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Original Research Article

Enhancing Reliability of Off-Grid Energy Systems through Combined Edge-Based Analytics and Predictive Maintenance Models

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ABSTRACT

Conventional energy generating strategies, such as reactive and scheduled maintenance, often lead to increased downtime, energy waste, and inefficiencies. This study integrates edge analytics with machine learning-based predictive maintenance to boost the reliability and sustainability of off-grid energy generating systems. Using Long Short-Term Memory and regression models, the approach enables early anomaly detection and fault prediction, reducing unplanned outages and maintenance costs. A comparative analysis between standard edge analysis and integrated edge-predictive methods shows that the integrated system achieves an accuracy of 91.6%, compared to the edge analytics model with an accuracy of 86.2% effectively stabilizing short-term fluctuations, generating fewer and more stable alerts, with a coefficient of determination R^2 of 0.98. Results highlight that combining predictive models with edge analytics enhances reliability, supports timely interventions, and strengthens system robustness in off-grid energy generating applications.

KEYWORDS

Off-grid renewable energy systems, Edge analytics, IoT-based monitoring, Real-time analytics, Predictive maintenance, Operation efficiency.

INTRODUCTION

Decentralized renewable energy generation systems are a viable method for extending access to electricity in remote and energy impoverished regions, improving quality of life and social outcomes [1]. Such systems are especially important in areas where expanding the traditional electrical grid is not feasible economically or technically [2]. However, their successful deployment and reliability are still a challenge due to the lack of monitoring, anomaly detection, and maintenance capabilities [3].

Conventional cloud-based sensor networks utilizing Internet of Things (IoT) sensors to monitor renewable energy generation and equipment status in real-time are extensively used [4].

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However, these systems face significant challenges, including processing latencies, limited capacities for real-time analytics, and a reliance on consistent internet connectivity [5]. Due to these limitations, the time between when an anomaly occurs and when it is found is increased, extending the time spent recovering from an anomaly and operational expenditures, creating demand for more innovative and adaptive approaches to monitoring [6]. To mitigate these, there is a growing shift towards edge artificial intelligence, where data processing occurs locally at the edge device or a local edge server, allowing real-time data processing and decision making, especially in environments where latency and bandwidth are critical concerns [7].

Edge computing has demonstrated potential in a variety of applications, such as renewable energy and environmental monitoring [8]. Yet, despite advances in edge analytics for monitoring renewable generating energy generation technologies, the detection of energy anomalies and maintenance of these systems continue to depend on proactive and scheduled maintenance interventions.

This study addresses these challenges by combining edge intelligence with predictive maintenance to enhance operational efficiency and enable real-time anomaly detection in off-grid energy harvesting systems. Edge analytics facilitates the detection of unusual trends in energy generation, which could indicate performance issues or anomalies, especially in resource constrained edge computing environments [9]. Additionally, it provides forecasts of energy production through automated systems that continuously adapt to evolving data patterns, reducing the impracticality of human intervention for timely alerts on maintenance needs and anomalies, and delivering relevant information to operators and technicians [10]. The integrated use of edge analytics and predictive maintenance enhances decision-making, supports proactive maintenance, and reduces system downtime, particularly in isolated areas, by leveraging both historical energy trends and equipment performance metrics [11].

The current literature reflects significant of edge analytics is expanding the potential of energy generation devices for off-grid energy systems. Studies have proposed new edge device designed to improve solar energy management systems, enabling real-time analytics and decision-making directly at the edge through edge computing. These edge devices provide accurate forecasts of energy generation, facilitating optimal energy utilization and planning. The system architecture also includes abnormality detection for early detection of deviations from normal operation in order to reduce down time and perform maintenance in a timely manner [12]. It is recommended that future studies use multiple solar development sites to provide significant amounts of data for more analysis and evaluation. These will be evaluated for scalability, versatility and performance in various solar applications.

A cloud and edge computing framework has also been proposed to improve the anomaly detection capabilities of PV generation units. The aim is to reduce the high costs associated with continuous cloud monitoring and to minimize bandwidth consumption. By processing data locally at the edge, this approach significantly decreases latency, resulting in better real-time performance in off-grid environments. Multiple machine learning models have been compared to identify the most accurate and low-latency methods for fault detection [13] Future enhancements could include developing predictive models that utilize both historical and real-time data to identify early warning signals of anomalies, enabling timely repairs and preventing costly system downtime.

Furthermore, a low-cost, real-time monitoring and anomaly detection system has been proposed and evaluated for remote solar farms based on edge analytics and deep learning. Applied to actual data collected under soiling conditions, the system demonstrated very low resource requirements in terms of processing power and energy consumption, making it particularly suitable for large-scale, decentralized off-grid deployments [14]. Future work should involve assessing the system’s effectiveness across a wider range of anomaly types, enhancing algorithms to detect various faults, and integrating predictive maintenance features.

Another approach involves implementing edge intelligence on wireless sensor nodes to estimate and predict the output voltage of solar panels. The methodology applies the Python

Scikit-learn package to test the performance of different regressors on the solar data collected. The random forest regressor tends to perform better than the decision tree regressor in estimating voltage. The approach relied on only one sensor, the BH1750 light intensity sensor, to predict the voltage of the solar panel, opening the possibility of running these models at the edge directly on devices **[15]**. Future study should focus on combining other sensor inputs, such as output voltage or temperature data at the time of prediction. Also, other machine learning frameworks (ML) and embedded ML models can be explored to find the optimal choices for sensor nodes with limited resources and help improve edge intelligence in energy harvesting systems even further.

Prediction of renewable energy generation is critical for operational and management decisions for off-grid energy harvesting systems. The application of Long Short-Term Memory (LSTM) models for solar energy prediction leveraging time-series data. As a key evaluation metric for prediction accuracy, the LSTM models achieved significantly lower RMSE values than other stand-alone models, especially when predicting solar irradiance and PV power generation **[16]**. Subsequent studies may involve a fusion between LSTM and edge analytics as a means to continue enhancing predictive capabilities for renewable energy harvesting predictions. This would also allow for processing and analytics of the data in real time at the source, allowing for lower latency and improved responsiveness.

In addition to forecasting, machine learning (ML) and deep learning models have been employed to predict solar panel maintenance needs. These models include LSTM, Decision Trees, Random Forests, Bagging, Gradient Boosting, Voting Regressor, and Stacking, offering a comprehensive comparison of their performances. Through analysis and experimentation, it was found that LSTM architectures work best for time series prediction in this context due to their superior predictive performance as compared to the other models tested **[17]**. Incorporating edge analytics can take PV generation unit a step further, allowing them to become even more autonomous and resilient, leading to an intelligent maintenance paradigm enabled by localized intelligence that can assist in performance improvements and cost savings.

Furthermore, machine learning methods are increasingly being applied to identify faults within renewable microgrids, which often include solar and wind energy sources. These systems face challenges due to the inherent uncertainty, irregularity, and weakness of their signals, complicating fault detection and classification. Supervised ML models tend to be more accurate but can suffer from fault misclassification, while unsupervised models are more adaptable but less precise **[18]**. To enhance fault detection, future studies should focus on producing more refined ML algorithms, boosting the performance of models, and enhancing their flexibility towards adapting to various kinds of anomalies. Also, the use of data edge analytics and monitoring in real-time systems would enhance even further the capacity to detect anomalies.

Real-time processing of data at the edge is an important part of the effective administration of energy generating solutions through its capability of on-time diagnosis of anomalies, leading to preventive maintenance. Data can thus be processed at the source in real time, minimising latency and increasing efficiency of operations **[19]**. This is particularly important for remote energy systems and in a resource-constrained context, where machine learning models can be useful for automated identification and classification of anomalies. These types of models are low on resource overhead and highly accurate and efficient, including some of the deep learning models **[20]**. In addition, the combination of forecasts of energy generating and predictive maintenance also has a strong impact on decisions that will be made and therefore on the overall performance of the system. These help to increase efficiency in energy conversion and decrease downtime of the system by relying on machine learning and IoT technologies, and thus make energy production more reliable. Examining historical as well as real-time data, predictive maintenance algorithms can detect potential failures in advance of their occurrence, thereby proactively reducing unplanned downtime and maintenance costs **[21]**.Integrating smart energy management systems allows for a more stable and sustainable system, decreasing operational costs as well as downtime and making the generating of renewable energy more resilient and efficient **[22]**.

From the literature review, several research trends are identified in which edge analytics and predictive maintenance are used separately to improve the operations and sustainability of energy generating systems. However, few studies have implemented both approaches at the same time despite their advantages. This study explores the combined use of edge analytics and predictive maintenance to improve off-grid energy generating systems with respect to reliability and sustainability in remote areas. These results are promising and show that this hybrid approach can be an important step forward in future studies and applications.

The proposed method involves developing an integrated framework that combines edge analytics with advanced predictive modelling, utilizing classification and regression Long Short-Term Memory (LSTM) models. The framework allows for the onsite identification of anomalies and predictive maintenance of systems that harvest renewable energy. The goal of this approach is to use data-driven insights at the edge to increase operational efficiency, minimized downtime in systems, and cut maintenance costs particularly in off-grid, remote operating environments. This hybrid model overcomes limitations in the energy system management, leading to a more sustainable and reliable system. This approach ultimately leads to an efficient and clean energy transition in off-grid regions.

Unlike existing works that are dependent on cloud-based analysis and more reactive approached, this research presents a stronger move towards a decentralised informed decision making by inculcating edge analytics onto renewable systems. This approach of allows for real-time understanding of data collected without the constraints of constant communication between systems and cloud applications, and in furtherance, the constraints attached to such a communication. Furthermore, combining the use of both classification and regression models presents further enhancements in detection of anomalies and improved accuracy of forecasting made.

MATERIALS AND METHODS

The study proposes an integrated edge analytics and predictive maintenance framework tailored for off-grid energy generating systems in resource-limited environments. The system ensures real-time data processing, enhances operational efficiency and reliability while maintaining high prediction maintenance accuracy. The energy generating system architecture is shown in **Figure 1**. Central to this architecture are solar panels that harvest renewable energy, regulated by a charge controller to ensure safe and effective energy transfer to both the energy storage system and the load. This harvested energy is stored in batteries, providing a reliable power source for continuous operation. A network of sensors continuously monitors energy input and environmental conditions, such as temperature and solar irradiance.

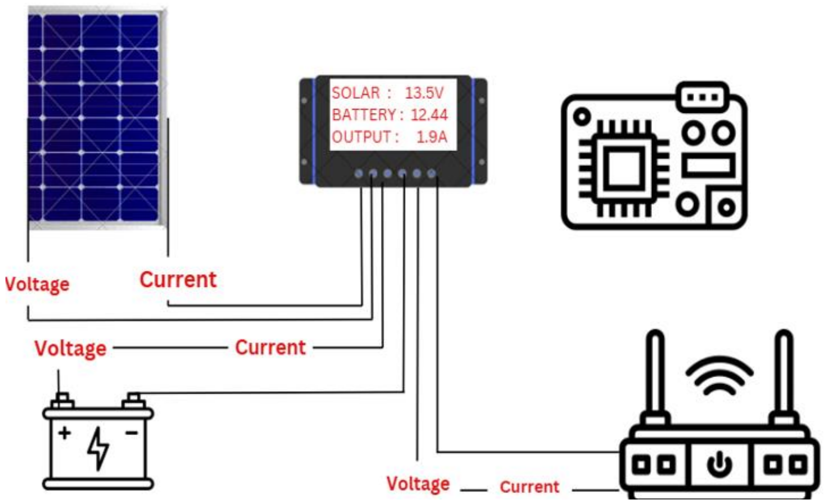

Figure 1. Energy Generating System Architecture

At the edge device, several variables were recognized to enhance the efficiency and sustainability of energy generating systems in off-grid scenarios. These variables included those related to the energy generating system, the collected solar energy and the hour of day. Other variables included were system response, such as faults, shading, and failure detection. Lastly, environmental variables include solar intensity and temperature. Data was captured by the sensor network and aggregated by the edge controller for real-time monitoring and predictive analytics.

The initial phase of data collection involved recording solar metrics, such as current and voltage, through sensors attached to the solar photovoltaic system, recordings of solar intensity through the BH1750 solar intensity sensor and temperature data with a thermocouple. All entries were then time-stamped, allowing for chronological analysis. Data were initially stored locally on an SD card, ensuring data integrity in case of a communication failure with their central servers.

The data underwent several essential pre-processing procedures. Initially, solar power generation and weather variables were subjected to a normalization technique to enhance model training efficiency and facilitate network convergence. Labels identifying the nature and date of anomalies were utilized for supervised learning in predictive models. Additional features, including smoothed energies, normalized irradiances, scaled hour-of-day, short-term averages, and energy change rates, were generated through feature engineering to enhance the dataset. The metrics chosen illustrate the trends and variations in energy production that provide significant and reliable predictive analysis.

Anomaly Detection in Edge Analytics

The study assessed an edge analytics method for real-time anomaly detection in off-grid solar energy generating systems. The Long Short-Term Memory (LSTM) deep learning model was selected for its effectiveness in capturing complex temporal relationships in time series energy generating data [18].

The architecture consisted of multiple layers, each designed to extract and process critical features:

1. Input Layer: The model was provided with pre-processed multivariate time series data, encompassing features such as solar intensity, temperature, energy output, and hour of the day.
2. LSTM Layers: An LSTM layer with 64 memory cells processed the input sequence to learn temporal dependencies in the data. This layer produced the final hidden state, which acts as a concise representation of the learned temporal dynamics.
3. Dropout Layer: A dropout layer was incorporated following the LSTM layer to improve model performance and mitigate overfitting. This layer randomly deactivated a portion of neurons during training, enhancing robustness.
4. The output from the LSTM, after undergoing dropout processing, was input into a fully connected dense layer consisting of 32 neurons utilizing ReLU activation. This layer converts temporal features into a more distinct representation relevant for classification tasks.
5. The output layer consisted of a fully connected layer with four neurons, each representing a distinct class: normal, fault, shading, or failure.

Predictive Maintenance for Off-Grid Energy Generating Systems

By analysing past sensor data, the system was capable of classifying each time step in four possible working conditions: normal operation, fault, shading, or failure. This was done by developing a multi-output Long Short-Term Memory network capable of performing multiple regressions and classifications from sequential sensor data. This method used voltage, current, irradiance, temperature, and time feature sequences to study energy generation from the system and detect deviations from normal operating conditions. Converting the models' predictions into actions, predictive intervention alerts were sent to technicians in case of a potential failure detection, with information about the nature of the anomaly and recommended preventive actions. A fully connected regression, eq. (1), is also applied to predict energy output, thus enabling proper and accurate management of the system proactively:

$$E_{\mathrm{t}} = W_{\mathrm{r}} \times h_{\mathrm{t}} + b_{\mathrm{r}} \tag{1}$$

The predicted energy, denoted as E_t, is computed using a fully connected regression layer characterised by a weight matrix W_r and a bias term b_r. This layer processed the hidden state vector h_t, which is the output from the LSTM layer after analysing the input sequence, to produce an accurate forecast of future energy generation.

The training function was designed as a regression branch that would predict solar energy from time features. The loss was calculated using Mean Squared Error (*MSE*), eq. (2), which increases the cost of large errors between predicted energy and actual energy values:

$$MSE = \frac{1}{N}\sum_{i=1}^{n}(x_i - \hat{x}_i)^2 \tag{2}$$

where x_i represents the ground truth energy and the $\hat{x}_i$ represent the predicted energy, and N is the number of training samples.

The classification branch was tasked with identifying the system's operating condition: normal, fault, shading, or failure. The loss is calculated using Categorical Cross-Entropy, eq. (3), which compares the predicted class distribution with the actual class labels:

$$\mathcal{L}_{class} = \sum_{i=1}^{N}\sum_{j=1}^{C} \times \log\hat{P}_{ij} \tag{3}$$

Performance evaluation metrics

The following key metrics are analysed using the dataset-driven approach to assess the system performance. The Accuracy, eq. (4), is used:

$$Accuracy = \frac{TP + TN}{TP + TN + FN + FP} \tag{4}$$

where *TP* = True Positives, *TN* = True Negatives, *FP* = False Positives, *FN* = False Negatives. This metric determines the efficacy of AI-driven fault prediction based on labelled datasets.

Coefficient of determination (R^2), eq. (5), is also used:

$$R^2 = 1 - \frac{\sum_{i=1}^{N}(x_i - \hat{x}_i)^2}{\sum_{i=1}^{N}(x_i - \bar{x})^2} \tag{5}$$

Here, x_i is the measured energy at time stamp i, while $\hat{x}_i$ while is the predicted energy at this time. Additionally, $\bar{x}$ is the mean of all actual energy values observed across the dataset.

Implementation Workflow

Through a data-driven scenario analysis, the study integrated edge analytics and predictive maintenance specifically for off-grid energy generating systems. Data were collected from an off-grid solar energy system, with sensors that measured solar intensity, voltage, current, and temperature, along with timestamps of readings. The data sets were divided into overlapping sliding windows of fixed length, with labels assigned according to the state of the system at the end of each window. This labelling produced sequences amenable to input into LSTM networks.

Two complementary deep learning models were then proposed to allow the monitoring and maintenance of the system. First, a LSTM-based sequence classification model was created to detect the state of the system among four different labels. Normal, stable energy output, fault, sudden energy fluctuations indicating a malfunction, shading, reduced harvest due to obstructions, failure, or no energy output during sun hours.

Second, a multi-step LSTM-based energy forecasting model was developed to forecast the energy output for the future using past solar energy output along with environmental features. This anticipatory nature of the predictions provides an ideal base for proactive maintenance since it acts as a forecast for expected behaviour of the system under observation for future time moments, and a preventative approach can be taken before failures are detected.

Both models were trained using supervised learning techniques with dataset partitions for training and testing to evaluate accuracy. The trained models were used in real-time at the edge to classify system states and predict future energy profiles based on a sliding window of sequential data. Unlike classic statistics, these LSTM-based models were able to adapt to noise, seasonality, and slow deterioration and exhibit increased accuracy, recall, and overall reliability.

To smooth predictions and decrease false alarms, a sliding window was used during inference. Whenever more than one abnormal classification, fault, shading, or failure exists within a specific time window, the system gives an early alarm, allowing for maintenance interventions at shorter times. This process is largely preventative in that it works to ensure that there are no total system failures, resultant downtime, or additional wear and tear on the system.

Scenario-based simulations were performed to assess the performance of the system under realistic conditions. In this case, existing datasets were processed using edge analytics combined with LSTM anomaly detection techniques to differentiate shading, failures, faults and normal operation in off-grid energy generating systems. The intent was to provide real-time alerts within a predictive modelling capability that informed the operator of a potential failure before the point of total system failure. The goal was to reduce downtime and increase the life of the energy systems by providing constant and intelligent monitoring.

The analysis aimed to evaluate the potential of the system to generate alerts only in the presence of persistent and verified anomalies, and therefore minimize false positives and increase reliability. The primary metrics for comparing edge analytics versus edge analytics combined with predictive maintenance included detection accuracy, timing and stability of alerts, overall performance and reliability, and prediction capabilities. This use case assessment also illustrated the benefits of merging predictive algorithms with edge analytics in enhancing proactive management of systems, increasing operational efficiency and improving robustness of off-grid energy generating systems.

RESULTS

This section presents the scenario-based analysis results to assess the operational efficiency and reliability of energy generating systems, utilizing edge analytics-powered predictive maintenance. To test the performance of the proposed system, anomaly detection was executed on datasets captured at the edge with an IoT sensor network.

To understand the effectiveness of the various anomaly detection and maintenance techniques, the study compared the performance of edge analytics and integrated edge analytics with predictive maintenance models. **Table 1** shows the performance on classifying anomalies for both configurations.

Table 1. Anomaly classification performance comparison

Model Type	Precision (%)	Recall (%)	F1-Score (%)	Accuracy (%)
Edge Analytics	85.9	87.5	85.0	86.2
Edge Analytics + Predictive Maintenance	89.7	91.2	90.8	91.6

Across all the review metrics, combining edge analytics with predictive maintenance gives observable stronger performance, especially in F1-Score and Accuracy. This combination suggests a more reliable approach to achieving improved system responsiveness and foresight by capturing potential faults, reducing false positives or misses. The 3.86% increase from 85.9% to 89.7% gives the system confidence from reduced false alarms and greater resource optimization. The Edge Analytics model achieved an accuracy of 86.2%, with a relatively high sensitivity but also a greater tendency to issue false alarms. In contrast, the integrated system with predictive maintenance improved overall accuracy to 91.6%, with significantly better F1-score and precision.

Timing metrics summarizing the promptness and reliability of anomaly detection are presented in **Table 2**.

Table 2. Anomaly detection timing and alert stability

Model Type	Mean Time Between Alerts (hours)	Average Anomaly Duration (hours)
Edge Analytics	2.3	1.2
Edge Analytics + Predictive Maintenance	3.7	3.5

The Edge Analytics model was to be the most reactive and also had more frequent alerts. Conversely, the model combining edge analytics and predictive maintenance showed a lag. While it is noticeable that the combined Edge analytics model and Predictive model react slower than the Edge analytics model on standalone, this demerit can be allowed because the combined model gives us better results from the F1-Score and Accuracy metrics, giving us reduced false alarms.

The edge analytics framework used a supervised time series learning LSTM classification model that was trained on solar energy generating system data. To categorize the operating condition of the PV system, it was created to identify one of four states: normal, fault, shading, and failure, based on the input features of solar voltage, solar current, solar irradiance, and time-based statistics.

Figure 2 depicts the distribution of anomaly classes for the validation set, where most of the samples were labelled as normal, indicating the reliability and stable operation of the solar system within the analysed timeframe. The model was able to detect different cases of anomalous behaviour; a substantial number were labelled as Failure, which are associated with complete drops of energy production that are possibly caused by major faults or shading. Shading was identified, defined as a lower energy production with sufficient solar exposure, along with faults, defined as an abnormal energy profile under average irradiance conditions.

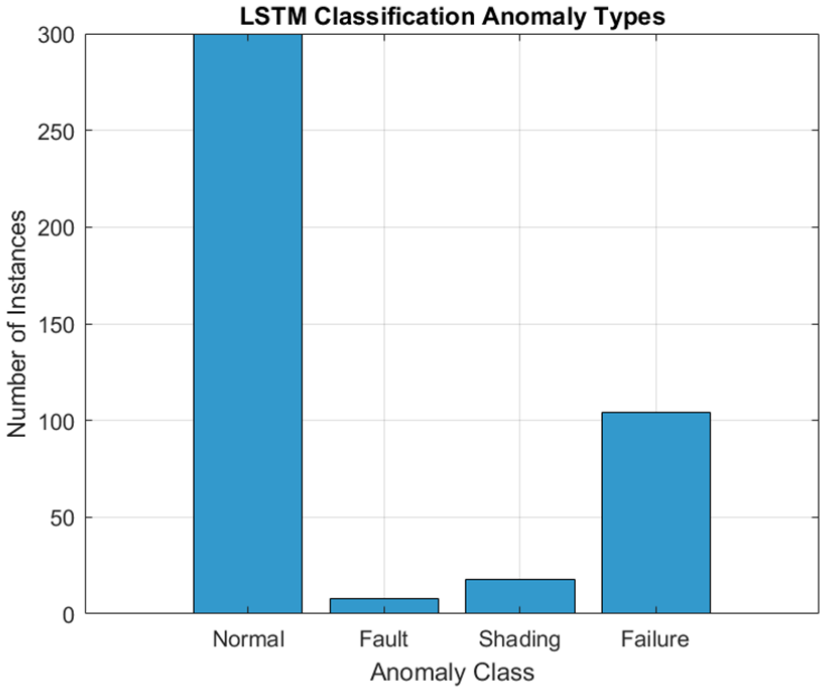

Figure 2. Distribution of detected anomaly classes

An edge analytics approach combined with predictive maintenance was sought to improve the ability of the existing system to interpret and learn from time series data of energy generating. To do this, a LSTM-based regression model was developed and trained. This model used historical sensor data of energy output, smoothed solar intensity, time of day, moving averages of energy output, gradients in energy output, and temperature to predict normalized energy output over time.

The energy prediction model's performance was assessed based on its ability to predict normalized energy from actual measurements. The actual energy and the predicted energy curves, as displayed in **Figure 3**, are in close agreement, suggesting that the model learned the temporal structure of the solar energy signal well. Quantitatively, this effectiveness is also evidenced by the model's R^2 value of .98 between predicted and actual values. Also, the low *MSE* of 0.00096 and root *RMSE* of 0.031 imply almost no deviation, indicating a confirming high prediction accuracy and reliability of the model in representing the energy generating patterns.

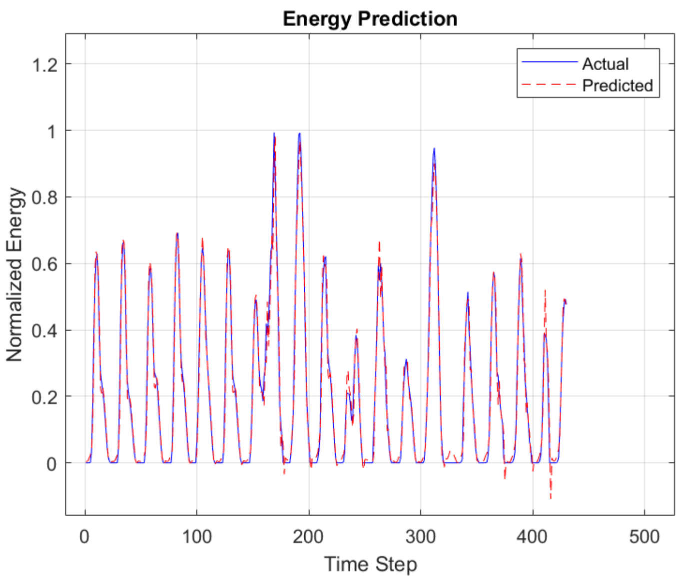

Figure 3. Comparison of actual and predicted normalized energy outputs

The expected states of the maintenance alert, over time, are depicted in **Figure 4**, based on the trained edge analytics with a predictive maintenance learning model. The model organized the system conditions in four operational categories: green for normal operation, orange for fault risk, blue for shading risk, and red for failure risk. Mapping these alerts over time gives early warning signals and contextual diagnostics to use in a risk-based maintenance paradigm.

Figure 4 shows how the classifier's projected outputs are transformed into a colour-coded alert system that categorizes each time step into different risk levels: green for normal, orange for fault risk, blue for shading, and red for failure risk. This tiered alerting method allowed operators to prioritize responses, with red warnings indicating total circumstances that required immediate intervention and orange or blue signals indicating possible onset of concerns, allowing for early preventative interventions. The fault categorization is consistent with best practices in predictive maintenance, which emphasize identification of anomalies but also their severity and nature to permit suitable responses **[23]**.

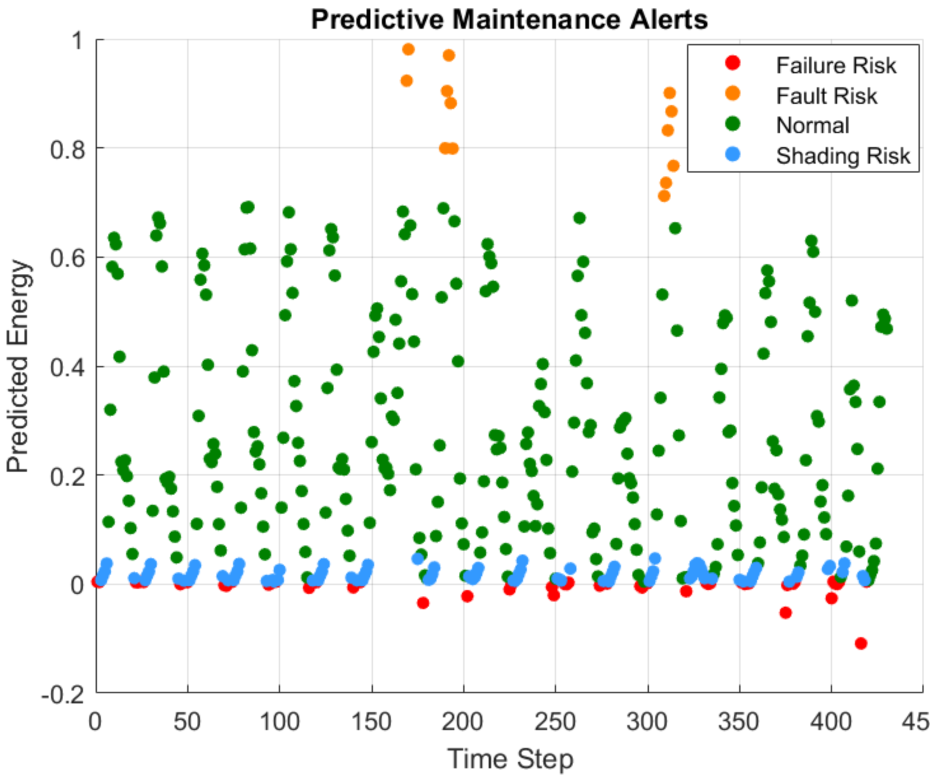

Figure 4. Predicted maintenance alert states over time

The main source of the economic efficiency over time of the proposed edge-based predictive maintenance framework is the capability of the system to reduce operational costs, to increase the lifetime of a system, and to decrease the unplanned downtime. By localizing the intelligence at the edge, the system is able to operate without the need of an expensive cloud infrastructure and costly data transmission. The selection and the use of classification and regression LSTM models enable them to be very accurate in their forecasting and also in the detection of anomalies at the earliest stage, thus, intervention in due time can prevent the occurrence of expensive failures. The principle of using the least expensive maintenance routine over time results in reduced occurrences of costly emergency repairs. In addition, the scalability and independence of the system lead to less human intervention, thus saving on labour costs. All these factors, considered together, result in the high return on investment (ROI) that makes the framework a financially viable solution for long-term deployment in decentralized energy systems.

DISCUSSION

The findings of this work show the significant improvements through the application of edge analytics and predictive maintenance for off-grid energy generating systems. The hybrid approach significantly enhances anomaly detection performance, achieving a higher precision of 89.7% compared to 85.9% and a recall of 91.2% to 87.5% than the edge-only model. This is an increase in F1 score from 85.0% to 90.8% and overall accuracy from 86.2% to 91.6% which suggests that the joint system not only increased the percentage of true positives but also decreased false positives.

The results align with recent studies showing how Internet of Things monitoring, through deep learning processing, improves precision and performance in executing maintenance operations by identifying early signs of minor system degradation [24]. The most interesting aspect of the higher precision is that it may be a consequence of the hybrid model being better at filtering false positive alerts. This combination has proven to be a more reliable and efficient method of detecting faults, ultimately leading to a more proactive and focused maintenance of off-grid energy systems [25]. Detection thresholds are a delicate balance in anomaly detection systems, as thresholds which are too high can lead to a proliferation of false alarms and thresholds which are too low will mean that actual faults go undetected.

There is a clear trade-off between stability and responsiveness in the detection of anomalies. This edge analytics-only model identified anomalies very quickly, but had a high false positive rate. This sensitivity increased the probability of a response to small, often inconsequential spikes or noise, which can result in false alarms and unnecessary maintenance. On the other hand, the combined approach of edge analytics and predictive maintenance, although it takes longer to initially detect an anomaly, produced fewer sustained true positive alerts.

This suggests that the integrated system had a sustained deviation requirement before it raised an alarm; it averages short-term fluctuations to prevent false positive events. This is consistent with the characteristic of forecasting models that attempt to identify the presence of important divergences in patterns and not short-term fluctuations, to make more accurate predictions [26]. This is a conservative method, which could be sensible when collecting energy in off-grid systems, where false alarms are expensive since these systems are in remote locations with difficult servicing. This integrated approach sacrifices the speed of collection and response, a sacrifice that is more than acceptable in this context to prevent unnecessary interventions.

The edge analytics LSTM classifier was trained on time series features of voltage, current, irradiance, as well as time-based statistics, to classify every interval of data into one of four labels: normal, fault, shading, and failure. The class distribution in **Figure 2** also reveals that the majority of the data points are classified as normal, which corresponds to the normal operation of the solar energy generating system when the solar intensity is normal. This class imbalance is typical in anomaly detection models, where the models learn a normal baseline and classify other inputs as deviating from normality [27].

The model was able to identify several other types of anomalies, despite the skewed ratio. Fault events were observed as small spikes or drops in the energy output meter when the solar intensity was normal, indicating a temporary problem. This situation reflected decreased energy production and shading, which was accurately diagnosed at high irradiance. Failure labels were applied to scenarios with minimal energy production, which exhibited sharp and persistent declines that likely indicate catastrophic defects, such as hardware failure or significant power outages. These alerts are important because they can alert to immediate maintenance needs, indicating system breakdowns.

In addition, the classifier was able to separate the different types of degradation patterns, as also by a previous study of Ibrahim *et al.* (2022), which showed that machine learning schemes are suitable to evaluate the health of PV systems by recognising abnormal states [28]. From a practical sense, the important aspect of this multi-class classification is that apart from identifying the presence of anomalous behaviour, the system also infers the probable reason for the anomaly, be it shading, faults or component failure, which allows for a more focused inspection of the array. The fact that this sensitivity exists for multiple classes is aligned with the objective of predictive maintenance, where the AI model should be used to alert when behaviour is deviating from the normal, so that interventions can be made proactively to prevent further deterioration [24].

To give the model forecasting capabilities, a predictive LSTM regression model was trained on the sequential sensor data to predict normalised energy output. The model analysed the time series data in both directions, forwards and backwards, to incorporate relevant context from the immediate past and future. As illustrated in **Figure 3**, the actual energy closely follows the predicted energy depicted over the test period. Quantitative evaluation confirms the model's robustness; it achieved an R^2 value of 0.98, indicating that approximately 98% of the variance in the energy signal is explained by the model. The very low *RMSE* of 0.031 further underscores the model's precision in capturing short-term fluctuations and daily solar patterns. These results compare favourably with other advanced deep learning models used in renewable energy forecasting, demonstrating the superior capacity of this approach to model complex, non-linear PV dynamics [29].

The integration of inputs, including solar intensity, time of day, short-term energy averages, gradients, and temperature, allowed the model to produce reliable forecasts of anticipated energy generation, thereby enhancing energy management precision. The system utilises continuous data analysis for early anomaly detection and executes proactive maintenance measures, in contrast to reactive maintenance, which entails scheduled quarterly inspections and servicing of generators, batteries, and inverters [30]. The forecasting method offers a more dynamic and responsive maintenance framework. The results in this study provide a basis for establishing thresholds that signify potential issues when variations from projected energy outputs occur. These thresholds facilitate the system's generation of prompt notifications for maintenance or required adjustments, hence enhancing dependability and efficiency.

By tracking alerts over time, the system provided early warning signs of performance decline before an entire shutdown occurred. This risk-based diagnostic technique permitted intelligent intervention scheduling. Where several shading-risk alarms on successive sunny days indicated the need for panel cleaning, and developing failure risks recommended inverter and sensor inspections. This solution integrated the essential benefits of AI-driven maintenance by lowering downtime and maintenance costs while increasing reliability [31].

In off-grid scenarios, where unplanned outages can be particularly disruptive, the advantage of obtaining advance notice of potential faults and differentiating fault types becomes especially significant. The integrated edge-predictive approach significantly enhances system reliability. While the edge-only LSTM model provided rapid anomaly detection crucial for immediate alerts, it tends to over-trigger. Incorporating a predictive layer results in a more balanced and accurate alert stream, offering higher reliability and contextual understanding. This reflects broader industry trends, where applying machine learning and IoT for real-time monitoring is transforming maintenance strategies from reactive responses to proactive management [32].

Furthermore, deploying edge analytics to minimize latency and combining it with forecasting capabilities allows operators to maintain a continuous, comprehensive view of system health. This integrated approach enables early intervention, preventing failures that lead to service interruptions and significantly enhancing the resilience of off-grid energy harvesting systems [33].

CONCLUSION

This study investigates an integrated edge analytics and predictive maintenance for health monitoring of energy generating systems. A scenario-based analysis was conducted to evaluate the effectiveness of the proposed system using a dataset collected from an energy generating system during the study period. The results demonstrate that integrating edge analytics with predictive maintenance models enhances anomaly detection performance, achieving a higher accuracy of 91.6% compared to the edge analytics model with an accuracy of 86.2% reducing false alarms. Timing metrics revealed a trade-off between responsiveness and stability in anomaly detection. The integrated model requires a sustained duration before raising an alarm, effectively smoothing out short-term fluctuations and reducing the false positive rate. The class distribution of data indicates that most data points are classified as normal, reflecting the stable operation of the energy generating system. Furthermore, assessing the health of the system, classification distinguishes different degradation patterns, identifying anomalies into shading, faults or failure, thus facilitating targeted maintenance. Predictive maintenance is achieved through energy forecasting enabled by regression models with a coefficient of determination, R^2 of 0.98, and predicted anomaly alert visualisation output. By mapping these alerts over time, the system delivers early warning signals of performance degradation before failure. This risk-based diagnostic approach enables the maintenance of the energy generating system, reducing unplanned outages, enhancing conversion efficiency and sustainability of the systems in off-grid regions

In summary, this analysis and research enhanced health monitoring systems by incorporating real-time surveillance and proactive maintenance powered by on-site anomaly detection and predictive maintenance, leading to increased system longevity, sustainable use and reduced deterioration. Furthermore, the integration of descriptive, diagnostic, and contextual data analyses supports smarter, evidence-based energy planning, thereby enhancing the reliability and scalability of off-grid solar systems. It is evident that the collection of data and real-time analysis of the data as the system operates gives insight into metrics that allow for predictive maintenance to be applied, resulting in unhindered operation. This work lays a foundation for enhanced, pliable and practical sustainable decentralized power systems especially those in remote or off-grid environments.

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NOMENCLATURE

Abbreviations

AI	Artificial Intelligence
ANN	Artificial Neural Network
IoT	Internet of Things
LSTM	Long Short-Term Memory
ML	Machine Learning
MSE	Mean Squared Error
ReLU	Rectified Linear Unit
RMSE	Root Mean Square Error
WSN	Wireless Sensor Network

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