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Editorial

Artificial Intelligence Techniques for Solar Irradiance and PV Modeling and Forecasting

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Solar Photovoltaic (PV) systems represent key and transformative technology at the forefront of the global shift towards sustainable energy solutions. These systems harness the renewable radiation of the sun, converting it into clean electricity. Their importance cannot be overstated as they play a fundamental role in mitigating climate change, reducing dependence on finite fossil fuels, and providing access to clean energy sources for both developed and developing regions. Solar PV systems are not only a key component of the renewable energy portfolio, but also a symbol of our commitment to a greener and more sustainable future for generations to come.

The main difficulty in solar energy production is the volatility and intermittency of photovoltaic system power generation, primarily stemming from unpredictable weather conditions. Variations in irradiance and temperature can have a profound impact on the quality and reliability of electricity production from solar PV systems. Since solar irradiance is intricately linked to the efficiency of solar power harvesting, its accurate prediction serves as a crucial indicator of power production potential. For large-scale solar plants, any power imbalance within the PV system can lead to significant economic losses. Therefore, precise solar irradiance prediction, coupled with the appropriate modeling of PV system behavior, has emerged as a vital necessity to mitigate the impact of uncertainty and control energy costs. Furthermore, it facilitates the seamless integration of PV systems into smart grids, a growing trend driven by the increasing adoption of PV technology.

Numerous studies were undertaken to develop models and algorithms that predict solar irradiance based on various routinely measured meteorological parameters, such as temperature and humidity, to address these challenges. These advancements in accurate solar irradiance forecasting and the sophisticated modeling of PV systems have now become the cornerstone of modern smart grid development, supporting the expansion of Renewable Energy Sources (RESs).

The importance of Artificial Intelligence (AI) methods in predicting, modeling, and fault detection in PV systems cannot be overstated in today's energy landscape. AI has emerged as a transformative force in addressing the inherent challenges associated with solar energy production. Through the utilization of advanced machine learning algorithms and data analytics, AI techniques can ingest vast datasets, including historical weather patterns, system performance data, and real-time measured parameters, to provide highly accurate solar irradiance predictions. This precision in forecasting enables PV systems to optimize their energy capture, adapt to changing weather conditions, and maximize their overall efficiency. Moreover, the AI-driven modeling of PV systems goes beyond mere prediction by providing a comprehensive understanding of how these systems behave under various operating conditions. These models allow for the fine-tuning of PV system

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parameters, such as PV array orientation and tracking mechanisms, to achieve ultimate performance. Additionally, AI-based modeling helps to identify potential issues and areas of improvement, contributing to system longevity and reducing maintenance costs. In fault detection, AI technologies offer real-time monitoring and anomaly detection capabilities. By continuously analyzing the performance data from PV systems, AI algorithms can swiftly identify deviations from expected behavior, such as PV module failures, inverter malfunctions, or shading issues. The early detection and identification of these anomalies is crucial in preventing downtime, reducing energy losses, and ensuring the overall reliability of the PV system. Furthermore, AI-driven insights are indispensable for the integration of PV systems into smart grids. These systems require precise forecasting, adaptive control mechanisms, and seamless coordination with other energy sources to ensure grid stability and reliability. AI plays a pivotal role in enabling this integration by providing real-time information on the expected power output from PV systems, allowing for grid operators to make informed decisions about load balancing and energy distribution.

After an exhaustive and thorough review process, eleven high-quality articles were finally accepted for their contributions to the topic.

In [1], Castillo-Rojas et al. presented forecast models for PV energy generation based on a hybrid architecture that combines Recurrent Neural Networks (RNNs) and shallow neural networks. Two categories of models are developed, the first utilizing records of exported active energy and meteorological variables as inputs, and the second relying solely on meteorological variables. The models are rigorously evaluated using real data from a solar plant, and the best-performing model from each category is selected. The selected model from the first category achieves impressive accuracy metrics, including a root mean square error (RMSE) of 0.19, mean square error (MSE) of 0.03, mean absolute error (MAE) of 0.09, correlation coefficient of 0.96, and determination coefficient of 0.93, demonstrating its robust forecasting capabilities. Although the second category model exhibits slightly lower accuracy, with metrics such as RMSE = 0.24 and MAE = 0.10, it still performs well, with a correlation coefficient of 0.95 and determination coefficient of 0.90. Both models exhibit good performance in forecasting weekly PV energy generation, offering valuable insights for efficient solar energy management.

In [2], Hamied et al. proposed a cost-effective monitoring system designed for an off-grid PV system located in the Sahara region of South Algeria, serving a small-scale greenhouse farm. The system incorporates a simple, yet accurate, fault diagnosis algorithm integrated into a low-cost microcontroller for real-time validation. Leveraging the Internet of Things (IoT) technology, the system remotely monitors critical data such as PV currents, PV voltages, solar irradiance, and cell temperature. Additionally, a user-friendly web interface is developed to visualize the data and remotely check the PV system's status, with the capability to notify users via phone SMS. The results of the study demonstrate the system's effectiveness under specific climate conditions, confirming its ability to supply the greenhouse farm. Moreover, the integrated algorithm exhibits good accuracy in detecting and identifying various defects. Impressively, the total cost of this IoT-based monitoring system is approximately EUR 73, with an average daily energy consumption of around 13.5 Wh, making it a viable and economical solution for PV system monitoring and management in arid regions.

In [3], Halassa et al. considered the challenges of partial shading (PS) on PV installations, where an uneven solar irradiance distribution can lead to multiple peaks in PV cell power–voltage characteristics. They propose a novel technique for achieving the global maximum power point (GMPP) based on the Dandelion Optimizer (DO) algorithm, inspired by dandelion seed movements in the wind. This innovative approach aims to enhance power generation efficiency in PV systems, particularly under PS conditions. The paper conducts a comprehensive comparison with various advanced Maximum Power Point Tracker (MPPT) algorithms, including Particle Swarm Optimization (PSO), Grey Wolf Optimization (GWO), Artificial Bee Colony (ABC), Cuckoo Search Algorithm (CSA), and Bat Algorithm (BA). The simulation results affirm the DO-based MPPT's superiority in terms of tracking efficiency, speed, robustness, and simplicity of implementation. Notably, the DO algorithm exhibits exceptional performance with an RMSE of 1.09 watts, a rapid convergence time of 2.3 milliseconds, and a MAE of 0.13 watts, positioning it as a highly efficient and reliable solution for MPPT in PV systems, especially in the presence of partial shading conditions.

In [4], Polo et al. investigated power forecasting for Building Integrated PV (BIPV) systems integrated into vertical façades. They employ machine learning algorithms based on decision trees, utilizing the skforecast library within the Python environment to facilitate various deterministic and probabilistic forecasting approaches. In the deterministic forecasting phase, hourly BIPV power predictions are made using the XGBoost and Random Forest algorithms across different scenarios. Notably, incorporating exogenous variables enhances forecasting accuracy. Subsequently, the study delves into probabilistic forecasting, employing XGBoost in conjunction with the Bootstrap method. The results underscore the effectiveness of Random Forest and gradient-boosting algorithms, particularly XGBoost, as regressors for the time-series forecasting of BIPV power. The deterministic forecast results reveal mean absolute errors around 40% and slightly below 30% for south- and east-facing arrays, showcasing the potential of these machine learning techniques for BIPV power forecasting.

In [5], Faris E. Alfaris investigated a significant challenge in deploying PV systems, particularly in desert regions, where dust accumulation on PV panels can hinder their performance. Unlike traditional methods involving cameras, sensors, and power datasets, this study proposes an intelligent, sensorless approach to detect dust levels on PV panels, optimizing attached Dust Cleaning Units (DCUs). The approach leverages comprehensive data on solar irradiation, PV-generated power, and forecasted ambient temperatures. An expert AI computational system, implemented using MATLAB, is employed to enhance data prediction and processing. This AI system estimates missing information, emulates provided measurements, and accommodates additional input/output data. The study demonstrates the feasibility of this innovative system using real-world field data collected under various weather conditions, presenting a promising solution to the dust-related challenges faced by PV installations.

In [6], Dhimish and Lazaridis introduced an innovative approach to estimating the shading ratio of PV systems, a critical parameter for identifying potential PV faults and degradation mechanisms. This technique utilizes an all-sky imaging system and follows a structured process: Firstly, four all-sky imagers are deployed across a 25 km^2 region. Next, cloud images are computed using a new Color-Adjusted (CA) model. Subsequently, the shading ratio is calculated, and Global Horizontal Irradiance (GHI) is estimated, allowing for the prediction of PV system output power. The accuracy of the GHI estimation is empirically evaluated against data from two different weather stations, demonstrating an average accuracy within a maximum $\pm$12.7% error rate. Furthermore, this study highlights the PV output power approximation's accuracy, reaching as high as 97.5% under shading-free conditions and decreasing to a minimum of 83% when the PV system is affected by overcasting conditions.

In [7], Harrou et al. proposed a robust method for accurately detecting anomalies in photovoltaic (PV) systems. With the growing adoption of solar energy worldwide, protecting PV plants from anomalies is crucial. This approach combines ensemble learning techniques, including boosting and bagging, with the Double Exponentially Weighted Moving Average (DEWMA) chart, enhancing modeling accuracy and sensitivity for anomaly detection. By employing Bayesian optimization for parameter selection and employing kernel density estimation to set decision thresholds, the method effectively identifies various anomalies, such as circuit breaker faults, inverter disconnections, and short-circuit faults. The results, based on measurements from a 9.54 kW PV small plant, demonstrate superior detection performance compared to traditional methods, underlining the effectiveness of this ensemble learning-based approach in PV plant management.

In [8], Zhang et al. proposed a novel approach based on multi-agent deep Reinforcement Learning (RL) that utilizes residuals of I–V characteristics. The RL agents are designed to operate in an environment defined by the high-dimensional residuals of I–V characteristics, with cooperative rewards. Actions for each agent, considering damping amplitude, are specified. The study shows the complete framework for modeling a PV array using multi-agent deep RL and demonstrates its feasibility and accuracy using one year of measured data from a PV array. The results indicate improved modeling accuracy compared to conventional meta-heuristic algorithms and analytical methods, with a daily RMSE starting at approximately 0.5015 A on the first day and converging to 0.1448 A on the last training day. The proposed multi-agent deep RL framework simplifies the design of states and rewards for parameter extraction, offering promising prospects for enhancing PV array modeling accuracy.

In [9], Santos et al. introduced the Temporal Fusion Transformer (TFT), an attention-based architecture that offers interpretability of temporal dynamics and high-performance forecasting across multiple horizons. To evaluate the proposed forecasting model, they use data from six different PV facilities located in Germany and Australia and compare the results with several other algorithms, including Auto-Regressive Integrated Moving Average (ARIMA), Long Short-Term Memory (LSTM), Multi-Layer Perceptron (MLP), and Extreme Gradient Boosting (XGBoost), using statistical error indicators. The findings indicate that TFT outperforms the other algorithms in terms of accuracy when predicting PV generation for the mentioned facilities, showcasing its potential for improving day-ahead PV power forecasting and contributing to enhanced grid stability and an energy supply–demand balance.

In [10], Sarwar et al. introduced a novel population-based optimization approach called the Horse Herd Optimization Algorithm (HOA) for maximizing power output from PV systems, especially under partial or complex partial shading conditions. The HOA is inspired by the natural behavior of a horse herd, particularly their surprise pounce-chasing style. This intelligent optimization strategy demonstrates superior performance compared to conventional techniques like "Perturb and Observe" (P&O), bio-inspired Adaptive Cuckoo Search (ACS) optimization, Particle Swarm Optimization (PSO), and the Dragonfly Algorithm (DA). The HOA stands out due to its ability to efficiently track the maximum power point even in challenging and varying weather conditions, its minimal computational time requirements, fast convergence, and its capacity to maintain stability and reduce oscillations once the maximum power point is reached, making it a promising technique for enhancing PV system performance under partial and complex shading scenarios.

In [11], Huang et al. presented an effective parameter estimation method for optimizing parameters in a two-diode PV power generation system. The proposed method comprises three stages. Firstly, it converts the original seven parameters of the two-diode model into seventeen parameters to account for varying environmental conditions, thus enabling a more precise parameter estimation for the PV model. Subsequently, a PV power generation model is established to capture the nonlinear relationship between inputs and outputs. The second stage involves a parameter sensitivity analysis using the overall effect method to identify and retain only the parameters that significantly impact the output. In the final stage, an Enhanced Gray Wolf Optimizer (EGWO) is applied in conjunction with measurement data to optimize the selected parameters from the second stage. After parameter estimation, the method calculates the predicted PV power output for specific solar irradiation and module temperature values. The effectiveness of this approach is demonstrated on a 200 kWp PV power generation system by comparing parameter estimation results before and after optimization and benchmarking them against other optimization algorithms, as well as a single-diode PV model, confirming its feasibility and potential advantages.

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