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Renewable Energy Systems of Smart Grids and DL scheme

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Abstract

Background: Solar energy systems are expanding rapidly, which increases the need for efficient power extraction and accurate power forecasting. Conventional maximum power point tracking methods show reduced performance under varying meteorological conditions, which leads to power losses. Machine learning offers data driven models that adapt to changing environmental patterns and improve system performance
Aims: The study aims to enhance solar power harvesting and forecasting through machine learning techniques. Multiple predictive models are evaluated to identify reliable approaches for photovoltaic system applications.
Methods: Solar and meteorological datasets were preprocessed through data cleaning, removal of missing values, and extraction of time based features to support time series modeling. Linear regression, random forest, and artificial neural network models were trained and evaluated through mean absolute error, root mean square error, coefficient of determination, and graphical performance analysis to achieve accurate solar power prediction and effective maximum power point tracking
Result: The proposed framework improves solar power collection and contributes to grid stability. Machine learning based models demonstrate fast and accurate maximum power point tracking with consistent power output and improved efficiency.
Conclusion: The integration of intelligent control and machine learning techniques enhances the efficiency and reliability of solar energy systems. The proposed approach supports increased power generation, improved grid stability, and stronger sustainability of renewable energy utilization.

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INTRODUCTION

This paper examines how machine learning method has the potential of improving power generation in photovoltaic panels under dynamic weather. Specific attention is paid to the optimization of the Maximum Power Point Tracking (MPPT) to make systems more efficient, as well as weather-related prediction-based models to approximate the solar power (Chandel et al., 2023). Different machine learning algorithms will be compared to identify the best and most reliable tool in terms of renewable energy systems.

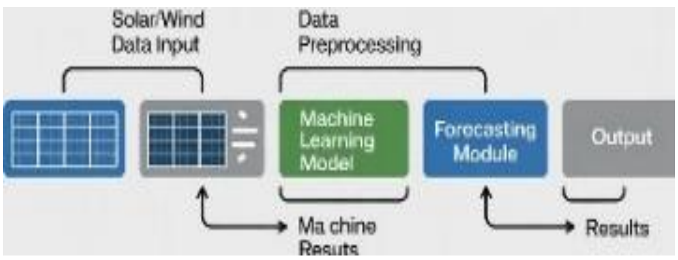

Figure 1. Processing Framework of The Model

Solar energy systems are growing fast; however, the question of extracting the best out of the solar panels is a thorny issue due to the ever-changing weather conditions (Yu et al., 2024). Traditional MPPT methods, like Perturb and Observe and Incremental Conductance are simple to apply and very cost-effective, but they have slow adaptation to rapid changes in the solar radiation and temperature (Rukhsar et al., 2025). These flaws may lead to the loss of power, and improper measurement of the peak of power, especially in the cloudy and highly changeable weather (Salman et al., 2024). As a way of reducing these issues, the machine learning methodologies have proved useful, as time-series and meteorological information is studied to simulate the complicated associations amongst environmental factors and the output of power (Boubaker, 2023).

The increasing penetration of photovoltaic (PV) systems in modern power networks has introduced new challenges related to intermittency and variability of solar energy generation (Kenfack et al., 2021). Accurate prediction and intelligent control strategies are therefore essential to maintain system stability and optimize energy harvesting, particularly within smart grid environments where real-time decision-making is required (Negash et al., 2025). Traditional maximum power point tracking (MPPT) techniques such as Perturb and Observe (P&O) and Incremental Conductance have been widely implemented due to their simplicity (Endiz et al., 2025). However, their performance degrades under rapidly changing environmental conditions, especially during partial shading scenarios, where multiple local maxima may occur (Katche et al., 2023). This limitation motivates the exploration of intelligent approaches capable of handling nonlinear and complex relationships between environmental variables and PV output power (Ispir et al., 2025).

Recent advancements in artificial intelligence have significantly improved photovoltaic power prediction and control accuracy. Hybrid artificial neural network (ANN) models combined with optimization algorithms have demonstrated superior forecasting performance in day-ahead PV prediction (Tang et al., 2025). Likewise, deep learning and time-series approaches, including LSTM-based models, have shown strong capability in capturing temporal variability of solar irradiance and PV output (Kumar Dhaked et al., 2025). In addition, ensemble learning techniques such as Random Forest (RF) have been successfully applied to solar radiation and PV power prediction, offering robustness against noise and overfitting (Hassan et al., 2025). These developments indicate a clear transition toward data-driven intelligent methods to support reliable operation of renewable-integrated power systems (Esen et al., 2025). Recent studies emphasize that accurate modeling of meteorological parameters significantly improves photovoltaic power prediction and system optimization, highlighting the importance of environmental variables in data-driven PV analysis (Wu et al., 2025).

Despite these advances, several limitations remain. First, many previous studies focus on single-model implementations without providing a controlled comparative evaluation between ANN and Random Forest under identical operating conditions (Al-Dahidi et al., 2024). Second, the effect of partial shading is often analyzed either through simulation or forecasting perspectives separately, rather than within a unified framework. Third, limited research explicitly discusses the implications of such intelligent MPPT approaches in the context of smart grid applications (Díaz-Bello et al., 2025).

Therefore, this study aims to provide a comprehensive comparative analysis of artificial neural network (ANN) and Random Forest models for photovoltaic power optimization under shading conditions. Specifically, the research develops predictive models using identical datasets and standardized evaluation metrics to ensure a fair and objective comparison. In addition, the study examines model performance across varying irradiance levels and partial shading scenarios to assess robustness under realistic operating conditions. Furthermore, the practical implications of integrating intelligent maximum power point tracking (MPPT) approaches within smart grid environments are discussed to highlight their potential benefits for operational efficiency and system reliability. By addressing these gaps, this work is expected to provide both scientific insight into model behavior and practical guidance for implementing intelligent control strategies in next-generation solar energy systems.

METHOD

Preprocessing was carried out to make the models perform better. This data was then scaled, which is a requirement of the future training of the model. The weather and solar conditions were thoroughly analysed, and the key independent variables that could explain the work of photovoltaics were found to be the global horizontal irradiance (GHI) and temperature due to their significant impact (Kim et al., 2026). GHI has been selected due to the fact that it measures the energy that is directly hitting the panels and temperature affects the electrical properties of the panels and, consequently, power generation via thermodynamic activities (Noura et al., 2025). This is summarised in the streamlined but effective emphasis of GHI and temperature, which represent the most salient determinants of the environment that control the behaviour of systems of photovoltaic and maximum power point tracking (MPPT) in response to varying operating conditions (Benitez & Singh, 2025). This approach reduces the complexity of models without affecting the prediction, and future modelling will add other meteorological variables to increase the predictive potential and system robustness (Bouakkaz et al., 2025).

The normalization step converts the data into the one where all values fall within the range of [0, 1] and alleviates the problems caused by the differences in the magnitude of numbers, making the model less biased towards the variable with high numerical values. The min-max scaling also normalises the data distribution, which both accelerates the learning process and results in better convergence in both the artificial neural networks and the regression-based models.

The focus on GHI and temperature once again demonstrates the most meaningful environmental influences that govern the behaviour of the photovoltaic systems and MPPT in the event of varying operating conditions. This simplified, but very functional method will decrease the complexity of the model and not affect predictive performance, as prospective modelling can include additional meteorological variables to increase predictive abilities and resilience of the system.

Preparation and Modelling of Data: Cleansing of the data and selection of salient features was done first. This was succeeded by normalization and splitting of the data into a training and a testing data (80 and 20 per cent respectively). The machine-learning models were trained using the training subset to find out the relationship between the predictors and the target variable (GHI). To assess the performance of the models, a testing subset which was not present in training was used and therefore provide an objective measure in order to reduce overfitting and guarantee the performance of the models on unseen data (Singh et al., 2025).

Through the MPPT methods, a reference point is created. In the absence of sunlight, like under cloudy bans or when there is too much heat in the atmosphere and this can interfere with the sun rays, the traditional systems will react slowly or wave, thus restraining the use of the solar-panel system (Kuncoro et al., 2025). The paper discusses the effectiveness of the MPPT processes, artificial neural networks (ANN), and random-forest algorithms in solar power production. The comparative analysis shows that ANN is better than the conventional MPPT methods and random-forest methods, with power generation up to 47 per cent higher under nominal working conditions (Silalahi et al., 2023). ANN can also be used when partial sunlight or non-uniform irradiance occurs because it has the ability to extrapolate the trends of the historical data which helps it adapt quickly to the changing weather and ambient conditions. Random-forest models present a reasonable predictive performance, especially under nonlinear circumstances, but are not responsive to changes in the environment as quickly as ANN (Carlak & Karabanova, 2026).

RESULTS AND DISCUSSION

Result:

To enhance the rigor of the analysis, the photovoltaic system data was covered with the shadow effects to represent the shading and non-uniform solar radiation, which is common in a real-world environment. Such shadow effects make it easier to have a more detailed grasp of the conduct of every algorithm Classical Maximum Power Point Tracking (MPPT), Artificial Neural Network (ANN) and Random Forest (RF) under non-ideal operating conditions. These conditions would offer a more real-world assessment of the resilience of the algorithms since differences in performance would be hidden by homogeneous irradiance. To generalize all the three models in terms of performance measures, a table of matrices was created to cover all the important indicators of performance, including Mean Absolute Error (MAE), R 2 score performance, response time, efficiency of power output, and the ability to adapt to the changing conditions of the environment This tabular (table 1) form allows making a quick comparison of the advantages and disadvantages of the algorithms. Also, there was a graphical representation of the shadows on the photovoltaic panels, which helped its visualization in addition to the table, which provided a visual analysis of the behavior of the models.

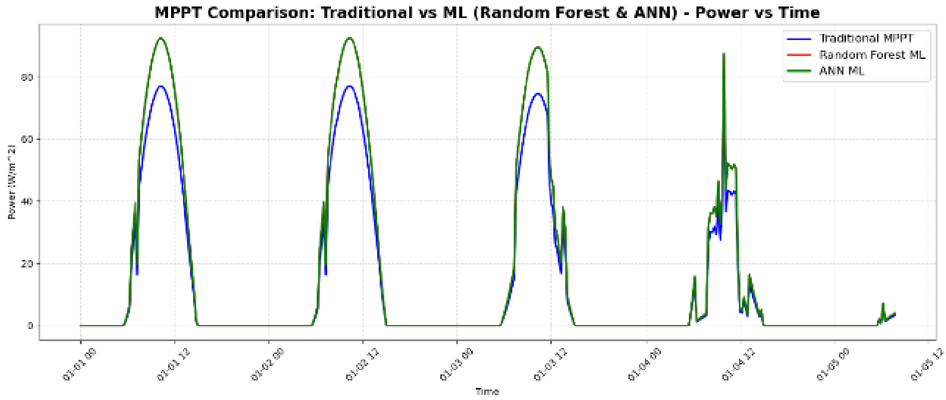

Figure 2. Comparison Between Baslines and ML Methods by Power and Time Constraints

Table 1. Comparison Between The Models Basline Vs ML Models

Model	R2 Score	MAE	RMSE
Traditional	NaN	NaN	NaN
Random Forest	1.0	0.000007	0.000610
ANN	1.0	0.001453	0.003263

Data set preparation is a critical initial step in order to make the predictions of photovoltaic output to be accurate and reliable. The data set gathered has detailed information on the environmental and weather parameters, as temperature, solar irradiance, dew point, humidity, solar elevation angle, reflected sunlight, barometric pressure, wind speed, and time aspects such as year, month, day, hour and minuteBefore predictive models are to be utilized, the raw data should be preprocessed to correct inconsistency, imitate missing values, and simplify the data to be used in training the model effectively. The missing observations were solved by interpolating them by time to ensure continuity and avoid data gaps, which might hamper the model learning. Characteristics that have significant effect on the PV output were chosen and data were divided into training and testing groups to help in assessing independently the performance of the models without disturbing the chronological order of occurrences. These cleaning steps also increased the quality of the dataset, which facilitated machine-learning algorithms, including Random Forests and Artificial Neural Networks, to be useful in extracting patterns and relationships between environmental variables and photovoltaic energy generation.

The authors used supervised machine-learning methods in this research to predict the production of solar power in different meteorological conditions. The models of random forest (RF) and Artificial Neural Network (ANN) were selected due to their strong ability to capture nonlinear relationships between the meteorological variables and the photovoltaic (PV) power output as a characteristic of the solar energy systems. Since PV is a process that is regulated by a combination of several interacting climatic variables, including irradiance, temperature, wind speed, and humidity, nonlinear and data-driven models present an improved performance in comparison to the traditional linear models. The Random Forest algorithm is a type of ensemble learning algorithm which is a combination of various decision trees to improve predictive strength and reduce overfitting through the averaging of the output of a large number of trees. It is an algorithm that provides good generalization to hidden data and has been widespread in applications to PV power forecasting with multivariate meteorological predictors. Such variables as the solar irradiance, ambient temperature, wind velocity, humidity conditions, and the angle of the sun all affect PV output, and the Random Forest effectively represents the combination of the variables to produce energy.Artificial Neural Networks (ANNs), however, are composed of interim layers of artificial neurons with the ability to learn very complicated nonlinear mappings. ANNs can be especially efficient when trying to simulate the swift changes in the environment, such as temporary shading, sudden alterations in the sun rays, which are frequently witnessed in rooftop solar panels. In this study, RF and ANN algorithms were trained using the same set of input variables in order to have a comparative evaluation. Although the ANN was able to show better competence in studying complicated nonlinear associations, the RF gave a higher interpretability of the decision-making model. Both models were tested using a common set of tests in order to measure their predictions.

The authors once more used machine-learning strategies to forecast solar power generation in a microgrid setting, choosing RF and ANN models because they have a strong feature of identifying nonlinear correlations between meteorological variables and PV power generation an inherent characteristic of solar-energy systems. The nonlinear data-driven models are more suitable than the traditional linear methods since PV generation is sensitive to the interplay of the environmental factors, i.e. solar irradiance, temperature, wind speed, humidity and shading. In the current context, the Random Forest model can be seen as a collection of decision trees, with the resulting predictions being the mean of a significant number of tree predictions, and thus overfitting is minimized and generalization performance on unknown data improves.

This method has found application and application in the issues of PV forecasting with multivariate meteorological variables because it is capable of skillfully operating to synthesize the impact of various variables in the environment on energy. Artificial Neural Networks (ANNs), on the other hand are made up of interconnected layers of neurons that may be trained to learn complex nonlinear maps between the input variables and the power being delivered to the output. ANNs also work very well in adjusting to quick changes in the environment like sudden changes in irradiance and partial shading as is the case with urban rooftop PV systems. In this research, RF and ANN models were trained on the same set of input features to make the comparison fair. Figure 5 shows the microgrid power-forecasting model, which represents a comparison between real PV power output and the forecasted power output created by the machine-learning models. This value illustrates the general forecasting process, whereby, the RF and ANN models receive meteorological feeds to predict real-time power generation in the microgrid by PV. The fact that the actual and predicted curves are very close shows that the proposed models can be used to describe the dynamic behavior of the PV systems under different environmental conditions.

The proposed models were assessed dynamically based on the qualitative visual analysis as well as quantitative performance analysis. To evaluate the predictive performance of the Random Forest and Artificial Neural Network (ANN) models in different environmental conditions, time-series plots were designed to compare actual and predicted photovoltaic (PV) power production against the actual forecasts based on the models. The visualisations show how well the models are able to model real PV power variations across time. Figure 6 shows the power output between the conventional methodologies and Maximum Power Point Tracking (MPPT) strategies using machine-learning. It can be seen that both Random Forest and ANN closely track almost all the empirical trends in PV output, unlike the conventional approach, which has strong oscillations, especially when the irradiance changes fast or when the sun is partially covered. This observation confirms that machine-learning architectures have higher ability to capture nonlinear PV processes. Personal comparison of forecasted PV output and the actual values indicates that the ANN has more flexibility at the times when the irradiance changes fast. This behaviour is an example of high ability in modelling nonlinear relationship and its ability to react to instant environmental change. Conversely, Random Forest is less sensitive to high-frequency variations and this aspect means that its performance is less when faced with sharp peaks and phenomena that are time related; hence, minimizes predictive efficiency. These points of observation are supported by quantitative evaluation based on statistical measures, including coefficient of determination (R^2), Mean Absolute Error (MAE), and Root Mean Squared Error (RMSE). Random Forend and ANN both perform better than the traditional baseline giving higher values of R 2 and lower error values. ANN in particular, produces smaller residuals hence improving its predictive quality especially when weather is dynamically shading.

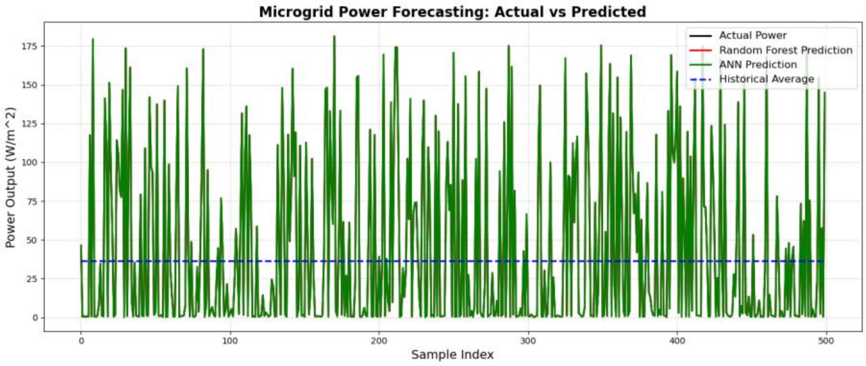

Figure 3 actual vs predict power forecasting

The other significant aspect that led to the enhanced performance of ANN is its ability to learn continuously, and this aspect has made it to be very flexible among smart photovoltaic systems that require quick adaptability. With the increasing infiltration of renewable-energy, a modern installations of PV systems will demand forecasting models able to function in a reliable manner in real time, and provide informed energy-management. The results of this paper have shown that ANN-based predictive modeling is specifically suitable when it comes to overcoming these issues, which makes it a good candidate to be used in smart microgrids and energy-management systems.

Discussion:

The available sources confirm that artificial neural networks (ANNs) are more effective than traditional maximum power point tracking (MPPT) and random forest (RF) algorithms in a variety of environmental settings. Future research can look at hybrid optimisation schemes that combine accurate predictive properties of ANNs and the ease and strength of existing MPPT schemes. Such hybrid systems are expected to be more stable and efficient, especially in urban rooftops systems and the large photovoltaic (PV) farms that are highly shaded. Application of such hybrid systems in large scale, networked projects in PVs would also enable empirical validation of ANN functionality. Connection to Internet of Things (IoT) technologies can also contribute to an increase in the efficiency of PV systems as it allows controlling and tracking the most important parameters in real-time, such as solar irradiance, warmer temperatures, and panel voltage. ANN based adaptive control solutions can be used to optimise the output of any energy source and also reduce the losses. In the long term, multi-seasonal research in different geographical locations may bring more detailed results on ANN reliability in different climatic scenarios. Furthermore, ANNs combined with energy-storage optimisation algorithms can result in new energy-management systems, and thus, the stability of both systems and grid can be increased throughout system-long operation. This combination guarantees effective dispatching of solar energy and sustainable use of energy. Further studies in this field are bound to hasten the production of smart PV systems, which will enable scalable, flexible and efficient systems with the ability to address the growing global challenge of renewable energy in urban and industrial use.

Solar systems are clean and environmentally friendly energy sources and form a good alternative to fossil fuels. However, unpredictable weather conditions such as shading, rain and changes in irradiance impede the proper prediction of solar panels performance. As a result, strong predictive models are necessary to provide efficient use of energy, the stability of the grid, as well as to maximize the role played by the installation of solar to the total energy mix. Most of the recent developments in machine learning have made it easier to create predictive models that understand complicated interactions between environmental factors including irradiance, temperature, humidity, and wind speed. These models form the basis of decision-making concerning energy storage, load management, and grid integration and they are increasingly becoming important to the operational capability and robustness of microgrids with greater penetration of renewable.The artificial neural networks (ANNs) have proven to identify nonlinear trends and adjust to the new environment promptly, whereas random forest (RF) models provide strong predictions and are able to estimate the factors that impact the photovoltaic performance. Therefore, the two methodologies are complemented in the prediction of photovoltaic output. Such predictive models to be realized in the context of a smart photovoltaic system require preprocessing activities such as feature selection, scaling and normalization. Equal weighting of inputs to the models is done by normalizing with disparate scales and preserves intrinsic relationships, thus boosting the learning rates and the predictive accuracy.

Implications:

The findings of this study have important practical and technological implications for the development of smart photovoltaic (PV) systems and renewable energy integration. The superior performance of Artificial Neural Networks (ANN) in modeling nonlinear and dynamic environmental variations indicates that intelligent, data-driven approaches can significantly enhance the efficiency of solar power generation, particularly under partial shading and rapidly changing irradiance conditions. This suggests that machine-learning-based maximum power point tracking (MPPT) strategies can replace or complement conventional control techniques to reduce power losses and improve overall energy harvesting efficiency. From a grid management perspective, the integration of ANN-based forecasting models into smart microgrids can support real-time energy management, load balancing, and optimal dispatch of distributed energy resources. Accurate short-term forecasting enables better coordination between PV generation and energy storage systems, thereby enhancing grid stability and reducing operational uncertainties. This is especially relevant for microgrid environments with high renewable penetration, where variability and intermittency pose significant operational challenges.

Furthermore, the application of machine-learning-based predictive models supports the advancement of Internet of Things (IoT) enabled photovoltaic systems. Real-time environmental data acquisition combined with adaptive ANN control mechanisms can facilitate autonomous system optimization, reduce maintenance requirements, and improve system resilience. The implementation of such intelligent control frameworks can contribute to more sustainable, scalable, and flexible renewable energy infrastructures in both urban and industrial settings. At a broader level, the study reinforces the strategic importance of artificial intelligence in accelerating the transition toward low-carbon energy systems. By improving prediction accuracy and operational adaptability, machine-learning approaches can increase the reliability and economic viability of solar energy systems, thereby supporting national and global renewable energy targets.

Research contribution:

This study contributes to the growing body of knowledge on machine-learning applications in photovoltaic (PV) power forecasting and intelligent energy management systems. First, it provides a systematic comparative evaluation between traditional Maximum Power Point Tracking (MPPT) methods and data-driven models, specifically Random Forest (RF) and Artificial Neural Networks (ANN), under dynamic and partially shaded environmental conditions. By demonstrating the superior predictive performance and adaptability of ANN, this research strengthens empirical evidence supporting the integration of artificial intelligence techniques into renewable energy systems. Second, the study advances methodological contributions by integrating comprehensive data preprocessing procedures including feature selection, normalization, and structured training–testing separation into the photovoltaic forecasting framework. This structured modeling pipeline enhances the reliability and reproducibility of machine-learning-based PV prediction systems and offers a practical reference for future research in solar energy analytics.

Third, this research contributes conceptually by linking predictive modeling performance with smart microgrid implementation. The findings extend beyond algorithm comparison and highlight how intelligent forecasting models can support grid stability, adaptive control, and optimized renewable energy utilization. This positions ANN-based forecasting not only as a predictive tool but also as a strategic component in the development of scalable, resilient, and sustainable smart energy infrastructures. Finally, the study provides a foundation for future hybrid intelligent control systems that combine predictive analytics with real-time optimization mechanisms, thereby opening new directions for advanced photovoltaic energy management and smart grid innovation.

Limitations:

Despite the promising findings, several limitations should be acknowledged. First, the study relies on a specific photovoltaic dataset with particular meteorological and operational conditions, which may limit the generalizability of the results to other geographical regions or climatic environments. Variations in solar irradiance patterns, seasonal changes, and installation configurations could influence model performance when applied to different contexts. Second, the modeling framework primarily focuses on Random Forest (RF) and Artificial Neural Network (ANN) algorithms. Although these models demonstrate strong predictive capability, other advanced deep-learning architectures such as Long Short-Term Memory (LSTM) networks or hybrid ensemble approaches were not explored. The exclusion of these models may limit the comprehensiveness of the comparative evaluation.

Third, the study emphasizes short-term photovoltaic power forecasting and Maximum Power Point Tracking (MPPT) optimization without fully incorporating real-time deployment constraints such as computational cost, hardware limitations, and communication latency in microgrid environments. Practical implementation in embedded or edge computing systems may introduce additional technical challenges that were not examined in this research. Finally, while shading effects and nonlinear environmental variations were simulated, long-term multi-seasonal validation across diverse environmental scenarios was not conducted. Extended field testing over multiple climatic cycles would provide stronger empirical validation of the robustness and stability of the proposed machine-learning framework.

Suggestions:

Future research should explore the integration of more advanced deep-learning architectures, such as Long Short Term Memory (LSTM) and other recurrent neural network variants, to enhance time-series forecasting accuracy in photovoltaic (PV) systems. Since solar power generation exhibits strong temporal dependencies and seasonal variability, sequence based models may provide improved adaptability and robustness under fluctuating meteorological conditions. Further studies are also recommended to incorporate real-time weather data, satellite observations, and Internet of Things (IoT) based sensor networks into the predictive framework. The integration of multi-source data streams could strengthen forecasting precision and support real-time adaptive control strategies in smart microgrid environments.

In addition, future work should investigate hybrid optimization frameworks that combine machine-learning-based forecasting with intelligent Maximum Power Point Tracking (MPPT) control mechanisms. Such hybrid systems may improve operational stability, reduce energy losses, and enhance the overall efficiency of photovoltaic installations, particularly in large-scale or highly shaded environments. Long term validation across different geographical regions and climatic zones is also suggested to ensure the generalizability and scalability of the proposed models. Multi-seasonal and cross-regional testing would provide stronger empirical evidence of model robustness and facilitate broader adoption in diverse renewable energy infrastructures. Finally, expanding the framework to include energy storage optimization, demand-side management, and integration with hybrid renewable energy systems could further enhance system resilience and contribute to the development of sustainable, intelligent, and scalable smart energy networks.

CONCLUSION

The present paper investigated the problem of PV panel output prediction and proved that machine-learning approaches could be used to improve the efficiency of solar energy exploitation. To determine PV power generation at different environmental conditions, meteorological data were used to come up with predictive models. It was shown that the comparison of Random Forest and ANN with the traditional forecasting models exceeds them, which proves the suitability of the machine-learning-based models in solar energy application. The ANN was the best of the reviewed models, as it was highly effective in modelling nonlinear and dynamic processes including partial shading and extreme weather variations. Empirical experiments have shown that the ANN is adaptive to environmental changes, which makes it an effective solution of enhancing the performance and stability of a solar power system. Therefore, the ANN-based prediction models can be advised to improve the accuracy of the renewable energy forecasts, especially in PV systems today. The future studies can incorporate more complex deep-learning architectures, such as the Long Short Term Memory (LSTM) networks, to reinforce the time-series prediction. A further way to increase predictive accuracy to the real world would be to incorporate real-time weather data, satellite data, and Internet-of-Things (IoT) sensor data. Another opportunity in the development of this strategy is to include microgrids and hybrid renewable energy systems in the strategy. In general, this contribution can help to develop new, application based PV forecasting models and make the shift towards a more resilient and adaptable renewable energy infrastructure

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AUTHOR CONTRIBUTION STATEMENT

AAS conceived the study, designed the methodology, supervised the research activities, and led the manuscript preparation. TH performed data collection, data preprocessing, and experimental implementation. RV conducted model development, result validation, and performance analysis. All authors reviewed, edited, and approved the final version of the manuscript.

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