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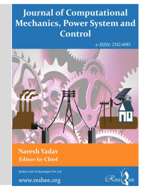


# An Extensive Review of Recent Development of Solar Power Prediction Models

**Charanjeet Madan**
*Department of Electrical & Electronics Engineering,*
*GJUST, Hisar*
*madan.charanjeet@gmail.com*

**Abstract:** Photovoltaic (PV) forecasting, another term for solar power prediction, is the practice of predicting the quantity of electricity that a solar power system will generate in the future. It is employed in grid operations management, energy system optimization, and even dynamic evaluation techniques, such as Time-of-Use (ToU) optimization. The current models for predicting solar power have several issues, including weather-related variations in solar radiation, inaccurate acquisition devices, and the intricacy of the models, which might make deployment on some systems difficult. Furthermore, advancements in machine learning, particularly deep learning-based forecasting models, have emerged as promising approaches for handling complex solar radiation fluctuations and improving prediction accuracy. Numerous optimization techniques based on solar power prediction have been investigated by researchers to solve this problem and ensure a continuous power supply. By using these techniques, system stability is preserved, and the negative consequences of the solar power forecast model are minimized. Hybrid approaches integrating statistical models with artificial intelligence methods have shown significant improvements in short-term and long-term solar power predictions, enabling more resilient energy system designs. To give an extensive overview of the current research, we performed a literature review that concentrated on the most important papers that were published in IEEE, Google Scholar, Science Direct, and Springer journals between 2015 and 2024. These investigations were examined using methods that take into consideration convergence time, tracking efficiency, and error metrics. To promote future developments in PV-based optimization, this survey aims to identify current challenges and constraints.

**Keywords:** Renewable Energy; Solar Power Prediction; Deep Learning; Artificial Neural Network; Optimization

***Nomenclature***

| Abbreviation | Description |
|---|---|
| PV | PhotoVoltaic |
| ToU | Time-of-Use |
| ETS | Exponential smoothing |
| ML | Machine Learning |
| PVLIB | Photovoltaic Library |
| ML | Machine Learning |
| ANN | Artificial Neural Networks |
| TESDL | Traditional Encoder Single Deep Learning |
| RF | Random Forests |
| LSTM | Long Short-Term Memory |
| SCADA | Supervisory Control and Data Acquisition |
| SVM | Support Vector Machine |
| NASA POWER | National Aeronautics and Space Administration -Prediction of Worldwide Energy Resources |
| RRVFLN | Robust minimum variance Random Vector Functional Link Network |
| MAE | Mean Absolute Error |
| MAPE | Mean Absolute Percentage Error |
| XAI | Explainable Artificial Intelligence |
| ARIMA | Autoregressive Integrated Moving Average |
| EWT | Empirical Wavelet Transform |
| AMVs | Atmospheric Motion Vectors |
| NRMSE | Normalized Root Mean Square Error |
| GEFCom2014 | Global Energy Forecasting Competition 2014 |
| HTPEG | presumably referring to Human-Technology-Environment-Governance |
| PDF | Portable Document Format |
| ASPF | Adaptive Solar Power Forecasting |
| WLOF | Weighted Local Outlier Factor |
| WD | Wavelet Decomposition |

| | |
|---|---|
| ANN | Artificial Neural Network |
| SVM | Support Vector Machines |
| RMSE | Root Mean Squared Error |
| VM | Vector Machines |
| CNN-LSTM | Convolutional Neural Network - Long Short-Term Memory |
| MSTF | Multiple Short-Term Functions |
| AnEn | Analog Ensemble |
| SPF | Solar Power Forecasts |
| NWP | Numerical Weather Prediction |
| MAPE | Mean Absolute Percentage Error |
| GBDT | Gradient Boosting Decision Tree |
| ECMWF | European Centre for Medium-Range Weather Forecasts |
| DL | Deep Learning |
| NMAE | Normalized Mean Absolute Error |
| SARIMA | Seasonal-ARIMA |
| IoT | Internet of Things |
| EMS | Energy Management System |
| k-NN | k-Nearest Neighbors |
| WT-PSO-SVM | Wavelet Transform, Particle Swarm Optimization, and Support Vector Machine |
| $R^2$ | Coefficient of Determination |

# 1. Introduction

The development of sustainable and renewable energy has gained international support due to the severe environmental problems and energy limitations caused by the huge use of fossil fuels [1][2]. With its widespread deployment worldwide, solar energy has become one of the most potential and rapidly expanding alternative energy sources [3],[4],[5],[6]. The continuous advancements in photovoltaic (PV) technology, including perovskite solar cells and bifacial modules, further boost the efficiency and scalability of solar power generation. Neural networks and a fuzzy method were used to suggest a long-term predictive model for PV power output correction [7],[8]. In [9], an efficient method for forecasting solar radiation was put forth. A general model was created to determine the hourly solar radiation at any time of day, at any location, using just one solar radiation measurement [10]. During the day, this model incorporates local variations in the mass of air and global solar radiation penetration. However, the prediction error grows significantly when the forecast time increases [11]. As a result, attempts were made to forecast solar radiation [12]. Recent studies emphasize hybrid forecasting models that integrate deep learning techniques with physical models, improving accuracy while mitigating uncertainties associated with extended forecast horizons.

A key component of energy management systems [14] is exact PV power forecasting, which is necessary for ensuring the safe and cost-effective integration of PVs into the smart grid [13]. By improving the quality of electricity provided to the electrical grid, accurate forecasting can lower the ancillary costs related to overall volatility [15]. Energy management in the smart grid also depends on solar irradiance forecast because PV power generation is strongly correlated with ground-level solar irradiance [16]. The necessity for various operation and control tasks, such as grid regulation, power scheduling, and unit commitment in both the distribution and transmission grids, is another reason why solar forecasts with numerous look-ahead times are important [17]. Additionally, AI-driven forecasting approaches incorporating reinforcement learning have shown promise in dynamically adapting predictions based on grid demand fluctuations, enhancing overall stability and efficiency.

The most recent methods for generating power forecasts for PVs are extensively examined in this study [18],[19]. Although several of the previous review articles have a broad depth as well (forecasting methods, input sources, performance measures, temporal and spatial coverage, etc.), the rapid growth of new research requires an original assessment that demonstrates current trends [20]. Among these most recent developments are the emphasis on the financial impact of forecasting, the need for cooperation of a uniform set of performance standards, and the need for probabilistic forecasting. Some earlier evaluations entirely address a single category of forecasting, including ensemble forecasting or various forecasting methods. This work presented a survey of the various existing prediction methods used in the solar power forecasting process. This survey further identifies the importance of integrating blockchain-based energy trading frameworks with PV forecasting, enabling transparent and decentralized solar energy transactions.

The contribution of the survey is presented below,

- To examine and evaluate current studies on different solar power forecast model compensating strategies.
- To analyze the efficiency, frequency, and power performance of the existing solar forecasting models.

- To explore emerging trends in hybrid forecasting methodologies, including deep learning-integrated ensemble models and probabilistic forecasting approaches tailored for real-time grid applications.

The organization of this paper is as follows: An overview of solar power forecasting is given in Section 1. In Section 2, research based on state of the art are reviewed. Similarly, Section 3 presented an in-depth examination of several methods used in the existing work. Section 4 represents the analysis and discussion of various methods used in the existing solar prediction process. Section 5 presents research gaps, whereas Section 6 highlights the conclusion and future scope of the work. Future scope discussions include advancements in federated learning for decentralized PV forecasting models, enhancing data privacy and cross-regional predictive capabilities.

## 2. Research Based on State of the Art

There are various methods have been presented for a solar power prediction model to increase the prediction efficiency. These techniques belong to the following categories: hybrid models, satellite and remote sensing models, heuristic, statistical, physical, ML, and DL techniques. Here, the conceptual design, implementation, application, and accuracy of each approach may vary, accordingly. However, solar irradiance is predicted by physical models using equations related to solar geometry and the atmosphere. To simulate clear-sky irradiance, this model included REST2, Bird Clear Sky Model, SMARTS, and PVLIB (open-source library), which combines several empirical and physical models. The physical method's strength lies in its physics foundation, which eliminates the requirement for historical information. It was constrained by less accuracy on complicated terrain or in conditions of fog. Recent advancements in hybrid physical models aim to enhance accuracy by integrating localized weather corrections and terrain adaptation techniques, making these models more applicable in diverse geographic settings. The statistical models find patterns for solar generation by analyzing historical data. ARIMA, SARIMA, and ETS were common time series forecasting approaches. For short-term prediction, the current research contrasted ARIMA with physical models. This model was feasible to understand and straightforward. It is also limited in its ability to handle nonlinear patterns and requires stationary time series. To address these limitations, researchers have explored adaptive statistical methods, such as autoregressive deep learning hybrids, that leverage nonlinear feature extraction while maintaining interpretability.

Finally, the ML modeled nonlinear correlations between weather and solar output using data-driven methodologies. Popular SVM, k-NN, RF, ANN, and Gradient Boosting (XGBoost, LightGBM) models were employed. The state-of-the-art DL included CNN-LSTM for spatiotemporal forecasting, LSTM for time series, and Transformers, which were most recently applied to weather-related time series. The current study comprised contrast studies between ANN-based solar forecasting and ML for solar radiation forecasting. Recent studies also incorporate generative AI models to synthesize weather scenarios and improve robustness against unpredictable environmental conditions. To increase accuracy and robustness, the hybrid models integrate data-driven and physical models. Its strategies may include ensemble methods that integrate ML and time-series models, as well as clear-sky models that incorporate ML to learn cloud-induced deviations. The hybrid CNN-LSTM model using meteorological input and the hybrid technique combining ANN and ARIMA are the two hybrid models used currently. The satellite and remote sensing models estimated current or predicted solar irradiance using satellite imagery. They made use of NASA POWER, Solcast, and HelioClim. It performs well with ML models for short-term forecasting and the process. Recent developments in cloud-based satellite data fusion methods have significantly improved real-time solar forecasting, facilitating more precise energy dispatch strategies in smart grids.

The evaluation metrics employed in the present solar power prediction model were standard metrics used in research to evaluate performance, including RMSE, MAE, MAPE, and $R^2$ (Coefficient of Determination). For time-series-based forecasting, DL (LSTM, CNN-LSTM, Transformers) was dominating, and hybrid models that combine physics and ML were cutting-edge in terms of precision and robustness. The use of spatiotemporal data (such as satellite and ground sensors) was essential for enhancing prediction in practical applications, and XAI was a new field that aimed to increase the transparency of ML-based solar forecasts. Furthermore, the integration of federated learning into solar forecasting models ensures privacy-preserving decentralized data analysis while maintaining predictive accuracy across diverse regions.

## 3. Survey Of Different Methods Used in the Solar Power Prediction Model

This section offers a comprehensive examination or overview of several methods and strategies that researchers and professionals have used to forecast or estimate solar power generation.

## 3.1. Machine Learning Techniques

A ML-based solar power forecasting model is mainly utilized for predicting the amount of electricity that the solar panels can generate now or in the future. This was crucial for enhancing grid connectivity, maximizing solar energy consumption, and assisting with energy management. In 2016, Jang *et al.* [1] proposed a solar power prediction model using a SVM learning system and a variety of satellite images. Cloud motion vectors are predicted from AMV satellite images. To provide several sets of input and output data for SVM training, they examined four years' worth of historical satellite imagery. The prediction accuracy decreases from the 180-minute horizon to $R^2$=0.8338; however, the irradiance of the 15–150-minute horizon might be accurately predicted with $R^2$=0.9770~0.8641. Consequently, these forecast data were used efficiently for EMS in smart grid and grid operation. This approach demonstrated the effectiveness of integrating satellite imagery with machine learning for improving short-term irradiance forecasts.

In 2017, O'Leary *et al.* [3] developed an innovative approach to solar power forecasting for small companies and individuals using sound classification, image processing, and ML approaches. Automated forecasting systems were necessary as consumer-level solar power production increased to reduce loss, expense, and influence on the environment for companies and households that generate and use electricity (prosumers). For these prosumers, who are the newest participants in the energy market, to produce accurate ANN forecasts, new ANN performance tuning methods were needed. Thus, the ANN tuning method is intended for picture edge identification and audio signal classification. The accuracy of the proposed ANN-based forecast model was higher than the traditional forecast model. According to the results, the $R^2$ value improves the measure prediction to target correlation and reduces the sample prediction inaccuracy by 14.4%. Furthermore, there was a 5.37% and 6.83% drop in MAE and RMSE, respectively. Furthermore, there was a 5.37% and 6.83% drop in MAE and RMSE, respectively. This study highlights the potential of multimodal data inputs (audio and visual) in enhancing ML model performance for solar forecasting.

In 2018, Zhang *et al.* [6] introduced a novel analogy ensemble technique for hourly-resolution day-ahead regional PV power forecasting. The robustness of the proposed method for PV forecasts at the region and single site levels was demonstrated using three different numerical weather prediction models: the North American Mesoscale Forecast System, the Global Forecast System, and the Short-Range Ensemble Forecast. Thus, three tested baselines were compared, and the NRMSE was lowered by 13.80%–61.21%. The ensemble technique's flexibility allows it to adapt to different weather models, increasing forecasting reliability across regions.

In 2024, Saxena *et al.* [7] suggested a hybrid ML model that combines the KNN and SVM ML techniques to improve the predicting accuracy of solar electricity from solar farms and enhance power system operators' dependability. The sensitivity, specificity, and accuracy of the KNN-SVM were 6.2%, 7.25%, and 7.1%, higher than those of the LSTM model in the configuration of HTPEG. The fusion of KNN and SVM demonstrates the effectiveness of combining models to compensate for individual limitations and boost predictive performance.

In 2017, Wang *et al.* [9] suggested a new method for predicting solar power by examining important meteorological variables from PV analytical modeling. In this approach, there were three models comprising the suggested method: i) PV system analytical modeling; ii) a deviation analysis for solar power forecasting; and iii) ML techniques for mapping meteorological characteristics with solar power. Using the primary meteorological variables obtained from PV models, forecasting performance might be greatly enhanced as demonstrated by case studies based on observed datasets from PV systems in Australia. This hybrid strategy bridged the gap between physical PV modeling and statistical learning, leveraging the strengths of both approaches.

In 2021, Jebli *et al.* [10] offered a method for solar energy prediction based on DL and ML approaches. To guarantee the best possible management and security requirements in this area, the researched models' applicability for short-term and real-time solar energy forecasting was evaluated. This was accomplished with an integrated solution built around a single tool and an appropriate prediction model. Based on their respective R-squared values of 94.81% and 92.61%, ANN and RF both perform better with very high accuracy. With corresponding precisions of 62.62% and 22.05%, SVR and LR perform lower than RF and ANN. Their integrated platform approach suggested a promising direction for practical deployment in energy management systems.

In 2016, Huang *et al.* [11] generated a probabilistic solar power forecast for the GEFCom2014. The goal was to provide hourly forecasts of the outputs from three solar farms using data from the ECMWF numerical weather prediction model. An evaluation on a 256-core Intel 2.6GHz platform for Task15 showed that the pre-processing stage took around 5 seconds, the modeling step cost about 17 seconds, the gradient boosting step took about 640 seconds, and the PDF estimation step took about 96 seconds. As a result, the program could be completed in 13 minutes. This research emphasized the scalability of solar forecasting algorithms on high-performance computing platforms.

In 2021, Liu *et al.* [13] proposed a simplified LSTM algorithm to predict solar power generation for a day in advance, built on a base of the ML methodological framework. Furthermore, the LSTM model's forecast was capable of accurately capturing intra-hour ramping under various meteorological conditions. With an average RMSE of 0.512, the recommended architecture and approach appeared to be the most appropriate for applications involving short-term solar power forecasting. The result showed that the optimal average RMSE was 0.497 with 200 hidden nodes and an activation function of Tanh. The LSTM model showed superior temporal pattern recognition, making it especially effective in handling rapid fluctuations in solar output.

In 2017, Sheng *et al.* [14] proposed a short-term PV power generation forecasting technique using Gaussian weighted regression. The suggested method makes use of WLOF along with nonlinear correlation measurement. Results from experiments showed that the suggested model performed better than other methods for multi-dimensional input data. This model underscores the role of weighted regression techniques in improving prediction under nonlinear and dynamic solar conditions.

In 2018, Wang *et al.* [15] suggested an ASPF technique for accurate solar power forecasting that combines data clustering, variable selection, and neural networks to capture the features of forecasting errors and update the forecasts appropriately. These algorithms, included ASPF, LARS, enhanced k-means, and BPNN, and were validated. Also, they confirm to ASPF algorithm's efficacy for various prediction models. The approach's modular structure makes it suitable for customizing forecasts based on regional or operational requirements.

In 2015, Zhu *et al.* [17] offered a technique that combined the advantages of ANN and WD to address the issue of conventional power forecast techniques based on time series or linear models becoming ineffective because of the periodicity and non-stationary behavior of PV power. To extract relevant information from disturbances, WD was employed to analyze the output power of the PV site. Models of the decomposed PV output power were constructed using ANNs. The predicted PV plant power was then calculated using the ANN models' results. The findings demonstrated that the approach presented had higher forecasting accuracy and consumed less computation time. This hybrid decomposition-modeling method provided a strong solution for noise handling and signal extraction in volatile solar environments.

In 2018, Wang *et al.* [19] suggested a GBDT-integrated algorithm to resolve the PV power prediction problem. In essence, the GBDT technique used the integrated gradient descent process to combine binary fissions and weak learners. By eliminating the over-fitting problem, the case studies showed that the proposed model, which was based on the GBDT method, could accurately correspond to the relationship between input features and PV power. The GBDT method's ability to generalize well to unseen data illustrates its potential in robust and scalable solar forecasting systems.

## 3.2. Deep Learning Techniques

In 2021, Chang *et al.* [4] suggested a TESDL approach that uses DL techniques for weather forecasts to address the issues of unpredictable and irregular electricity supply while integrating renewable energy sources into the grid. For creating prediction models, several regression techniques were examined, such as low linear squares and assisted VM utilizing MSTF. To verify the accuracy of the model, developers integrate previous TESDL forecasts with sunlight intensity estimates based on nearly a year of weather station use. The results demonstrate that VM-based forecast models outperform traditional techniques with a 27% increase in accuracy factor. This approach underscores how deep learning can enhance resilience in power grid operations by improving short-term solar prediction under varying atmospheric conditions.

In 2019, Torres *et al.* [12] presented the feed-forward neural network-based DL technique for massive data time series, which breaks down the forecasting difficulty into multiple smaller challenges. Using two years of Australian solar data, they performed an in-depth investigation, evaluating accuracy and training time, and contrasting the performance of DL with two other state-of-the-art methods based on neural networks and pattern sequence similarity. They examined the impact of varying historical window sizes and the utilization of numerous data sources, including weather and solar power data from the past few days, as well as forecasts for the prior day. The results show that DL was an excellent method for enormous data situations since it scales effectively and produces results with competitive accuracy. Their findings validated deep learning's capability for parallelizing learning across timeframes, which is crucial for processing and interpreting high-dimensional spatiotemporal solar datasets.

## 3.3. Statistical Methods

In 2015, Prema, V., and K. Uma Rao [2] suggested time series models for predicting solar irradiance in the short term, which would allow for solar power prediction. The forecasts were made one day in advance using various time-series models. The results showed that, with an error of about 9.28%, the prediction using the decomposition model for two months' worth of data produced the best result. The calculated MAPE of 25.3% was still within the allowed limits even if it was greater than the error for sunny days. This highlights the continued relevance of classical statistical techniques in providing interpretable and reasonably accurate forecasts for clear weather scenarios.

In 2015, Alessandrini *et al.* [5] suggested the AnEn approach to produce probabilistic SPF. AnEn was built on a historical collection of solar power data and forecasts from deterministic NWP models. A collection of historical production data was used to generate the solar power ensemble projection for every predicted lead time and location. These measures were selected because they were comparable to earlier deterministic NWP predictions for the same location and lead time. For this data set, it is possible to quantify the influence of more cloudy weather and a polluted environment on predictability in the 1–72-hour range as 7–10% of MAE/MP. Dealing with areas that experience more overcast weather and more power variability may have a greater impact on this rating. The AnEn method effectively quantifies prediction uncertainty, offering a robust tool for risk-aware energy dispatch and planning.

In 2016, Guo e*t al.* [18] suggested an approach for forecasting solar power output that combines the most advanced statistical learning techniques with ensemble learning. Through comparison with a benchmark using various metrics, the model's performance was assessed, and the statistical results validated the model's efficacy. The highest RMSE for the next day and week is 7.98% and 10.27%, respectively, while the smallest RMSE is 1.00% and 4.42%, based on the performance measures. Their results revealed that integrating ensemble strategies with statistical learning substantially improves prediction robustness across multiple forecast horizons.

## 3.4. Hybrid Model

In 2018, Eseye *et al.* [8] suggested a hybrid WT-PSO-SVM for estimating the short-term generation power of an actual microgrid PV system. The typical computation time is less than 15 seconds, and the daily MAPE and NMAE outperform seven other prediction algorithms with average values of 4.22% and 0.4%, respectively. This model demonstrates the value of wavelet transform for signal preprocessing, while PSO optimizes the SVM parameters for improved learning efficiency.

In 2018, Abedinia *et al.* [20] suggested a novel forecasting method that uses a hybrid forecasting engine that combines a neural network and a meta-heuristic algorithm. The neural network's free parameters are optimized via the metaheuristic algorithm. Furthermore, this method incorporates a two-stage feature selection filter that eliminates inefficient input features using the information-theoretic parameters of mutual knowledge and interaction gain. On 2PV generation prediction evaluations related to the real-world case study, it had been proven that the suggested prediction strategy performs better than nine different forecasting techniques. The layered feature selection approach enhanced the input relevance, allowing the hybrid model to achieve superior generalization performance. In 2021, Dash *et al.* [16] analyzed a novel and effective hybrid forecasting method that combines RRVFLN and EWT with a functionally extended direct link from input nodes to the output node and a random weight vector for improving nodes. To assess the accuracy of the proposed EWT-RRVFLN model's solar power forecast, historical solar power data for the various seasons in Alabama, Ikitelli, and Berlin are taken into consideration. This model architecture improved seasonal adaptability and reduced noise sensitivity, leading to better performance across geographically diverse test cases.

***Table 1.*** *Comparison of various methods of solar power prediction*

| Method Type | Description | Examples | Strengths | Limitations |
|---|---|---|---|---|
| **Physical Models** | Based on solar geometry and atmospheric physics | REST2, SMARTS, PVLIB, Bird Model | Interpretable, location-independent, no training needed | Inaccurate in cloudy conditions, requires detailed weather data |
| **Hybrid Models** | Combine two or more methods (e.g., physics + ML) | ARIMA-ANN, CNN-LSTM + physical model | More robust, balances bias-variance tradeoff | Complex to implement and tune |
| **Satellite/Remote Sensing** | Use satellite imagery & weather sensors to forecast irradiance | HelioClim, Solcast, GOES data + ML | Real-time cloud tracking, large area coverage | Requires access to high-resolution imagery and processing tools |
| **Machine Learning (ML)** | Learn nonlinear patterns from input features | SVM, k-NN, Random Forest, XGBoost | Handles complex relationships, good for medium-term forecasting | Needs labeled data, performance drops in unseen conditions |
| **Deep Learning (DL)** | Neural networks for complex temporal/spatial relationships | ANN, LSTM, CNN-LSTM, Transformers | High accuracy, good for long-term & time-series forecasting | Data-driven, black-box nature, high computational cost |
| **Statistical Models** | Use historical patterns and time series analysis | ARIMA, SARIMA, ETS, Holt-Winters | Easy to interpret, effective for short-term prediction | Assumes linearity, needs stationarity, weak on nonlinear data |
| **Heuristic Methods** | Rule-based or optimization-driven manual modeling | Fuzzy logic systems, Genetic Algorithms, PSO | Simple to implement, low computational cost | Less accurate, not adaptive to changing conditions |

## 4. Analysis and Discussion

The performance evaluation of several techniques utilized in the solar power prediction process, such as hybrid models, satellite/remote sensing models, ML, DL, statistical, heuristic, and physical models, is explained in this section. The analysis depends on standard evaluation criteria, including interpretability, adaptability, computational complexity, accuracy, and data dependency. These criteria provide a comprehensive framework for comparing the strengths and limitations of each method across different application scenarios, such as short-term forecasting, real-time monitoring, and regional energy planning. In the solar power forecast process, the performance analysis of the different methodologies is shown in Fig. 1. This visual comparison enables clearer insights into which techniques are more effective under specific meteorological and operational conditions. Likewise, table 2 lists the research papers that were employed for the various approaches in the process of Solar Power Prediction. This tabular reference acts as a foundational index for readers, linking methodologies with real-world case studies and outcomes. By systematically evaluating these approaches, stakeholders such as grid operators, researchers, and policymakers can make informed decisions regarding model selection, deployment strategies, and technology investments.

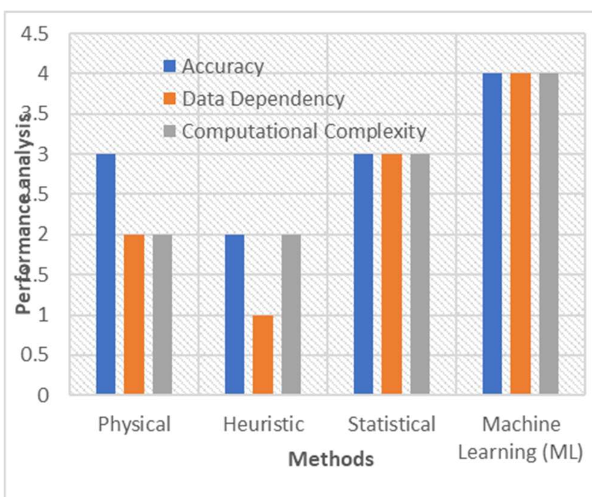


***Fig. 1.*** *Performance analysis of various methods used in the solar power prediction process*

***Table 2.*** *Topology of solar power prediction methods*

| Methods | Research papers |
|---|---|
| Statistical | [5][2][18] |
| ML | [1] [3][10][6][7][9][14][13][11][15][17][19] |
| DL | [4][12] |
| Hybrid Models | [8][20][16] |

## 5. Research Gaps and Future Directions

**(a) Shortcomings**

The following list summarizes the drawbacks of several techniques used in the solar power prediction process, including hybrid models, heuristic, statistical, ML, DL, physical, and satellite/remote sensing approaches:

- ➢ Heuristic and physical approaches are straightforward, but they are not accurate or flexible.
- ➢ Statistical models work well in the short run but fall short in dynamic, nonlinear situations.
- ➢ ML and DL models are more accurate, but they need a lot of data and processing power.
- ➢ Hybrid vehicles are more sophisticated, but they offer the best performance.
- ➢ Satellite-based techniques are effective for large-scale forecasting, but they are restricted by data latency and require infrastructure.

→ Furthermore, many models lack robustness in the face of sudden weather shifts, which significantly reduces their reliability in real-world deployment.

→ The trade-off between model complexity and interpretability also remains a challenge, particularly for regulatory adoption and end-user trust.

**(b) Future Works**

- ❖ **Data Fusion:** Integrating several data sources, such as satellites, weather stations, SCADA, and the IOT.

→ Leveraging data fusion can significantly enhance contextual awareness and fill in gaps caused by individual data source limitations.

- ❖ **Uncertainty Quantification**: Utilizing confidence intervals and probabilistic predictions.

→ Including uncertainty estimates improves decision-making and supports risk-aware energy management strategies.

- ❖ **Real-Time Prediction**: Creating incredibly quick models for grid use.

→ This is particularly essential for smart grids and microgrids that rely on instantaneous forecasting for load balancing.

- ❖ **Sustainability and Scalability**: Ensuring that models function in instances with limited resources or that are remote.

→ Lightweight and edge-compatible algorithms can ensure feasibility in off-grid or developing regions.

- ❖ **Policy Integration**: Assisting with demand response, grid planning, and renewable integration tactics.

→ Bridging the gap between model outputs and policy-level applications will be vital for broad-scale deployment and utility compliance.

## 6. Conclusion

This study examines 20 chosen research papers to present an in-depth evaluation of different prediction methods for solar power generation. Each result's concept and performance are thoroughly examined, with special attention to computational complexity, data dependency, and forecast accuracy. The study examines different preprocessing methods including ML, DL, Statistical Methods, Hybrid Models, and so on.

- ➢ With a focus on computational complexity, data dependency, and prediction accuracy, an extensive assessment of computational selections was conducted.
- ➢ By defining specific future scopes, this survey offered researchers a road map for further solar power forecast studies.

To ensure long-term optimal performance for solar power prediction, future research should examine whether solar power prediction systems will focus on generating extra resilient besides flexible models and may maintain their high effectiveness and dependability in challenging environments. In addition, incorporating real-time data acquisition, adaptive learning mechanisms, and region-specific modelling could enhance predictive capabilities under dynamic weather conditions. These directions would not only improve prediction reliability but also support more efficient integration of solar energy into smart grid systems.

## Compliance with Ethical Standards

**Conflicts of interest:** Authors declared that they have no conflict of interest.

**Human participants:** The conducted research follows the ethical standards and the authors ensured that they have not conducted any studies with human participants or animals.

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