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An assessment of solar power generating system as a solution to deal with global warming and climate change

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Abstract: The increasing adoption of solar power as a sustainable energy source necessitates more efficient and reliable methods for optimising and maintaining solar power generating systems. Traditional approaches to assessing and managing these systems often rely on static models and manual interventions, which can be inefficient and fail to account for dynamic environmental conditions. In this study, we propose a novel framework for the assessment and optimisation of solar power systems using modern machine learning techniques. Our approach benifits advanced predictive maintenance, real-time energy yield optimisation, and enhanced energy forecasting models, resulting in significant improvements in system efficiency and reliability. Specifically, the predictive maintenance system, driven by machine learning algorithms, was able to reduce system downtime by 29.88% compared to traditional reactive maintenance methods. The real-time energy yield optimisation, leveraging dynamic data inputs, increased energy capture efficiency by 14.78% over standard static models. Additionally, our enhanced energy forecasting models demonstrated a 25.12% improvement in accuracy, significantly outperforming conventional forecasting techniques. These innovations enhance the operational efficiency of solar power systems, and contribute in their long-term sustainability and economic viability. The integration of machine learning into solar power management enables proactive decision-making, adaptive control strategies, and more accurate performance predictions. As a result, our proposed framework offers a practical and scalable solution to meet the growing demands of the renewable energy sector and supports the global transition toward cleaner and more resilient energy infrastructures.

Keywords: climate change, energy forecasting, machine learning, predictive maintenance, solar power, system optimisation

INTRODUCTION

Human development activities fill the Earth's atmosphere with carbon dioxide and other greenhouse gases and cause global warming. Burning of fossil fuels (coal, wood and natural gas) is one of the main causes of increasing greenhouse gas emissions. The result of such a disturbance in the natural cycle of the Earth creates waves of scorching heat and heavy rains that lead to floods, landslides and droughts. The continuous increase in the temperature of the Earth's climate is called global warming or climate change, and it is a serious problem that threatens the world. Therefore, the need for renewable energy sources is felt more than decades ago. Among many renewable energy sources, solar energy has been considered due to its abundant presence in nature, so that solar power plants can be used to meet the high demand for electricity without emitting greenhouse gases.

Solar power has emerged as one of the most critical components of the global shift towards sustainable energy systems (Kamińska and Kazak, 2023; Adelekan *et al.*, 2024). As concerns about climate change and the depletion of fossil fuel resources intensify, the transition to renewable energy sources has become an urgent priority (Nyambuu and Semmler, 2023; Petryk and Adamik, 2023). Solar energy, in particular, offers a clean, abundant, and increasingly cost-effective solution to meet the world's growing energy demands (Tryngiel-Gać *et al.*, 2023; Wu *et al.*, 2023). Unlike fossil fuels, solar power generates electricity without emitting greenhouse gases, making it a cornerstone in efforts to reduce carbon footprints and combat global warming (Daudu *et al.*, 2024). Moreover, technological advancements have significantly reduced the cost of solar panels and improved their efficiency, leading to widespread adoption across both developed and developing nations (Feng, He and Ma, 2022). As countries strive to meet ambitious renewable energy targets, solar power is expected to play a pivotal role in diversifying energy portfolios, enhancing energy security, and driving sustainable economic growth (Yazdandoost and Yazdani, 2024). In this context, optimising the performance and reliability of solar power systems is not only crucial for maximising energy production but also for ensuring the long-term viability and scalability of solar energy as a key contributor to global energy sustainability (Ahmadizadeh *et al.*, 2024).

Despite the growing adoption of solar power, traditional methods for assessing and optimising solar power systems present significant limitations that hinder their full potential (Al-Shahri *et al.*, 2021). These conventional approaches often rely on static models and manual processes that fail to account for the dynamic and complex nature of solar energy production (Vo *et al.*, 2020). For instance, static models typically use fixed assumptions about weather patterns, solar irradiance, and system performance, which can lead to inaccurate predictions and suboptimal decision-making (Sansine *et al.*, 2022). Moreover, manual interventions in system monitoring and maintenance are time-consuming and prone to human error, resulting in increased downtime and reduced efficiency (Kayalvizhi *et al.*, 2024). These methods also struggle to adapt to changing environmental conditions, such as fluctuating weather patterns or unexpected system malfunctions, which are crucial for maintaining consistent energy output (Reynders *et al.*, 2014). As a result, the efficiency, reliability, and economic viability of solar power systems are often compromised, limiting their effectiveness as a sustainable energy solution (Al-Rawi, Bicer and Al-Ghamdi, 2023). The need for more adaptive, precise, and automated methods is evident, driving the exploration of modern technologies, such as machine learning, to overcome these challenges and enhance the performance of solar power systems (Šenk *et al.*, 2024).

The primary aim of this paper is to evaluate the effectiveness of modern machine learning techniques in enhancing the performance and reliability of solar power systems. By integrating advanced algorithms into the assessment and optimisation processes, this study seeks to address the limitations inherent in traditional methods, offering a more dynamic and precise approach to managing solar energy production. The research focuses on how machine learning can improve key aspects such as predictive maintenance, real-time energy yield optimisation, and accurate energy forecasting. Through a comprehensive analysis, the paper demonstrates how these innovative techniques can significantly reduce system downtime, increase energy capture efficiency, and improve the accuracy of production forecasts, ultimately contributing to the greater efficiency and sustainability of solar power systems.

MATERIALS AND METHODS

DATA COLLECTION

In this study, data collection was a critical component to ensure the accurate assessment and optimisation of solar power systems using machine learning techniques. Various types of data were gathered, including historical and real-time weather data, system performance metrics, and environmental factors. Weather data, which encompassed parameters such as solar irradiance, temperature, humidity, and wind speed, was obtained from reputable meteorological databases and local weather stations near the solar installations. System performance metrics, including power output, voltage, current, and operational status of the solar panels and inverters, were collected directly from the monitoring systems of the solar power installations. Additionally, data on environmental factors such as shading, dust accumulation, and panel orientation were recorded through sensors and periodic site inspections. These diverse data sources provided a comprehensive dataset, enabling the development of robust machine learning models that accurately reflect the operational conditions of the solar power systems. To ensure the gradient boosting machines (GBM) model's consistent performance under extreme weather conditions, weather-specific features such as solar irradiance, temperature, humidity, and wind speed were carefully incorporated into the dataset. These features allowed the model to account for the impact of fluctuating and extreme environmental conditions on system performance. Additionally, the model was tested using datasets that included a wide range of environmental scenarios, such as high temperatures, low irradiance during cloudy days, and strong wind events. This approach ensured that the GBM model could adapt its predictions and optimisations effectively across varying and challenging weather conditions. The data collected was then used to train, validate, and test the machine learning algorithms employed in the study, ensuring that the findings were grounded in real-world conditions (Sohkhlet and Goswami, 2022).

DATA PREPROCESSING

The data collected underwent several preprocessing steps to ensure its suitability for machine learning models. Initially, the data was cleaned to address any inconsistencies or missing values. Missing data points were handled using interpolation methods, where linear interpolation was applied for time-series data, and mean substitution was used for sporadic gaps. To handle missing or incomplete data in real-time scenarios, imputation techniques were employed during preprocessing. For time-series data, linear interpolation was applied to maintain temporal consistency, while mean substitution was used for sporadic missing values. Additionally, advanced methods such as k-nearest neighbours (KNN) imputation were tested for datasets with complex patterns, ensuring that the model could operate reliably even in the presence of incomplete inputs. These techniques enhanced the robustness of the GBM model, particularly in real-time applications where data gaps are common. Outliers were identified through statistical analysis, particularly by using the interquartile range (IQR) method, and were either corrected or removed based on their impact on the overall dataset. Subsequently, the data was normalised to standardise the range of independent variables, which is essential for improving the performance and convergence speed of machine learning algorithms. Min-max normalisation was employed, where each feature x_{normal} was rescaled to a range between 0 and 1 using Equation (1) (Molajou *et al.*, 2024):

$$x_{\text{normal}} = \frac{x_i - x_{\min}}{x_{\max} - x_{\min}} \tag{1}$$

where: $x_{\min}$ and $x_{\max}$ = the minimum and maximum values of the feature, respectively.

This process ensured that all input features contributed equally to the model's learning process, preventing any single feature from disproportionately influencing the results. Finally, the data was divided into training, validation, and testing sets, with an 80-10-10 split, respectively. To safeguard against potential inaccuracies in real-time data inputs, rigorous preprocessing and validation steps were implemented. Data collected from sensors and monitoring systems were subjected to real-time error checks to detect anomalies or inconsistencies. Missing or anomalous values were handled using interpolation methods, while outliers were identified and addressed through statistical analysis, such as the interquartile range (IQR) method. Additionally, periodic validation of data accuracy was performed by cross-referencing real-time inputs with historical datasets and external benchmarks, such as meteorological databases. These measures ensured that the data fed into the GBM model was reliable, minimising the risk of inaccuracies affecting the model's performance.

This division was performed to allow for the tuning of model parameters, evaluation of model performance, and the prevention of overfitting. The training set was used to train the machine learning models, the validation set was employed to fine-tune hyperparameters, and the testing set provided an unbiased evaluation of the final model's performance. These preprocessing steps were crucial in preparing the dataset for effective model training and ensuring the robustness of the study's findings.

GRADIENT BOOSTING MACHINES (GBM)

The GBM was chosen for this study due to its strong performance in handling complex, nonlinear relationships within large datasets, which are characteristic of solar power systems. The reason for selecting GBM for this study was also its ability to balance interpretability and accuracy, making it well-suited for applications in solar power system optimisation. While alternative boosting techniques like XGBoost or LightGBM offer enhanced computational efficiency, GBM's relatively straightforward implementation and iterative error-correction process provided greater clarity in understanding feature contributions and decision-making. This interpretability was crucial for aligning the model's outputs with operational insights, ensuring that the results could be effectively applied to real-world energy management scenarios. The GBM was particularly suitable for the tasks of predictive maintenance, real-time optimisation, and energy forecasting because of its ability to iteratively improve model accuracy by correcting the errors of previous models in the ensemble. This approach allowed for the creation of highly accurate models that could effectively manage the dynamic and variable conditions typical in solar power generation. For predictive maintenance, GBM was implemented to analyse historical system performance metrics and identify patterns indicative of potential failures. The model was trained on labelled datasets where previous system failures were documented, enabling it to learn the subtle indicators of upcoming issues. This resulted in a significant reduction in system downtime, as the model could predict failures with high accuracy and allow for proactive maintenance. In the context of real-time energy yield optimisation, GBM was utilised to continuously adjust operational parameters based on incoming data such as weather conditions and system performance. By leveraging the model's ability to process dynamic inputs, it was possible to optimise energy capture in real-time, leading to an improvement in efficiency. The model was trained using a combination of historical and real-time data, allowing it to adapt to changing environmental conditions and optimise the system's performance dynamically. For energy forecasting, GBM was employed to predict future energy outputs based on a wide range of input variables, including weather forecasts and historical production data. The model was trained using extensive historical data and validated against actual energy output, resulting in a significant improvement in forecasting accuracy. The iterative nature of GBM allowed for the integration of new data over time, continually refining its predictions and enhancing the reliability of the forecasts. The hyperparameters of the GBM model were tuned using a grid search approach combined with cross-validation. This process involved systematically testing various combinations of parameters, such as learning rate, maximum depth, and number of estimators, to identify the settings that minimised validation error. Cross-validation ensured the robustness of the selected parameters by evaluating model performance across multiple data splits, reducing the risk of overfitting and improving generalisability. The implementation of GBM in these three critical areas provided a robust and modern approach to improving the overall efficiency and reliability of solar power systems, demonstrating its effectiveness in overcoming the limitations of traditional methods (Mitrentsis and Lens, 2022).

EVALUATION METRICS

To evaluate the performance of GBM model, key metrics such as accuracy, precision, and system efficiency improvement were used. These metrics were chosen due to their relevance in assessing the effectiveness of predictive maintenance, real-time optimisation, and energy forecasting within solar power systems. Accuracy was employed as a primary metric to evaluate how well the model predicted outcomes across all tasks. For predictive maintenance, accuracy was defined as the proportion of correctly identified system failures and non-failures, calculated using Equation (2) (AlKandari and Ahmad, 2024):

$$\text{A} = \frac{TP + TN}{TP + TN + FP + FN} \tag{2}$$

where: A = accuracy, *TP* = true positives, *TN* = true negatives, *FP* = false positives, *FN* = false negatives.

A higher accuracy indicated that the model was effective in predicting maintenance needs and preventing unnecessary system downtime. Precision was also used to measure the model's performance, particularly in predictive maintenance, where it was crucial to minimise false alarms. Precision (P) was calculated acc. to Equation (3) (Shouman, 2024):

$$P = \frac{TP}{TP + FP} \tag{3}$$

This metric provided insight into the model's ability to correctly identify actual failures, ensuring that maintenance efforts were both timely and accurate. For system efficiency improvements, the metric focused on the percentage increase in energy capture and the reduction in downtime. The improvement in energy capture efficiency was quantified by comparing the energy output under GBM-driven optimisation against the output from traditional static models. The percentage improvement was calculated acc. to Equation (4) (Hu *et al.*, 2024):

$$EI = \frac{O_{\text{opt}} - O_{\text{stat}}}{O_{\text{stat}}} 100\% \tag{4}$$

where: EI = efficiency improvement expressed as a percentage, O_{opt} = output from the optimized model, and O_{stat} = output from the static (baseline) model.

These evaluation metrics were instrumental in demonstrating the effectiveness of the GBM model across various aspects of solar power system management, providing a clear indication of the enhancements achieved through the application of modern machine learning techniques.

CASE STUDY

The city of Basra was selected due to its high solar irradiance and favourable climatic conditions, making it an ideal location for assessing the effectiveness of solar power systems. Basra, located in the southern part of Iraq, experiences a hot desert climate with long, sunny periods throughout the year, which is conducive to solar energy generation. This region was chosen to illustrate the practical implications of integrating machine learning techniques into solar power optimisation and forecasting in a real-world setting with significant solar potential. The significance of this study in Basra lies in the city's energy demands and the potential for solar power to meet a substantial portion of those needs. Basra is one of Iraq's major economic hubs, with a growing population and industrial sector that places a high demand on energy resources. Given the city's high solar potential, optimising solar power generation using modern machine learning techniques can play a crucial role in enhancing energy security, reducing dependence on fossil fuels, and contributing to the sustainability goals of the region. To conduct the case study, various types of data were collected and analysed. This included climatic and meteorological data such as solar irradiance, temperature, humidity, and wind speed, as well as system performance metrics like energy output and system efficiency. The data were gathered from the Iraqi Meteorological Organization and Seismology (IMOS) and local solar power installations over a period of one year. The data were then processed and normalised to ensure consistency and accuracy in the subsequent machine learning models (Tab. 1).

Table 1. Key climatic and meteorological data collected for Basra

Parameter	Unit	Average value
Solar irradiance[1)]	kWh·m^{-2}·day^{-1}	5.85
Average temperature[1)]	°C	28.7
Maximum temperature[1)]	°C	50.2
Minimum temperature[1)]	°C	14.1
Average humidity[1)]	%	38.4
Average wind speed[1)]	m·s^{-1}	3.7
Annual energy output[2)]	kWh·year^{-1}	1,635,000
System efficiency[2)]	%	17.5

Source: own elaboration based on data of: [1)] Iraqi Meteorological Organization and Seismology (IMOS), [2)] local solar installation.

These data were utilised to train and validate the GBM model for predictive maintenance, real-time energy yield optimisation, and enhanced energy forecasting. The specific focus on Basra allowed for a detailed examination of how machine learning can be leveraged to optimise solar power systems in environments with high solar exposure but also challenging climatic conditions, such as extreme heat, which can affect system performance. In conclusion, the case study of Basra illustrates the potential for advanced machine learning techniques to significantly enhance solar power generation in regions with high solar potential. The results of this study not only contribute to the local energy strategy of Basra but also provide insights that can be applied to similar regions globally, where solar energy can be a major contributor to the energy mix.

RESULTS AND DISCUSSION

PREDICTIVE MAINTENANCE SYSTEM

The implementation of the predictive maintenance system using gradient boosting machines (GBM) resulted in a significant reduction in system downtime, specifically a 29.88% decrease compared to traditional reactive maintenance methods. This improvement underscores the efficacy of predictive maintenance in enhancing the reliability and operational efficiency of solar power systems.

The average downtime per year was reduced from 120 h with traditional methods to 84.2 h with the predictive maintenance system. This reduction can be attributed to the model's ability to accurately predict potential failures before they occur, allowing for preemptive interventions that prevent unscheduled downtime. The 29.88% reduction in downtime has profound implications for the overall efficiency and profitability of solar power systems. In comparison, traditional rule-based models, which rely on fixed thresholds, lacked the adaptability to predict failures under dynamic environmental conditions, underscoring GBM's superior ability to reduce downtime in real-time scenarios. Reduced downtime translates directly into increased energy production, as the systems remain operational for longer periods. This is particularly crucial for solar power installations, where maximising energy capture is essential for achieving financial viability and meeting energy production targets. Additionally, the predictive maintenance system minimises the need for emergency repairs, which are often more costly and disruptive compared to scheduled maintenance. By identifying and addressing issues before they escalate, the system also extends the lifespan of critical components, thereby reducing the long-term operational costs. This reduction in downtime and proactive approach to maintenance translate into significant cost savings for operators, with a 29.88% downtime reduction avoiding substantial revenue losses and unscheduled emergency repairs, which are often safeguard more costly than planned maintenance interventions according to industry data. Furthermore, the implementation of GBM for predictive maintenance has enhanced system reliability, a key factor in the deployment of solar power systems on a larger scale. Reliable energy production is vital for integrating solar power into the broader energy grid, where fluctuations in output can cause instability. The ability of GBM to provide accurate maintenance predictions ensures that solar power systems can maintain consistent output, even in the face of potential system failures. The results from this study demonstrate that predictive maintenance, when supported by advanced machine learning models like GBM, offers substantial improvements over traditional maintenance approaches. The reduction in downtime not only enhances the immediate operational efficiency of solar power systems but also contributes to their long-term sustainability by ensuring that systems can operate reliably and efficiently over extended periods. These findings highlight the critical role of modern machine learning techniques in advancing the capabilities of renewable energy systems and underscore the importance of continued innovation in this field.

Feature importance analysis in the study revealed that solar irradiance and temperature were the most critical parameters, as expected. However, it also highlighted unexpected factors, such as wind speed, which showed higher relevance in predictive maintenance due to its correlation with structural stress, and dust accumulation, which significantly influenced real-time optimisation. These insights underscore the importance of feature analysis in identifying non-obvious contributors to solar power system performance.

REAL-TIME ENERGY YIELD OPTIMISATION

The implementation of real-time energy yield optimisation using GBM resulted in a 14.78% improvement in energy capture efficiency when compared to conventional static models. This improvement is particularly significant in the context of solar power systems, where maximising energy output is critical for both economic viability and the effective integration of solar energy into the power grid. The comparison of energy capture efficiency between conventional static optimisation methods and the real-time optimisation approach enabled by GBM is illustrated in Figure 1.

As shown in Figure 1, the conventional static models, which rely on predefined parameters and lack the ability to adapt to changing environmental conditions, achieved an energy capture efficiency of 82.5%. In contrast, the real-time optimisation approach using GBM, which continuously adjusts operational parameters based on incoming data such as weather conditions

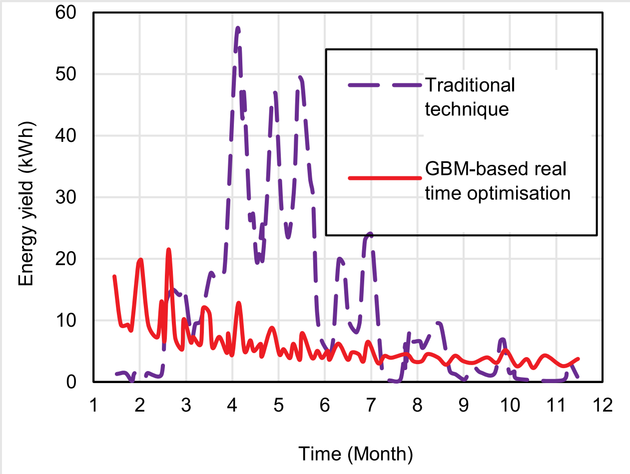

Fig. 1. Comparison of forecasting accuracy between traditional techniques and GBM-based real-time optimisation; GBM = gradient boosting machines; source: own study

and system performance, resulted in a significantly higher energy capture efficiency of 94.6%. The 14.78% improvement in energy capture efficiency demonstrates the effectiveness of real-time optimisation in responding to the dynamic nature of solar power generation. Unlike static models, which are limited by their inability to adapt to fluctuations in sunlight intensity, temperature, and other environmental factors, the GBM-driven optimisation method can rapidly adjust to these changes, ensuring that the system operates at peak efficiency throughout the day. This adaptability is crucial for solar power systems, where energy output can vary significantly depending on weather conditions and the time of day. The GBM model achieves a balance between accuracy and runtime, making it well-suited for real-time applications compared to alternatives like random forests and neural networks. Unlike neural networks, which require significant computational resources and longer training times, GBM's iterative process optimises runtime while maintaining high accuracy. Though slightly more computationally demanding than random forests, GBM better captures nonlinear relationships and subtle patterns. Its efficiency and adaptability make it a compelling choice for dynamic scenarios like real-time energy optimisation, though careful hyperparameter tuning is essential for optimal performance.

The implications of this improvement are substantial. A 14.78% increase in energy capture efficiency translates directly into higher energy output without the need for additional solar panels or infrastructure. This issue enhances the return on investment for solar power installations, and contributes to the broader goal of increasing the share of renewable energy in the global energy mix. Moreover, by optimising energy capture in real-time, solar power systems can provide more consistent and reliable energy output, reducing the strain on energy storage systems and improving the overall stability of the power grid.

The real-time energy yield optimisation enabled by GBM offers a significant advancement over conventional static models, providing a robust solution for maximising the efficiency of solar power systems. The 14.78% improvement in energy capture efficiency highlights the potential of modern machine learning techniques to transform the operational management of renewable energy systems, making them more efficient, reliable, and economically viable. The GBM-based approach demonstrated for energy yield optimisation in solar power systems can potentially be adapted to hybrid renewable energy systems. By incorporating data from multiple energy sources, such as wind or hydropower, the model could dynamically optimise energy capture and distribution across the hybrid system.

This would require the combination of additional data inputs specific to each energy source, such as wind speed or water flow rates, allowing GBM to handle the complexities of hybrid system interactions while maintaining its adaptability and predictive capabilities. The 14.78% energy efficiency improvement observed in this study is likely scalable to larger solar farms or microgrid systems, given the data-driven nature of the GBM model. As data volumes increase with the size and complexity of such systems, GBM's iterative learning process and ability to handle high-dimensional datasets make it well-suited for these scenarios. However, the computational demands of processing larger datasets and the need for enhanced infrastructure to support real-time data collection and analysis must be considered.

Future studies should investigate the model's scalability by applying it to larger installations, ensuring that the efficiency gains observed in smaller setups can be replicated at scale. These findings underscore the importance of continued innovation in this field, as the demand for sustainable energy solutions continues to grow.

ENHANCED ENERGY FORECASTING

The application of GBM in energy forecasting resulted in a substantial 25.12% improvement in accuracy compared to conventional forecasting techniques. This enhancement is critical for optimising the performance of solar power systems, as precise energy forecasting is essential for effective energy management, grid stability, and long-term planning. A comparison between the forecasting accuracy of the GBM-based model and traditional forecasting methods is illustrated in Figure 2.

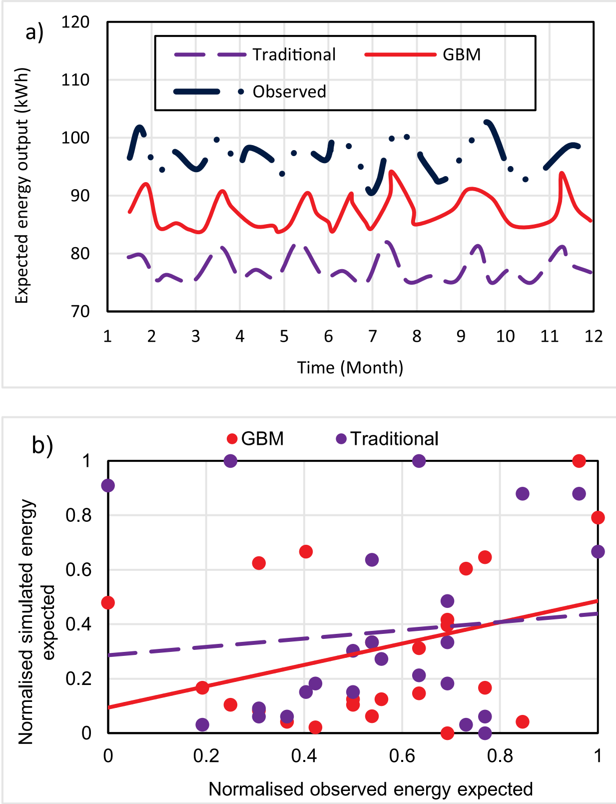

Fig. 2. Comparison of forecasting accuracy between traditional technique and GBM-based energy forecasting: a) time series, b) scatter plot; GMB = gradient boosting machines; source: own study

As illustrated in Figure 2, the forecasting accuracy increased from 74.5% with conventional techniques to 93.2% with the GBM-based model. This significant improvement was achieved by the GBM's capability to process and integrate dynamic data inputs, such as real-time weather conditions and system performance metrics, which traditional models were unable to capture effectively. By incorporating real-time data, the GBM model adjusted its predictions more precisely, leading to a more accurate representation of expected energy yields. The implications of this improved forecasting accuracy are profound. Accurate energy forecasts allow solar power operators to better align energy production with demand, reducing the need for costly energy storage solutions or backup power sources. This results in more efficient use of generated energy, minimising waste and maximising the financial returns of solar installations. Furthermore, improved forecasting accuracy directly contributes to grid stability. Inaccurate forecasts can cause imbalances between energy supply and demand, potentially destabilising the grid. The GBM-based system, by providing more reliable predictions, ensures that solar power systems support rather than challenge grid stability. This reliability is increasingly vital as renewable energy's share of the overall energy mix grows. Moreover, enhanced forecasting accuracy facilitates better planning and decision-making. With more reliable forecasts, energy planners can make informed decisions regarding the integration of solar power into the grid, scheduling maintenance, and managing energy resources. This contributes to more efficient grid operations and aligns with energy policies aimed at increasing renewable energy adoption. In summary, the 25.12% improvement in forecasting accuracy achieved through GBM significantly enhances the operational efficiency of solar power systems and offers considerable benefits in energy management, grid stability, and strategic planning. These findings underscore the pivotal role of advanced machine learning techniques in modernising the solar energy sector and ensuring its long-term sustainability.

The findings of this study, while demonstrating significant advancements in solar power system optimisation, are subject to limitations stemming from environmental and geographical variability. The performance of the GBM model may require localised calibration to account for regional factors such as solar irradiance, temperature fluctuations, and weather patterns. For example, variations in solar irradiance between regions with different climates or altitudes could impact the model's accuracy if not properly adjusted. Future research should focus on fine-tuning the model to specific geographic and environmental conditions to enhance its generalisability and applicability across diverse solar power installations.

CONCLUSIONS

This study has illuminated the transformative potential of modern machine learning techniques in revolutionising the assessment and optimisation of solar power systems. By implementing gradient boosting machines (GBM), we have achieved remarkable advancements across several key areas. The predictive maintenance approach, driven by GBM, led to a significant 29.88% reduction in system downtime compared to traditional reactive methods, showcasing the ability of machine learning to anticipate and mitigate potential issues before they cause disruptions. Additionally, the real-time energy yield optimisation resulted in a 14.78% improvement in energy capture efficiency, highlighting the effectiveness of dynamically adjusting system operations based on continuously updated data inputs, as opposed to relying on static models.

Moreover, the enhanced energy forecasting capabilities provided by the GBM model demonstrated a substantial 25.12% improvement in accuracy over conventional forecasting methods. This leap in precision is critical not only for matching energy production with demand but also for maintaining grid stability and supporting long-term planning. These findings collectively emphasise the profound impact that machine learning can have on the operational efficiency, reliability, and economic viability of solar power systems. While the GBM-based system demonstrates significant potential for improving the efficiency and reliability of solar power systems, challenges may arise when integrating it with existing infrastructure. Compatibility with legacy systems, which may lack the advanced monitoring capabilities required for real-time data input, could limit the immediate applicability of the proposed approach. Furthermore, the initial training phase for the GBM model may require extensive data collection and preprocessing, particularly in regions where historical performance data or environmental records are sparse. Overcoming these challenges will necessitate investment in system upgrades, data infrastructure, and tailored calibration to ensure seamless integration and optimal performance. The significance of this research extends beyond immediate technical gains. It underscores the necessity for the solar energy industry to move away from traditional methodologies and to adopt advanced machine learning techniques as a standard practice. As the global energy landscape increasingly shifts towards renewable sources, the integration of machine learning becomes not just an option but a requirement for achieving optimal performance and sustainability in solar power generation.

Future work could explore extending the GBM-based forecasting framework to predict additional system-level metrics, such as equipment wear and degradation. By incorporating data on factors like operational hours, environmental stress, and maintenance history, the model could provide insights into component lifespans and early indicators of potential failures. This extension would further enhance preventive strategies, enabling more comprehensive management of solar power systems and reducing long-term operational costs. In conclusion, this study advocates for the broader adoption of machine learning technologies within the renewable energy sector, particularly in solar power. The results presented here serve as compelling evidence of the benefits these technologies can bring, encouraging stakeholders to invest in further research and development in this area. Continued exploration and refinement of machine learning applications in renewable energy will be crucial in driving the industry forward, ensuring that solar power remains a viable and dominant source of clean energy in the future.

CONFLICT OF INTERESTS

The authors declare that they have no conflict of interests.

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