International Journal of Scientific and Cognitive Innovation (www.ijsci.org)
|| Volume 2, Issue 7, July 2026 || Impact Factor: 3.5 |

Review of Machine Learning Technique for Solar Irradiance Forecasting

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***Abstract*— Accurate solar irradiance forecasting is essential for reliable integration of solar PV generation into modern power systems. This review analyzes various Machine Learning (ML) techniques such as ANN, SVR, Random Forest, Decision Tree, and ensemble models for predicting solar irradiance. The study examines the use of historical irradiance and meteorological parameters such as temperature, humidity, cloud conditions, and wind speed. ML techniques can effectively capture nonlinear relationships and improve forecasting accuracy. Accurate irradiance prediction supports PV power forecasting, energy storage scheduling, grid stability, and renewable energy management. The review also discusses key challenges and future directions for developing robust ML-based solar irradiance forecasting systems.**

Keywords: Solar Irradiance, Machine Learning, Solar Forecasting, PV System, Renewable Energy, Smart Grid.

I. Introduction

The increasing installation of solar photovoltaic (PV) systems has made solar energy an important component of modern electrical power systems. Since solar PV generation is directly dependent on available solar irradiance, variations in irradiance can cause significant changes in PV output power. Accurate solar irradiance forecasting is therefore essential for reliable power generation planning, energy scheduling, and efficient integration of solar power into the electrical grid [1]. Solar irradiance varies with geographical location, time of day, season, atmospheric conditions, cloud movement, temperature, and humidity, making its prediction a challenging task [2].

From a power-system perspective, accurate irradiance forecasting helps utilities estimate future solar generation and maintain a suitable balance between generation and demand. It can also support voltage regulation, power-flow management, and reduction of uncertainty associated with renewable energy sources [3]. In solar PV plants, irradiance information can be used to estimate the expected power output and improve operational planning. Therefore, forecasting irradiance is an important step toward reliable utilization of solar-based electricity generation [4].

Conventional solar irradiance forecasting methods generally include statistical and physical approaches based on historical observations and atmospheric models. Although these methods can provide useful predictions under relatively stable conditions, their performance may decrease when irradiance changes rapidly due to cloud cover and other atmospheric variations [5]. The nonlinear and time-varying characteristics of solar irradiance have consequently encouraged the use of Machine Learning (ML) techniques for more accurate forecasting.

Machine Learning techniques can learn complex relationships between historical irradiance and meteorological parameters without requiring an explicit mathematical representation of the physical process. Methods such as Artificial Neural Networks (ANN), Support Vector Regression (SVR), Decision Trees, Random Forest, and Gradient Boosting have been investigated for solar irradiance prediction [6]. These models can utilize input parameters such as previous irradiance values, temperature, humidity, wind speed, solar position, and cloud-related information to estimate future irradiance [7].

The forecasting horizon is another important consideration in solar irradiance prediction. Short-term forecasting is particularly useful for real-time PV power management, battery energy storage, and grid operation, whereas day-ahead forecasting can support generation scheduling and electricity-market planning. The selection of an appropriate ML model depends on forecasting horizon, data availability, weather conditions, and required prediction accuracy [8].

The quality of available data also has a major influence on forecasting performance. Solar irradiance datasets may contain missing measurements, sensor errors, noise, and sudden fluctuations caused by changing atmospheric conditions. Proper data preprocessing, feature selection, normalization, and selection of relevant meteorological variables are therefore necessary for developing reliable ML-based forecasting models [9].

Hence, a systematic review of Machine Learning techniques for solar irradiance forecasting is important to understand their forecasting capabilities, advantages, limitations, and suitability for electrical power-system applications. This paper reviews major ML approaches and their use in solar irradiance prediction, with emphasis on forecasting accuracy, input parameters, forecasting horizons, and applications in PV power forecasting, energy storage, renewable-energy integration, and smart-grid operation [10].

II. LITERATURE SURVEY

Roga et al., [1] investigated machine learning algorithms for solar irradiance forecasting and developed a customized deep neural network approach. Their study focused on learning the nonlinear relationship between historical solar irradiance and relevant forecasting variables. The proposed deep learning approach demonstrated the potential of neural networks for improving irradiance prediction accuracy. The work highlights the suitability of customized AI models for renewable-energy forecasting applications.

Jalali et al., [2] presented an automated deep CNN-LSTM architecture design for solar irradiance forecasting. The CNN component was used to extract important features from the input data, while LSTM captured temporal dependencies in solar irradiance sequences. The automated architecture design reduced the need for manual model selection and configuration. Their study demonstrated the effectiveness of combining convolutional and recurrent learning for solar irradiance prediction.

Singh et al., [3] studied solar photovoltaic energy forecasting using both machine learning and deep learning techniques. The research focused on predicting solar PV energy by learning patterns from historical and relevant input data. Different learning approaches were analyzed to understand their suitability for renewable-energy forecasting. The study indicated that intelligent forecasting techniques can support improved prediction and management of solar power generation.

Parida et al., [4] developed a medium-term solar power prediction method using a stacked LSTM-based deep learning technique. The stacked architecture was designed to learn complex temporal relationships within solar power generation data. The study focused on medium-term prediction, which is important for planning and scheduling solar-based electricity generation. The results demonstrated the potential of stacked LSTM networks for handling time-dependent renewable-energy data.

Kartini et al., [5] developed a hybrid deep learning neural-network model for probabilistic solar irradiance forecasting. The study considered forecasting uncertainty in solar-cell irradiance prediction rather than relying only on a single deterministic value. The probabilistic approach can provide useful information about possible future irradiance conditions. Such forecasting can support improved economic operation and planning of solar PV systems.

Obiora et al., [6] investigated the optimum forecasting horizon for short-term solar irradiance prediction using an LSTM network. Their work examined how the forecasting horizon influences the performance of the deep learning model. The study emphasized that selecting an appropriate prediction horizon is important for obtaining reliable irradiance forecasts. The findings are relevant to short-term PV power management and real-time renewable-energy applications.

Thirunavukkarasu et al., [7] presented a multilayered LSTM approach for very short-term solar irradiance forecasting. The multilayered structure was used to learn temporal characteristics and short-term variations in solar irradiance. Very short-term prediction is particularly useful for managing rapid changes in PV generation. The study demonstrated the applicability of LSTM-based models for forecasting rapidly varying solar irradiance.

Pi et al., [8] developed a short-term solar irradiation prediction model based on WCNN-ALSTM. The approach combined convolutional feature extraction with an attention-enhanced LSTM structure to capture both important input characteristics and temporal dependencies. The attention mechanism helped the model focus on relevant information within the time-series data. The study demonstrated the effectiveness of hybrid deep learning architectures for short-term solar irradiation prediction.

Fathima et al., [9] investigated the role of temporal information in multi-step-ahead solar irradiance forecasting. Their study emphasized the importance of historical temporal characteristics for predicting irradiance at multiple future time steps. Proper representation of temporal information can improve the ability of forecasting models to track changing solar conditions. The work is particularly relevant to multi-step forecasting applications in solar energy systems.

Obiora et al., [10] investigated the implementation of a Convolutional Long Short-Term Memory (ConvLSTM) network for solar irradiance forecasting. The ConvLSTM architecture combines convolutional feature extraction with LSTM-based temporal learning, making it suitable for complex time-dependent irradiance patterns. The study demonstrated the potential of ConvLSTM for improving solar irradiance prediction. Such forecasting can contribute to better prediction of PV generation and more reliable integration of solar energy into electrical power systems.

Table 1: Literature Review Comparison Table

Sr. No.	**Author & Year**	**Technique / Model**	**Forecasting Focus**
1	Roga et al. (2025) [1]	Custom Deep Neural Network	Solar irradiance forecasting
2	Jalali et al. (2022) [2]	CNN-LSTM	Solar irradiance forecasting
3	Singh et al. (2022) [3]	ML & Deep Learning	Solar PV energy forecasting
4	Parida et al. (2022) [4]	Stacked LSTM	Medium-term solar power prediction

5	Kartini et al. (2022) [5]	Hybrid DL-NN	Probabilistic irradiance forecasting
6	Obiora et al. (2022) [6]	LSTM	Short-term irradiance forecasting
7	Thirunavukkarasu et al. (2022) [7]	Multilayered LSTM	Very short-term forecasting
8	Pi et al. (2021) [8]	WCNN-ALSTM	Short-term solar irradiation
9	Fathima et al. (2021) [9]	Temporal Information-based Forecasting	Multi-step-ahead forecasting
10	Obiora et al. (2021) [10]	ConvLSTM	Solar irradiance forecasting

III. CHALLENGES

Solar irradiance forecasting is an important aspect of solar photovoltaic (PV) generation and modern electrical power-system operation, because the electrical power produced by a PV system is directly related to the available solar irradiance. Accurate forecasting helps in generation scheduling, power balancing, battery energy storage management, voltage regulation, demand response, and reliable integration of renewable energy into the grid. However, several challenges limit the accuracy and practical implementation of Machine Learning (ML)-based solar irradiance forecasting. These challenges are particularly important in electrical engineering because forecasting errors in irradiance ultimately produce errors in expected PV power generation and can influence the operation of the interconnected electrical network.

1. Solar PV Power Variability

The major challenge is the continuous variation of solar irradiance and corresponding PV output power. Unlike conventional generation units, solar PV systems cannot maintain constant power output because their generation depends on available solar radiation. Irradiance changes throughout the day due to solar position, seasonal conditions, and atmospheric variations. These changes produce fluctuations in PV generation and make accurate generation scheduling difficult. An ML model must therefore accurately represent both normal daily irradiance patterns and sudden changes to provide useful information for electrical power-system operation.

2. Cloud-Induced Power Fluctuations

Cloud movement is one of the most important factors responsible for rapid changes in PV generation. When clouds pass over a PV plant, solar irradiance can decrease sharply, resulting in a corresponding reduction in electrical output. When the clouds move away, generation can increase rapidly. Such fluctuations can create power ramps and affect generation-load balance. In distribution systems with high solar PV penetration, these variations may also contribute to voltage fluctuations. Therefore, forecasting cloud-related irradiance changes is essential for maintaining reliable PV power operation.

3. Generation and Load Balance

Accurate solar irradiance forecasting is necessary for maintaining an appropriate balance between electrical generation and load demand. If the forecast predicts higher solar generation than what is actually available, the system may experience an unexpected generation deficit. Similarly, overestimation or underestimation of PV generation can affect the scheduling of conventional generating units. Reliable irradiance forecasting allows system operators to estimate future PV power availability and coordinate solar generation with conventional sources and electrical demand.

4. Voltage and Power-Quality Issues

High penetration of distributed PV systems can influence the voltage profile and power quality of distribution networks. Sudden changes in PV output caused by irradiance fluctuations can result in variations in feeder voltage, particularly in weak distribution networks. Accurate irradiance forecasting can provide advance information about expected PV output and support appropriate control actions through voltage regulators, reactive-power control, and inverter-based PV control. Therefore, forecasting accuracy has a direct relationship with reliable distribution-system operation.

5. Energy Storage Management

Battery Energy Storage Systems (BESS) are increasingly integrated with solar PV systems to compensate for renewable-generation variability. However, efficient battery operation requires knowledge of future PV generation. Accurate irradiance forecasting can help determine when the battery should charge during high solar generation and discharge during low generation or peak-demand periods. Forecasting errors can result in inappropriate charging or discharging decisions, unnecessary battery cycling, and inefficient utilization of stored electrical energy. Thus, irradiance forecasting is important for coordinated PV and energy-storage operation.

6. Renewable Energy Integration

Increasing solar PV penetration introduces uncertainty into electrical power networks because solar generation depends on weather conditions. Accurate forecasting can reduce this uncertainty and help utilities plan the operation of conventional generators, distributed energy resources, storage systems, and transmission/distribution networks. Without reliable forecasting, higher solar penetration may increase operational uncertainty and require additional reserve capacity. Improved ML forecasting can therefore support the smooth integration of solar generation into smart grids and renewable-rich power systems.

7. Data Quality and Measurement Issues

Reliable forecasting requires accurate historical irradiance and electrical-generation data. Sensors used in solar plants may produce measurement errors because of calibration problems, dust accumulation, environmental exposure, communication failures, or other disturbances. Missing and noisy measurements can negatively affect ML model training. Furthermore, irradiance data and PV power data should be properly synchronized because incorrect time alignment can produce inaccurate relationships between irradiance and generated power. Proper data cleaning, normalization, outlier detection, and preprocessing are therefore essential for electrical forecasting applications.

8. Real-Time Forecasting and Computational Requirements

For practical power-system applications, irradiance forecasting should be available within an appropriate time period so that corrective actions can be taken before significant changes occur in PV generation. Advanced ML and deep learning models can provide accurate predictions but may require substantial computational resources and large datasets. Excessively complex models can create difficulties for real-time PV plant control, energy management systems, and distribution-network applications. Therefore, an appropriate balance between forecasting accuracy, computational complexity, processing time, and implementation cost is required.

IV. CONCLUSION

Solar irradiance forecasting using ML provides an effective approach for reducing the uncertainty associated with solar PV power generation. ML techniques can learn complex relationships between historical irradiance, weather conditions, and temporal parameters to improve prediction accuracy. Accurate irradiance forecasting enables better estimation of PV output and supports generation scheduling, generation-load balancing, battery energy storage management, voltage regulation, and renewable-energy integration. It also helps power-system operators anticipate fluctuations in solar generation and take suitable control actions. However, rapid cloud movement, weather variability, data-quality issues, forecasting uncertainty, and computational requirements remain important challenges. From an electrical engineering perspective, improving irradiance prediction is essential for maintaining reliable and stable operation of power systems with high solar PV penetration. Future research should focus on robust, adaptive, and computationally efficient ML models capable of providing accurate real-time forecasts. Such developments can enhance PV power management and support the reliable, economical, and stable integration of solar energy into modern electrical grids.

REFERENCES

[1] S. Roga, M. Lonkar, V. Mishra, P. Chakraborty, V. Dhanorkar and S. Bardhan, "Machine Learning Algorithms for Solar Irradiance Forecasting: A Custom Deep Neural Network Approach," 2025 IEEE 5th International Conference on Sustainable Energy and Future Electric Transportation (SEFET), Jaipur, India, 2025, pp. 1-6, doi: 10.1109/SEFET65155.2025.11255077.

[2] S. M. J. Jalali, S. Ahmadian, A. Kavousi-Fard, A. Khosravi and S. Nahavandi, "Automated Deep CNN-LSTM Architecture Design for Solar Irradiance Forecasting," in IEEE Transactions on Systems, Man, and Cybernetics: Systems, vol. 52, no. 1, pp. 54-65, Jan. 2022, doi: 10.1109/TSMC.2021.3093519.

[3] P. Singh, N. K. Singh and A. K. Singh, "Solar Photovoltaic Energy Forecasting Using Machine Learning and Deep Learning Technique," 2022 IEEE 9th Uttar Pradesh Section International Conference on Electrical, Electronics and Computer Engineering (UPCON), 2022, pp. 1-6, doi: 10.1109/UPCON56432.2022.9986446.

[4] A. K. Parida, D. Kumar, R. R. Sahoo and B. K. Balabantaray, "Medium term Solar Power Prediction using stacked LSTM based deep learning Technique," 2022 IEEE 4th International Conference on Cybernetics, Cognition and Machine Learning Applications (ICCCMLA), 2022, pp. 19-26, doi: 10.1109/ICCCMLA56841.2022.9989067.

[5] U. T. Kartini, Hariyati, W. Aribowo and A. L. Wardani, "Development Hybrid Model Deep Learning Neural Network (DL-NN) For Probabilistic Forecasting Solar Irradiance on Solar Cells To Improve Economics Value Added," 2022 Fifth International Conference on Vocational Education and Electrical Engineering (ICVEE), 2022, pp. 151-156, doi: 10.1109/ICVEE57061.2022.9930352.

[6] C. N. Obiora, A. Ali and A. N. Hasan, "Finding the Optimum Horizon for Short-Term Solar Irradiance Forecasting Using Long Short-Term Memory (LSTM) Network," 2022 11th International Conference on

Power Science and Engineering (ICPSE), 2022, pp. 148-152, doi: 10.1109/ICPSE56329.2022.9935346.

[7] G. S. Thirunavukkarasu et al., "Very Short-Term Solar Irradiance Forecasting using Multilayered Long-Short Term Memory," 2022 7th International Conference on Smart and Sustainable Technologies (SpliTech), 2022, pp. 1-8, doi: 10.23919/SpliTech55088.2022.9854244.

[8] M. Pi, N. Jin, X. Ma and K. Yan, "Short-term Solar Irradiation Prediction Model Based on WCNN_ALSTM," 2021 IEEE Intl Conf on Dependable, Autonomic and Secure Computing, Intl Conf on Pervasive Intelligence and Computing, Intl Conf on Cloud and Big Data Computing, Intl Conf on Cyber Science and Technology Congress (DASC/PiCom/CBDCom/CyberSciTech), 2021, pp. 405-412, doi: 10.1109/DASC-PICom-CBDCom-CyberSciTech52372.2021.00075.

[9] T. A. Fathima, V. Nedumpozhimana, J. Wu, Y. H. Lee and S. Dev, "Role of Temporal Information for Multi-step Ahead Forecasting of Solar Irradiance," 2021 Photonics & Electromagnetics Research Symposium (PIERS), 2021, pp. 2342-2346, doi: 10.1109/PIERS53385.2021.9695089.

[10] C. N. Obiora and A. Ali, "Effective Implementation of Convolutional Long Short-Term Memory (ConvLSTM) Network in Forecasting Solar Irradiance," IECON 2021 – 47th Annual Conference of the IEEE Industrial Electronics Society, 2021, pp. 1-5, doi: 10.1109/IECON48115.2021.9589934.