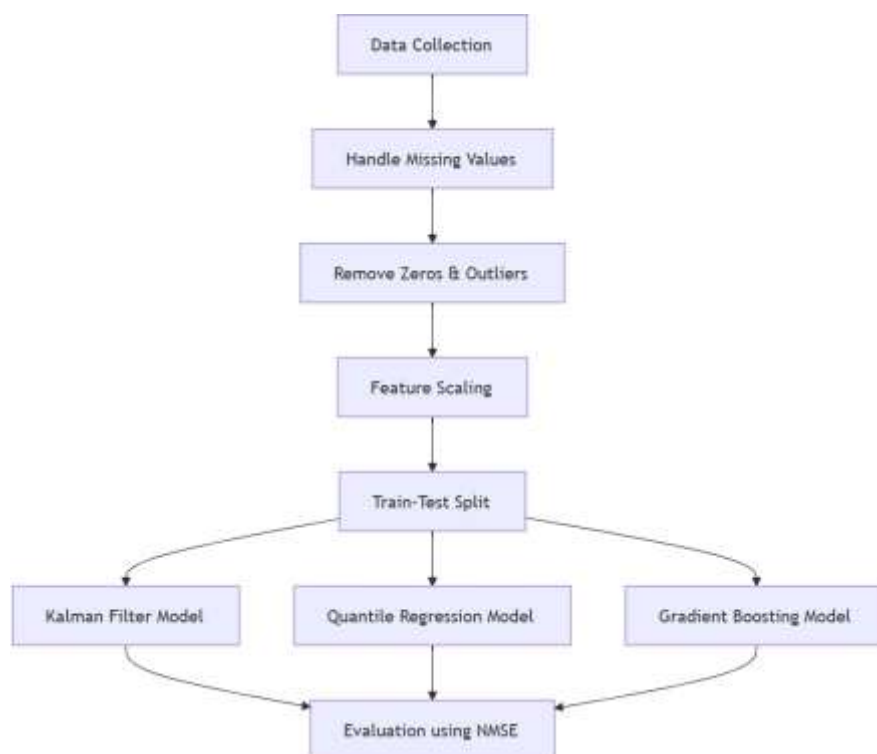


Fig. 1. Workflow of the proposed methodology using Kalman Filter, Quantile Regression, and Gradient Boosting models with NMSE evaluation.



Fig. 2. Aerial Image of a solar power plant

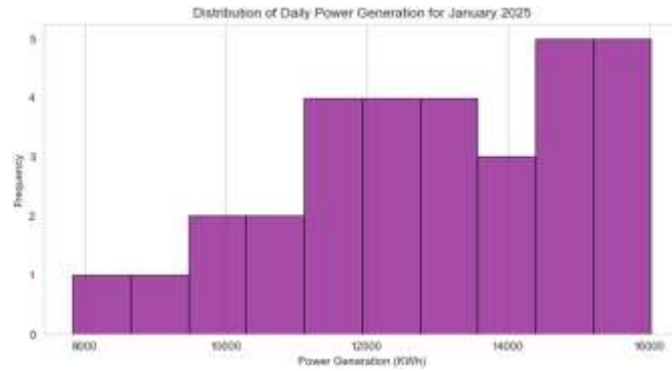


Fig. 3. Frequency vs. power generation for January

The histogram in Fig.3 shows the distribution of daily solar power generation for January 2024. The x-axis has values of daily power generation, whereas the y-axis shows the frequency. Most of the daily power generation values occur between 12,000 and 16,000 kWh, with the highest frequency observed in the 14,000–16,000 kWh range. Lower generation levels became less common, particularly those under 10,000 kWh. Lower power generation, most likely due to varying weather, as shown in Fig. 4, indicates that the solar power plant operated consistently well throughout the month.

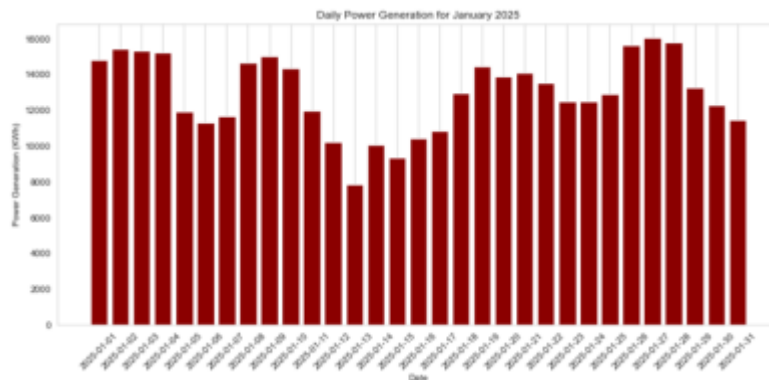


Fig. 4. Bar chart for daily power generation of January

The daily solar power generation (in kWh) for January 2024 is displayed in Fig.4. The X-axis represents the date, and the Y-axis shows the energy produced. The power generation fluctuates throughout the month. The generation values regularly exceed 14,000 kWh on the starting days and decrease on the end days. Changes in the weather, cloud cover, or other environmental factors that impact solar irradiance could be the cause of this variability. Therefore, this analysis allows us to understand the proper trend and create an accurate model.

IV Mathematical Formulation

This section formulates the short-term solar power forecasting problem and presents the mathematical foundations of the applied models, with particular emphasis on Quantile Regression for probabilistic prediction. Let $\{(x_t, y_t)\}_{t=1}^N$ denote a time-indexed dataset collected from a photovoltaic (PV) plant, where

- $y_t \in \mathbb{R}^+$ represents the actual solar power output (kW) at time instant t ,
- $x_t \in \mathbb{R}^d$ is the feature vector comprising meteorological and operational parameters, such as solar irradiance, ambient temperature, module temperature, voltage, and current.

The objective is to predict the future solar power output $\hat{y}_{t+\Delta}$ over a short-term horizon Δ , given historical observations.

A. State-Space Representation

The PV power generation process is modeled as a stochastic dynamic system:

$$y_t = f(x_t, t) + \varepsilon_t$$

where $f(x_t, t)$ denotes an unknown nonlinear mapping, and ε_t represents zero-mean random disturbances caused by atmospheric variability, sensor noise, and unmodeled dynamics.

B. Kalman Filter Model

For recursive estimation, the system is represented in state-space form:

$$z_t = Az_{t-1} + w_t$$

$$y_t = Hz_t + v_t$$

where z_t is the system state, A is the state transition matrix, H is the observation matrix, and w_t, v_t are Gaussian noise terms with covariances Q and R , respectively. The Kalman filter recursively estimates z_t and produces a

one-step-ahead prediction $\hat{y}_{t+1}$.

C. Quantile Regression Formulation

Unlike conventional regression models that estimate the conditional mean, $E[y_t | x_t]$, Quantile Regression (QR) estimates conditional quantiles of the response variable.

For a given quantile level $\tau \in (0, 1)$, the τ -th conditional quantile of y_t given x_t is defined as:

$$Q_{y_t}(\tau|x_t) = x_t^T \beta_\tau,$$

where β_τ is the quantile-specific parameter vector. The estimation of β_τ is obtained by minimizing the asymmetric pinball loss function:

$$\hat{\beta}_\tau = \arg \min_{\beta} \sum_{t=1}^N \rho_\tau(y_t - x_t^T \beta),$$

where the loss function is defined as:

$$\rho_\tau(u) = \begin{cases} \tau u, & u \geq 0, \\ (\tau - 1)u, & u < 0. \end{cases}$$

By estimating multiple quantiles $\tau \in \{0.1, 0.2, \dots, 0.9\}$, a probabilistic envelope of solar power generation is obtained, capturing uncertainty and variability due to weather fluctuations.

D. Prediction Interval Construction

The prediction interval at confidence level $(1 - \alpha)$ is constructed as:

$$\mathcal{I}_{t+\Delta}^{(1-\alpha)} = [Q_{y_{t+\Delta}}(\alpha/2|x_t), Q_{y_{t+\Delta}}(1 - \alpha/2|x_t)].$$

This probabilistic representation is particularly suitable for grid integration, reserve planning, and risk-aware energy management.

E. Performance Metric

The Normalized Mean Squared Error (NMSE) is a metric employed to evaluate the accuracy of a prediction or estimation model. NMSE compares the performance of the model against a simple mean-based prediction. A lower NMSE indicates better performance. The mathematical representation of NMSE is shown below.

$$NMSE = \frac{\|y - \hat{y}\|_F^2}{\|y\|_F^2}$$

where,

- y : Actual (true) values
- $\hat{y}$: Predicted (estimated) values
- $\|y - \hat{y}\|_F^2 = \sum_{i=1}^n (y_i - \hat{y}_i)^2$: Squared error
- $\|y\|_F^2 = \sum_{i=1}^n y_i^2$: Normalization term
- n : Number of samples

V. Simulations and Results

This section presents simulation results of algorithms such as the Kalman filter and quantile Regression are demonstrated. All the simulations were carried out in Python with a system configuration of Intel(R) Core (TM) i5 and a 64-bit operating system. The paper focuses on predicting the next step of solar power using a real-time dataset. The actual power is estimated and measured to get an accurate solar power output. We have simulated a comprehensive evaluation of six prediction models—SVR, MLP, LSTM, Gradient Boosting, Kalman Filter, and Quantile Regression.

The Kalman filter analysis graph for the seventeenth day in Fig.5 illustrates solar power generation variation and the accuracy with which the filter can estimate and forecast the system's behavior. The observed power output increased after sunrise, reaching 745.02 kW by 10:00 AM. The system generated 1758.0 kW at 14:00, during peak solar irradiance. After the peak, the output decreased significantly from 891.23 kW to 111.39 kW, indicating a usual reduction in generation during late afternoon hours. The Kalman filter predictions shown by the red dashed line were closely related to the observed values represented by the blue line, effectively smoothing out fluctuations in the short term. Additionally, the next phase estimates are 123.1 kW for the next two hours.

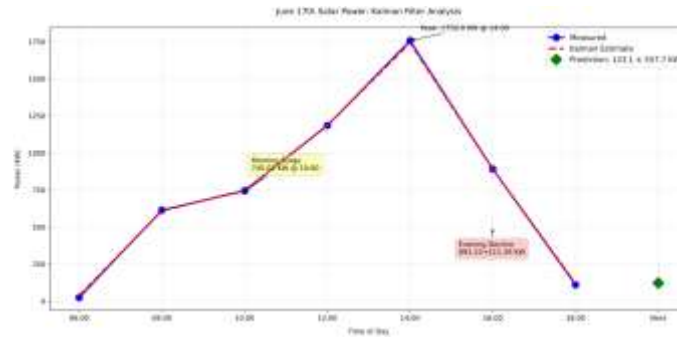


Fig. 5. Next-2 hours solar power prediction for seventeenth day

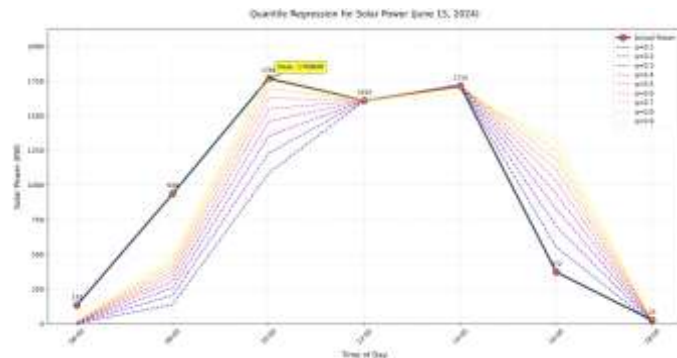


Fig. 6. Quantile regression graph for the fifteenth day

Fig. 6 illustrates the quantile regression-based prediction model. At 08:00, production surges to 938 kW, surpassing the previous 883 kW recorded. However, the peak is recorded at 1769 kW between 10:00 and 11:00 hours. This oscillating pattern captured by the model reflects the stable characteristics of the predictive model employed for solar power output prediction. The quantile regression quantiles follow the actual graph. Fig. 7 presents the quantile regression analysis of solar power generation from 06:00 to 18:00 hours. The actual power output starts at a very low 25 kW at 06:00, reflecting minimal irradiance at sunrise. A sharp increase occurs soon after, with power reaching 614 kW by 08:00 and 1185 kW by midday. The peak generation is observed at 1758 kW in the early afternoon, followed by a gradual decline to 891 kW at 16:00 and finally 111 kW by 18:00. The actual curve has nine quantile regression lines ($q=0.1$ to $q=0.9$) that define the conditional distribution of solar output across time.

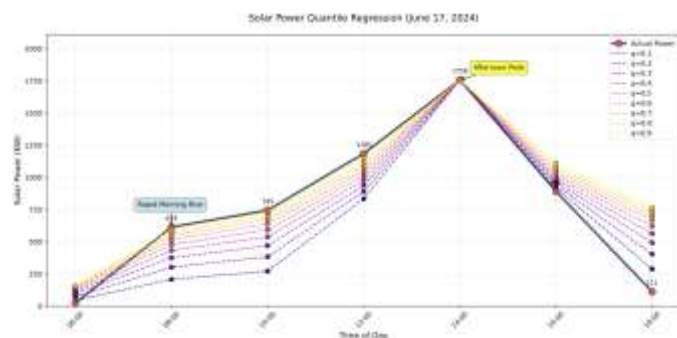


Fig. 7. Quantile regression graph for the seventh day

Fig.8 illustrates the relationship between the actual solar power values and the values predicted by the SVR model. It can be seen from the plot in Fig. 8 that the maximum prediction points are closer to the diagonal line representing model accuracy.

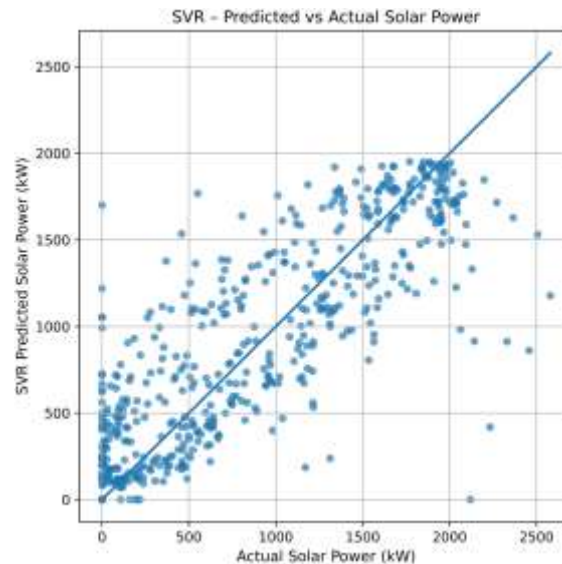


Fig. 8. SVR Predictive Model

Fig. 9 represents normalized pinball loss as a function of the quantile level from τ (0.1–0.9). Lower values imply better quantile-forecast accuracy. The lowest losses occur near the median ($\tau = 0.5$), while higher losses at extreme quantiles ($\tau = 0.1$ and $\tau = 0.9$) illustrate greater uncertainty in the back end of the PV power distribution. Fig. 10 illustrates the coverage accuracy of the prediction interval for short-term solar power forecasting; the Prediction Interval Coverage Probability (PICP) metric is used for this evaluation. The X-axis represents the time period, while the Y-axis indicates solar power generation in kilowatts (kW). The data points are divided into two groups: “Not Covered” and “Covered.” A point is considered covered when the actual solar power value lies within the predicted upper and lower quantile prediction interval, and it is considered not covered when the actual value falls outside the predicted interval. The graph shows a Prediction Interval Coverage Probability (PICP) of 85.6% because of some non-linearity in the dataset, and is essential for calibration of probabilistic forecasting.

Fig. 11 explains the distribution of CRPS contributions across quantile levels τ . Lower CRPS signifies better probabilistic calibration. The results illustrate relatively higher CRPS for lower quantiles ($\tau = 0.1$ to 0.3), which can be attributed to increased uncertainty during low-output periods, while the median quantile ($\tau = 0.5$) exhibits the lowest CRPS. Higher quantiles ($\tau = 0.7$ to 0.9) suggest uncertainty near peak generation.

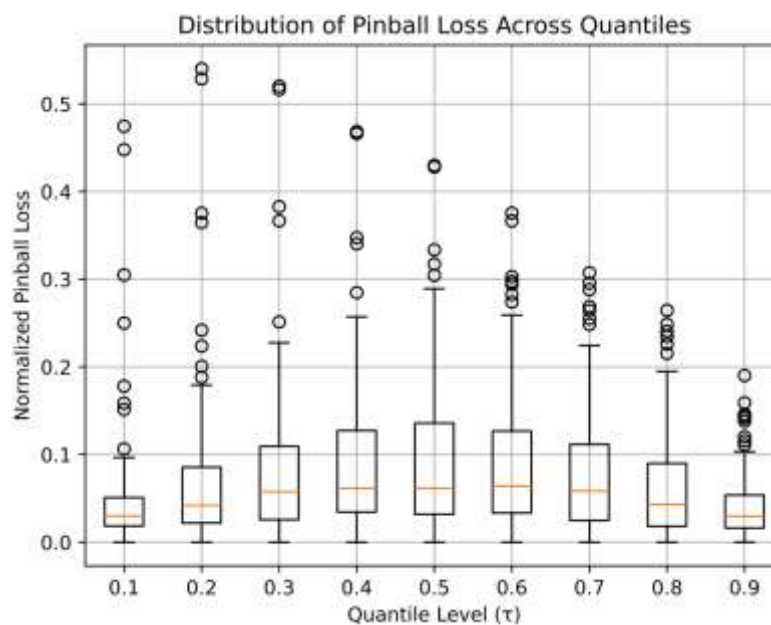


Fig. 9. Pin Ball loss

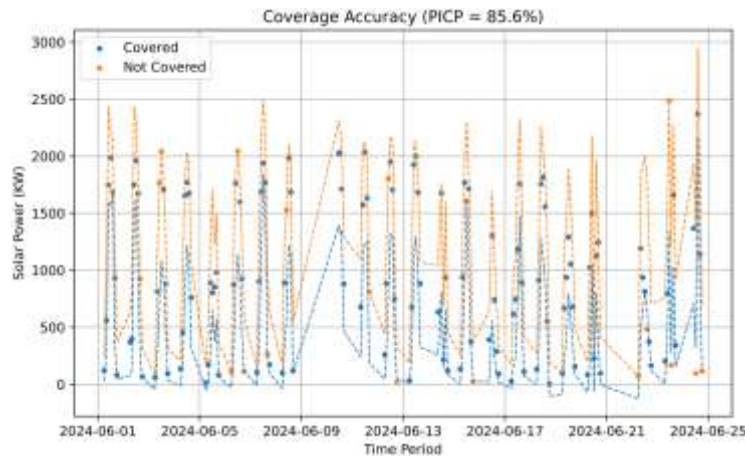


Fig. 10. Prediction Interval Coverage Probability(PICP)

Table II shows the comparison of six models based on their Average NMSE, where a lower value indicates better prediction accuracy. Among all the models, Quantile Regression achieves the lowest NMSE value of 0.220, demonstrating the best performance in terms of accuracy. The Kalman Filter represents an NMSE of 0.350, showing better predictive capability. LSTM and Gradient Boosting models provide moderate performance with NMSE values of 0.445 and 0.480, respectively. Also, SVR and MLP exhibit NMSE values of 0.620 and 0.705, suggesting comparatively lower accuracy. Overall, the table suggests that Quantile Regression is the most effective model for the collected dataset.

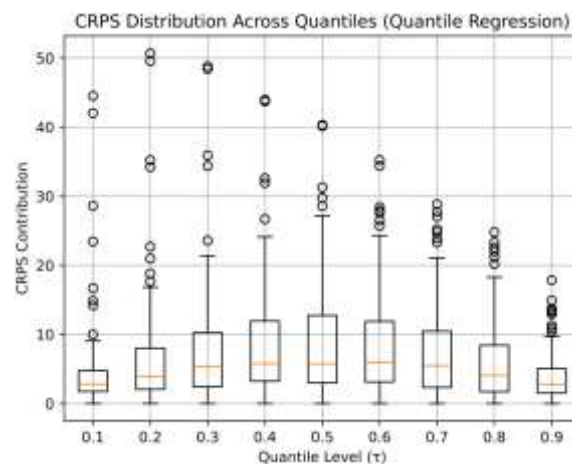


Fig. 11. Continuous ranked probability score (CRPS) using quantile regression.

Table II: Average NMSE Values for Different Models

Model	Average NMSE
SVR	0.620
MLP	0.705
LSTM	0.445
Gradient Boosting	0.480
Kalman Filter	0.350
Quantile Regression	0.220

VI. Conclusion

In this work, we conducted a comprehensive evaluation of six prediction models—SVR, MLP, LSTM, Gradient Boosting, Kalman Filter, and Quantile Regression—with average NMSE as the primary performance metric. The results show that the models possess varying strengths, highlighting the relevance of model selection in time series prediction.

As evident from the simulations, the Quantile Regression model performed best, especially during periods of high variability in the time series. The ability to estimate distinct quantiles enables better handling of asymmetrical datasets. Accurate forecasting is mandatory for effective grid operation [16, 27]. This research work builds a comprehensive foundation for a probabilistic forecasting algorithm on real-time data. Hence, provides a pathway for a data-driven energy management system in the modern power sector.

References

1. D. K. Sharma, S. Vohra, T. Gupta, and V. Goyal, "Predicting the algorithmic time complexity of single parametric algorithms using multiclass classification with gradient boosted trees," in 2018 Eleventh International Conference on Contemporary Computing (IC3). IEEE, 2018, pp. 1–6.
2. M. Abdelsattar, M. A. Ismeil, M. A. Azim, A. Abdelmoety, and A. Emad-Eldeen, "Assessing machine learning approaches for photovoltaic energy prediction in sustainable energy systems," IEEE Access, 2024.
3. N. Vahedi, A. Jolfaei, S. U. Rehman, and R. S. Ravi, "Hybrid deep learning model for electricity price forecasting in renewable-dominated markets: The case of south australia," IEEE Transactions on Consumer Electronics, 2025.
4. G. Nassreddine, A. El Arid, M. Nassereddine, O. Al-Khatib, A. Arram, and A. El Abed, "Enhancing the efficacy of short-term prediction models for solar photovoltaic systems: An influence examination of chronological and meteorological factors," IEEE Access, 2025.
5. H. S. Jang, K. Y. Bae, H.-S. Park, and D. K. Sung, "Solar power prediction based on satellite images and support vector machine," IEEE Transactions on Sustainable Energy, vol. 7, no. 3, pp. 1255–1263, 2016.
6. Q.-T. Phan, Y.-K. Wu, and Q.-D. Phan, "Enhancing one-day-ahead probabilistic solar power forecast with a hybrid transformer-lube model and missing data imputation," IEEE Transactions on Industry Applications, vol. 60, no. 1, pp. 1396–1408, 2023.
7. R. Asghar, F. R. Fulginei, M. Quercio, and A. Mahrouch, "Artificial neural networks for photovoltaic power forecasting: a review of five promising models," IEEE Access, vol. 12, pp. 90 461–90 485, 2024.
8. W. Castillo-Rojas and J. P. Salinas, "Forecasting models applied in solar photovoltaic and wind energy: A systematic mapping study," IEEE Access, 2024.
9. B. D. Dimd, S. Völler, U. Cali, and O.-M. Midtgård, "A review of machine learning-based photovoltaic output power forecasting: Nordic context," IEEE Access, vol. 10, pp. 26 404–26 425, 2022.
10. X. Dong, Y. Liu, X. Zhang, and S. Mei, "A data-driven dynamic temporal correlation modeling framework for renewable energy scenario generation," IEEE Transactions on Sustainable Energy, vol. 17, no. 2, pp. 1048–1058, 2026.
11. S. Tajjour, S. S. Chandel, M. A. Alotaibi, H. Malik, F. P. G. Márquez, and A. Afthanorhan, "Short-term solar irradiance forecasting using deep learning techniques: A comprehensive case study," IEEE Access, vol. 11, pp. 119 851–119 861, 2023.
12. M. J. Sammar, M. A. Saeed, S. M. Mohsin, S. M. A. Akber, R. Bukhsh, M. Abazeed, and M. Ali, "Illuminating the future: A comprehensive review of ai-based solar irradiance prediction models," IEEE Access, vol. 12, pp. 114 394–114 415, 2024.
13. N. Jannah, T. S. Gunawan, S. H. Yusoff, M. S. A. Hanifah, and S. N. M. Sapihie, "Recent advances and future challenges of solar power generation forecasting," IEEE Access, 2024.
14. K. Olcay, S. G. Tunca, and M. A. Özgür, "Forecasting and performance analysis of energy production in solar power plants using long short-term memory (Lstm) and random forest models," IEEE Access, 2024.
15. B. Kim and D. Suh, "Solar pv generation prediction based on multisource data using roi and surrounding area," IEEE Transactions on Geoscience and Remote Sensing, vol. 62, pp. 1–11, 2024.
16. T. Yao, J. Wang, Y. Wang, P. Zhang, H. Cao, X. Chi, and M. Shi, "Very short-term forecasting of distributed pv power using gstan," CSEE Journal of Power and Energy Systems, vol. 10, no. 4, pp. 1491–1501, 2022.
17. A. Patel and O. G. Swathika, "Off-grid small-scale power forecasting using optimized machine learning algorithms," IEEE Access, 2024.
18. Y. Yang, T. Yu, W. Zhao, and X. Zhu, "Kalman filter photovoltaic power prediction model based on forecasting experience," Frontiers in Energy Research, vol. 9, p. 682852, 2021.
19. S. Suksamorn, N. Hoonchareon, and J. Songsiri, "Post-processing of nwp forecasts using kalman filtering with operational constraints for day-ahead solar power forecasting in thailand," IEEE Access, vol. 9, pp. 105 409–105 423, 2021.
20. Y. Ozone and D. Kodaira, "Quantile regression for probabilistic electricity price forecasting in the u.k. electricity market," IEEE Access, vol. 13, pp. 10 083–10 093, 2025.
21. R. Nelega, D. I. Greu, E. Jecan, V. Rednic, C. Zamfirescu, E. Puschita, and R. V. F. Turcu, "Prediction of power generation of a photovoltaic power plant based on neural networks," IEEE Access, vol. 11, pp. 20 713–20 724, 2023.
22. M. Alaraj, A. Kumar, I. Alsaidan, M. Rizwan, and M. Jamil, "Energy production forecasting from solar photovoltaic plants based on meteorological parameters for qassim region, saudi arabia," IEEE Access, vol. 9, pp. 83 241–83 251, 2021.
23. T. Chen and C. Guestrin, "Xgboost: A scalable tree boosting system," in Proceedings of the 22nd acm sigkdd international conference on knowledge discovery and data mining, 2016, pp. 785–794.
24. R. Dixit, A. S. Bedi, R. Tripathi and K. Rajawat, "Time Varying optimization via Inexact Proximal Online Gradient Descent," 2018 52nd Asilomar Conference on Signals, Systems, and Computers, Pacific Grove, CA, USA, 2018, pp. 759–763, doi: 10.1109/ACSSC.2018.8645323.
25. Y. Hui, S. Wenzhu, Z. Xiuzhi, Z. Guotao, and H. Wenting, "Heuristic sample reduction based support vector regression method," in 2016 IEEE international conference on mechatronics and automation. IEEE, 2016,

- pp. 2065–2069.
26. H. Alla, L. Moumoun, and Y. Balouki, "A multilayer perceptron neural network with selective-data training for flight arrival delay prediction," *Scientific Programming*, vol. 2021, no. 1, p. 5558918, 2021.
27. G. Mishra, P. Sahu and R. Tripathi, "Solar Energy Prediction Using LSTM and MLP: Performance Evaluation on Real-World Data," *2025 International Conference on Electrical and Electronics Engineering (ICE3)*, Gorakhpur, India, 2025, pp. 1-5, doi: 10.1109/ICE367573.2025.11448805.