Sustainable Energy, Grids and Networks 43 (2025) 101765

Contents lists available at ScienceDirect

Sustainable Energy, Grids and Networks

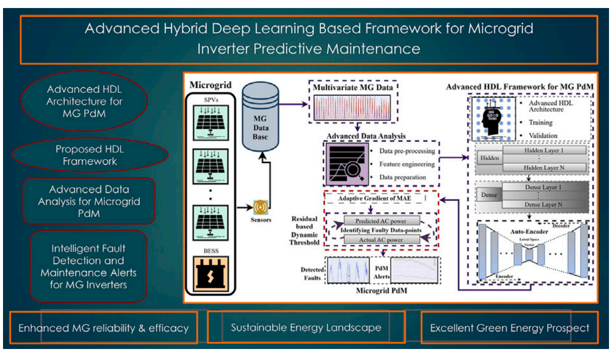
journal homepage: www.elsevier.com/locate/segan

Advanced hybrid deep learning based framework for microgrid inverter predictive maintenance

M.Y. Arafat*, M.J. Hossain

School of Electrical and Data Engineering, University of Technology Sydney, 2007, New South Wales, Australia

GRAPHICAL ABSTRACT



ARTICLE INFO

Keywords:
Microgrids
Inverters
Predictive maintenance
Fault detection
Maintenance alerts
Advanced hybrid deep learning

ABSTRACT

The increasing complexity of microgrids (MGs) demands sophisticated strategies for improved maintenance and reliable operation. The integration of artificial intelligence (AI) into microgrids allows for the analysis of system performance, anomaly detection, malfunction identification, and the generation of alerts through continuous monitoring in case of any unexpected drop in performance enabling reliable operations and maintenance, enhancing predictive maintenance capabilities and sustainable decision making. To improve system reliability and performance, accurate fault identification and the generation of maintenance alerts according to the performances over time are becoming crucial for enhanced predictive maintenance (PdM) of MGs. This study introduces an intelligent data-driven hybrid framework for microgrid PdM utilizing a hybrid deep learning (HDL) architecture, combined with advanced data analysis and a residual-based dynamic threshold technique. The loss function of the proposed hybrid algorithm has been optimized to enhance microgrid PdM. The results show significant accuracy in predicting the maintenance needs within MGs. This research offers valuable insights for designing and enhancing hybrid algorithms for advanced maintenance in MG systems, contributing to advancements in PdM technology and promoting a resilient and cost-effective operation of MGs.

1. Introduction

A new era of proficiency and resilience in sustainable energy systems has emerged through the integration of microgrids (MGs) into modern power systems. MGs are attracting significant research interest due to their advantages in terms of stability, controllability, economic efficiency, and reliability [1]. In today's evolving energy landscape,

* Corresponding author.
Email address: MdYeasir.Arafat@student.uts.edu.au (M.Y. Arafat).

https://doi.org/10.1016/j.segan.2025.101765
Received 10 December 2024; Received in revised form 6 May 2025; Accepted 2 June 2025
Available online 4 June 2025

MGs are advancing by seamlessly integrating diverse distributed energy resources (DERs) and loads within the extensive networks of AC grids [2]. The rapid growth of DERs in distribution systems, specifically the solar photovoltaic (SPV) generations, is contributing to transforming the conventional passive networks [3] into more active entities, for example MGs. Being the key sources of energy in MGs, DERs encompass a number of small-scale generation sources. In this context, the SPVs stand out as a promising generation source for microgrids by capturing the abundant availability of renewable and clean solar energy from sun [4]. SPV systems are experiencing a boom [5] in power systems at present. The recent widespread adoption of this technology has been fueled by its cost-effectiveness and scalability. Yet, the diverse intermittent attributes of SPV systems cause major protection concerns. To address these protection concerns and enhance the operational reliability within MG network, fault detection in MG predictive maintenance (PdM) has become an essential tool [6] and is one of the most significant challenges that demands the greatest research attention [7]. Besides, the high dependence of SPV systems on environmental factors, i.e., irradiation and temperature, causes many challenges, specifically in the context of desired output power in MG systems which demands for more advanced fault detection and maintenance alerts over time based frameworks for an enhanced predictive maintenance of MGs.

Fault detection is one of the most critical steps of PdM for getting rid of any potential catastrophic failures [8]. For detecting and responding to various faults in power systems, machine learning (ML) based techniques are emerging as a robust solution, extending the potential of upgrading PdM and improving the MG system resiliency. Various industries are widely implementing these data-driven ML-based PdM applications for instance in manufacturing [9,10], mining [11], healthcare [12], and transportation [13]. However, the implementation of ML-based PdM frameworks for MG systems is still a relatively new field that demands further investigation. Moreover, most of the recent research works on MG systems are mainly focused on the economic dispatching [14] as well as energy management [15–17].

Besides, research has been performed by [18] on MG challenges, specifically focused on cyber attack detection. Another study was conducted in [19] focusing on digital twin technology specifically for MG energy management. For DC microgrid clusters, a support vector machine integrated classification technique has been presented in [20] for high-impedance faults. A multi-layer perceptron neural network (MLPNN)-based classification method for locating DC arc faults in DC microgrids has been proposed by [21] with a testing accuracy of 93.3 %. A morphological operator based classification technique integrated with multi class AdaBoost algorithm has been implemented for DC microgrids in [7] for detecting the feeder faults. A study in [22] explored a protection strategy for low-voltage (LV) AC microgrids by analyzing features such as active power flow direction, voltage sags, and current magnitudes. Using MATLAB/Simulink, the results demonstrated strong performance under low-impedance faults in balanced conditions but were less effective in unbalanced scenarios.

Another study [23] investigated LV microgrid protection issues related to the point of common coupling, distributed generation, and line faults through harmonic distortion measurements. Simulations were conducted using MG test systems on the PSCAD/EMTDC platform. Further research in [24] expanded on MG protection techniques, analyzing islanded microgrid scenarios with short-circuit faults using PSCAD/EMTDC. Similarly, [25] employed PSCAD/EMTDC to detect high- and low-resistance DC faults in LV microgrids based on inductor voltage and relay ground current. Additional research [26] examined MG faults under varying impedance conditions using a power quality control scheme.

Machine learning (ML)-based approaches have also been explored. In [27] a decision tree and wavelet transform-based method was developed to classify MG faults with 97 % accuracy on a dataset of 3860 samples. Another ML technique integrating wavelet transforms in [28] achieved an overall classification accuracy of 97.76 % in test cases. A data-driven approach has been presented in [5] for locating short-circuit line faults that occur in DC microgrids by utilizing a transfer learning technique where an overall classification accuracy of 90 % has been reported. Another work on multi-criterion system integrated neural network technique has been conducted by [29] for detecting different low impedance line faults for low voltage DC microgrids. Besides, study conducted by [30] explored different scheduling issues of microgrid DERs, and [31] presented various experimental platforms for hydrogen-based MGs focused on energy management. In the current literature, there is no study conducted on advanced HDL architectures regarding microgrid PdM with respect to exogenous factors, especially on fault detection and continuous monitoring through maintenance alerts over time integrated frameworks for MG inverters.

With the integration of different DERs and inverters, MG structures have recently become more complex. As a result, the vulnerability to faults and malfunctions is escalating within the power system. Being the core of the MG structures, inverters perform the major role of power conversions suitable for main grid integration and end-user consumption. Faults or anomalies are identified through any irregularities with respect to the normal or expected values. To ensure a resilient and steady power flow within MG systems, developing advanced hybrid ML-based techniques for fault identification integrated with MG inverter continuous performance monitoring by generating maintenance alerts over time has become essential. Besides, deep learning (DL) techniques with their deeper network layers and powerful feature vectors having higher dimensions [32] could be more effective compared to the conventional ML methods.

HDL-based architectures have proven highly effective in capturing complex temporal patterns and fluctuations from vast and intricate input data. This is achieved by leveraging robust feature vectors and the deeper network layers of DL models in combination with other techniques [33]. As a result, there has been a significant increase in adopting HDL-based methods. Developing such techniques presents a promising opportunity for predictive analytics applications, particularly in fault detection and continuous monitoring based maintenance alert generation for microgrid inverters.

From the literature gap, there is no present study based on advanced HDL-based MG inverter performance monitoring system by identifying faults and generating priority-based maintenance alerts over time with respect to complex external factors. This study introduces multiple technical innovations, including an advanced HDL framework that integrates multi-parameter analysis of domain-specific features. In addition to output power, key factors such as inverter efficiency, ambient and module temperatures, and irradiance are incorporated through advanced data analytics to enhance real-world applicability. Furthermore, the hybrid model architecture, combined with a residual-based dynamic threshold framework, improves algorithm accuracy in predicting maintenance needs based on external factors. The research contributions of this study are threefold:

- **Advanced Data Analysis for Microgrid PdM:** The first contribution of this work is the development of an advanced multi-parameter based data analysis technique integrating domain-specific features for the proposed HDL framework. This technique is vital for uncovering underlying patterns, identifying external factors, and detecting potential issues that may hinder MG operations. The developed data analysis technique establishes a strong foundation for model training, which can enhance the accuracy and interpretability of the PdM framework for MG inverters, ultimately improving PdM capabilities within the MG network.
- **Advanced HDL Architecture Based PdM for MG:** The second contribution of this work is the the design and integration of an intelligent HDL architecture that incorporates an advanced long short-term memory-autoencoder (LSTM-AE) algorithm, specifically tailored for this study. The HDL architecture is specifically designed to capture dynamic and complex patterns within the AC power signals of MG

inverters with respect to exogenous factors. Additionally, the mean absolute error (MAE) loss function of the proposed hybrid algorithm has been optimized to improve the adaptability of the model. By minimizing MAE rates between actual and predicted data points, the error distribution is optimized, which can significantly improve PdM effectiveness within the MG system.

- **Residual Based Dynamic Threshold Integrated PdM Framework:** Another notable contribution of this work is the deployment of a residual-based dynamic threshold technique within the algorithm. Traditional approaches often struggle to adapt to the complexity and dynamics of MG inverters, which can lead to delayed responses and false alarms in the presence of critical, fluctuating data points. Proposed technique enhances PdM capabilities by dynamically adjusting threshold points with respect to deviating external factors. This increases the responsiveness of the HDL framework to subtle deviations under varying operational conditions, enabling it to more effectively distinguish between potentially critical anomalies and normal variations during MG operation.

By advancing predictive maintenance (PdM) frameworks, this research contributes valuable insights into the evolving landscape of renewable energy-powered microgrids. Identifying inverter performance degradation before critical failure can provide significant practical benefits for microgrid operators and maintenance teams, enabling proactive maintenance strategies that reduce costs and system downtime. Addressing the urgent need for effective microgrid maintenance, this study strengthens PdM capabilities, enhancing system resilience, reliability, and efficiency which resonates with UN's sustainable development goals.

The remainder of this paper is structured as follows: Section 2 summarizes the problem statement of the study. Section 3 provides a detailed overview of the proposed methodology. Section 4 presents the results and discussion of the advanced HDL framework. Finally, Section 5 concludes the work with summary and concluding remarks.

2. Problem statement

With the increasing rapid applications of RES in microgrid systems, specifically by integrating the promising SPV technology, a new dawn of sustainable and decentralized energy sector has been emerging. Nevertheless, several challenges have appeared as well with this transition. Among these concerns, the major challenge is to ensure the resiliency as well as reliability of the inverter operations within the MG network, because it is the prerequisite for ensuring the efficient and stable generation and distribution of power through MG networks that are equipped with a variety of inverter based resources. Therefore, monitoring the performance of inverters throughout MG systems is very significant. This can be performed by anomaly or fault detection which is one of the most critical cores of predictive maintenance. Through accurate identification of faults, and continuous performance monitoring by generating priority based maintenance alerts over time, the PdM competency can be enhanced significantly within the MG network. Fig. 1 illustrates a clear overview of a microgrid network which includes SPVs as the DER, BESS, and several local loads.

One of the major issues regarding microgrid DERs, and particularly SPVs, includes the intrinsic high reliance on the external aspects for example solar irradiation as well as ambient temperature. In case of any deviations influenced by these external aspects, abnormalities or faults may occur in the context of the produced AC power by the MG inverters. Consequently, it is essential to determine whether there are any irregular limitations due to the external factors or if it is the malfunctioning inverters. The successful identification of these abnormalities is crucial for enhancing the stable performance as well as the resiliency of MG system.

A combined DL-based architecture with other efficient techniques can be more robust in identifying the nuanced pattern deviations from

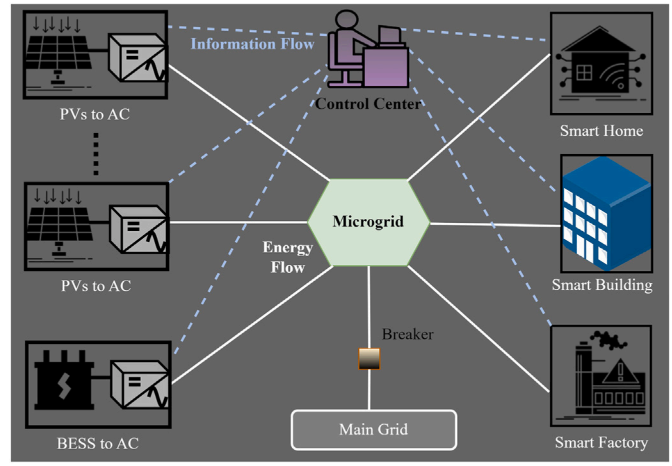


Fig. 1. Microgrid system overview.

MG inverter AC output signals. Besides, there is a research gap in implementing advanced HDL frameworks in the current literature in terms of PdM in MG applications. Moreover, in power grid applications, implementing advanced DL models and their performance comparison [34] still remain an unexplored research topic.

In the case of recent real-world, dynamic MG operational scenarios, ML-based traditional algorithms are not efficient enough to identify the variety of nuanced failure scenarios and varying patterns. Furthermore, traditional artificial neural network (ANN)-based methods do not have robust interpretability in terms of predictive analytics. Moreover, the learning algorithms of these methods converge slowly [21]. All these limitations highlight the need for developing advanced hybrid models possessing adaptive PdM capabilities that can address these varying nuanced patterns from the MG inverter power signals with respect to deviating external factors.

Developing an advanced hybrid architecture for the detection of faulty operations and continuous performance monitoring by generating priority based maintenance alerts over time for MG inverters under complex and dynamic operational scenarios is getting essential to enhance the microgrid PdM competency. In contrast to conventional ML models which are not strong enough to discern the complex temporal dependencies and deviations from the input data-points, hybrid DL models include deeper network cores and advanced feature vectors to overcome these issues. Relevant features can be extracted significantly, the sequential patterns can be modeled, and the nuanced abnormalities from the data-points can be detected with higher robustness and performance by combining different efficient techniques in hybrid models.

Through implementing real-world MG data, this study aims to investigate the effectiveness of advanced HDL framework under diverse operating conditions. The outcome of this research can offer significant insights into the modeling and implementation of advanced HDL frameworks that can open an outstanding avenue towards the future development of advanced PdM plans for the rising adoption of MG systems, directing to a greater resilient and efficient green energy landscape.

3. Proposed methodology

Being an advanced HDL architecture, the proposed algorithm possesses the strength of combining both traditional statistical techniques and advanced DL methods for identifying the anomalous patterns from the multi-sensor MG data. The advanced HDL model is capable of capturing both spatial and temporal dependencies, which have been leveraged in the context of microgrid systems where there are numerous external factors that can impact the performance of the inverters.

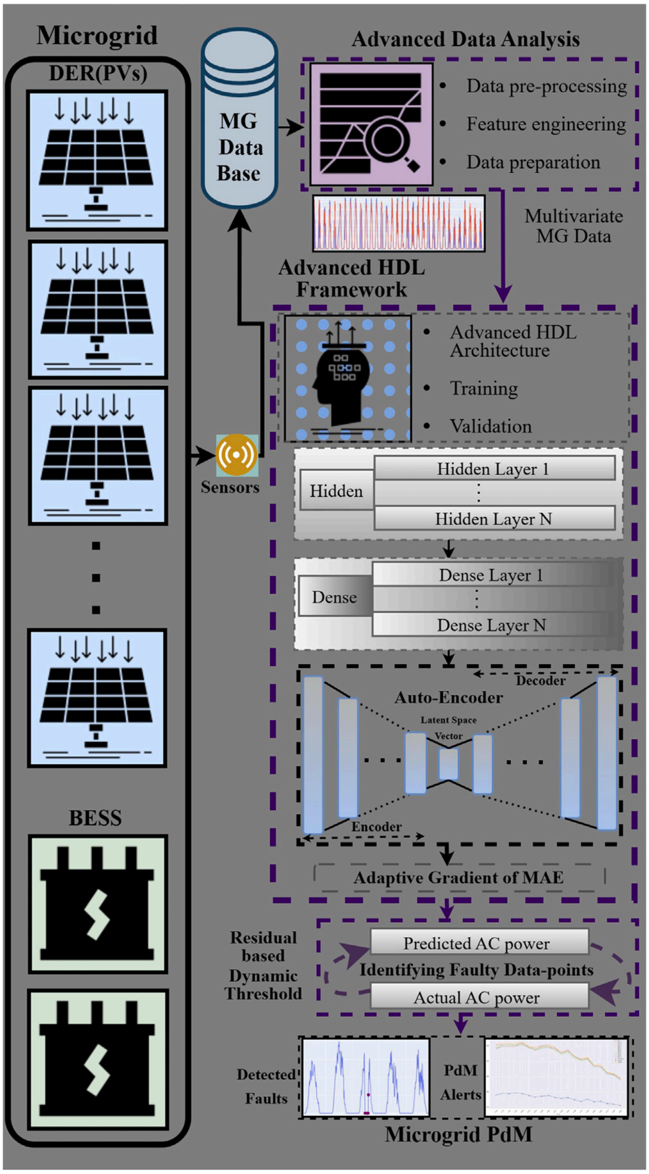


Fig. 2. Proposed advanced HDL framework for microgrid PdM.

An overview of the implemented MG dataset in this research, an advanced data analysis procedure incorporating different data assessment techniques for the required features selection and preparation of dataset, the proposed advanced HDL architecture, adaptive gradient of MAE estimation technique for the hybrid architecture, subsequently integrated with a residual based dynamic threshold framework have been described in this section. Fig. 2 illustrates the proposed structure of the advanced hybrid DL framework for MG predictive maintenance.

3.1. Data set

A microgrid dataset possessing real-world scenario has been utilized in this research. Data was collected from December 2022 for 30 days until January 2023. Diverse operational scenarios which reflect different inherent real world challenges have been incorporated into this dataset. Prime features like ambient and module temperatures, DC power produced by the DER, solar irradiation, and yielded AC power converted by the inverters were recorded that captures a real-world, complex microgrid dynamic.

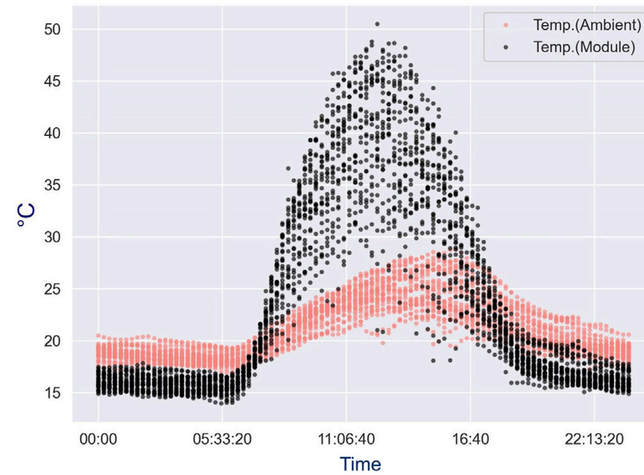


Fig. 3. Temperature assessment of the MG data.

Python programming language was utilized for this research work. Intel Core i7 with 3.00 GHz processor having 16 GB RAM on 11th Gen machine with Python 3.10 and 64-bit OS had been implemented. Different frameworks and libraries from Python, i.e., Matplotlib, TensorFlow, Pandas, scikit-learn, Keras, and NumPy had been implemented that enabled different stages of the algorithm such as data visualization and processing, data cleaning, model building, statistical analysis, and model implementation for microgrid PdM.

3.2. Advanced data analysis

For designing an accurate and robust PdM framework, the role of data analysis is crucial for ensuring the data quality, discerning underlying patterns, and identifying potential issues such as missing values, outliers, or any external factors that hinder the performance of the MG inverters. An advanced data analysis technique has been designed and integrated with this HDL framework to determine the potential problems in the MG system.

3.2.1. Temperature assessment

The module and ambient temperatures from the MG dataset have been analyzed in this step to figure out if there are any abnormal temperature fluctuations in the system which might be caused by any issues regarding poor ventilation, weather issues, or shading.

Fig. 3 illustrates the module and ambient temperature analysis carried throughout 1 month. There is no irregularity or sudden drop in the module and ambient temperatures during the day, indicating the system is getting enough sunlight. The module temperature is ranging around 25–50 °C and the ambient temperature is ranging around 20–28 °C during the day, and there is no drastic fluctuation in the data, indicating no abnormal temperature behaviour.

3.2.2. Checking for dirty arrays

This step focuses on finding if there are dirty arrays in the system. For this purpose, the irradiance received through the arrays over 1 month period during the day has been investigated. If there is any significantly reduced irradiance data during the maximum sunlight hours (11 am to 4 pm), then there might be any shading issues or potential dirt accumulation on the arrays.

Fig. 4 depicts the sunlight intensity captured through the arrays where the irradiation index ranges around 0.6–0.9 during the maximum sunlight hours and there had been no drastic fall or zero values which means the system should be receiving adequate sunlight intensity without any significant obstruction, dust, or shading.

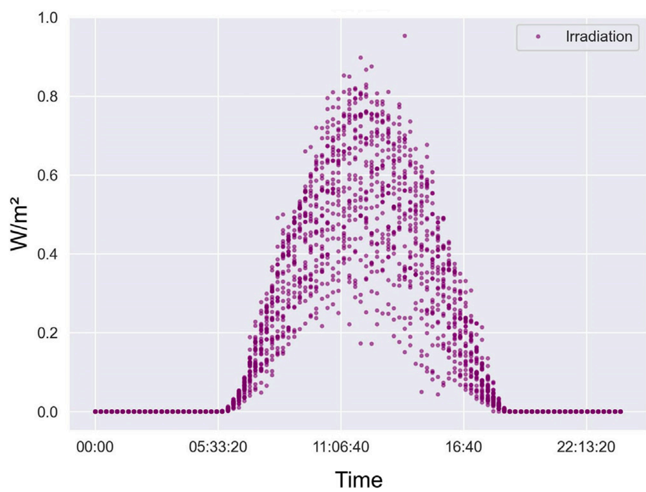


Fig. 4. Irradiation analysis from the MG data.

3.2.3. Inverter output power assessment

The converted power by the inverters has been analyzed in this step. All the data-points from the AC output of the inverters have been normalized and scaled. Fig. 5 illustrates the converted AC power by the MG inverters. It can be seen that almost all of the inverters are converting regular output power during the maximum sunlight hours. However, there have been some irregularities like 0 output power values during this time (11 am to 4 pm) when both the irradiance and temperature were high according to the previous assessments. This indicates potential fault scenarios in the inverter operations within the MG system.

Moreover, the power conversion efficiency has been analyzed on a daily basis all throughout 30 days where the conversion trend was downward most of the time with respect to the average efficiency (70.51 %) as can be seen from Fig. 6.

3.2.4. Under-performing inverter identification

In this step, all the parameters from the analysis have been utilized to identify if there is any under-performing inverter in the system. The parameters have been modeled using the following equation:

$$AC(t) = a \cdot I(t) \left[1 - b \cdot \frac{T(t) + I(t)}{800(c-20) - 25} - d \cdot \ln I(t) \right] \cdot \eta_{\text{inv}} \tag{1}$$

Here, $AC(t)$ indicates the performance of the inverters in converting to AC power, $I(t)$ denotes the irradiation values over time t, temperature has been indicated by $T(t)$, η_{inv} indicates the efficiency of the inverters, and a, b, c, d represent the model co-efficients.

Fig. 7 depicts the individual inverter performances in the MG system in terms of converting the produced power to AC. During the maximum sunlight hours, almost all the inverters are performing similarly except INV-9 which is showing some drastic fall in the converted AC power as can be seen from the figure in blue line. From the analysis, it is evident that INV-9 is losing power during the conversion. Now, the identification of the faulty operations and the generation of maintenance alerts will be investigated in depth in the next stages of this advanced HDL framework.

3.2.5. Data processing

There are plenty of features having numerous information on a raw dataset normally. All the features do not possess the information of interest always. As a result, it is very important to find the most significant features from the dataset [6] in order to minimize the training complexity and enhance the PdM performance. For this advanced HDL framework, a statistical analysis-based procedure has been deployed to find the most relevant features from the dataset. The Pearson's correlation coefficient (γ_{UV}) that represents the association between a pair of features such as U and V, has been enumerated using the following equation:

$$\gamma_{UV} = \frac{\sum (U_i - \bar{U})(V_i - \bar{V})}{\sqrt{\sum (U_i - \bar{U})^2 \sum (V_i - \bar{V})^2}} \tag{2}$$

Where,

- The individual data points from features U and V are represented by U_i and V_i respectively,
- The means of U and V are $\bar{U}$ and $\bar{V}$ respectively.

The correlations (γ_{UV}) within every pair of features U and V had been enumerated to identify the redundant features. The linear association within the features is high in terms of a higher positive value ($\gamma \approx 1$). Fig. 8 depicts the correlation (γ_{UV}) coefficients within every pair of features of the dataset. The strongest positive correlation ($\gamma_{\text{DC, AC}} = 1$) within the features DC and AC powers can be observed here. The DC power feature had been omitted consequently for the model training to minimize the model complexity through reducing multi-collinearity.

Data (X) had been prepared, scaled and divided into sequences (X_{Seq}) after that having a test size of (T_s) according to the Algorithm 1.

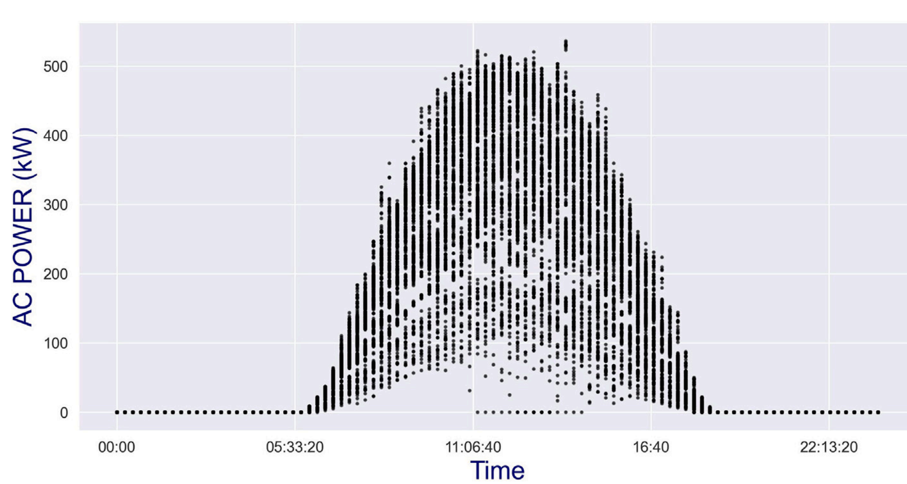


Fig. 5. AC output power analysis.

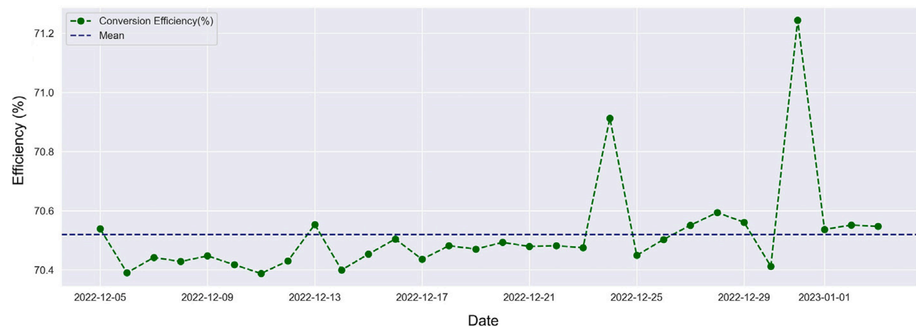


Fig. 6. Conversion efficiency analysis.

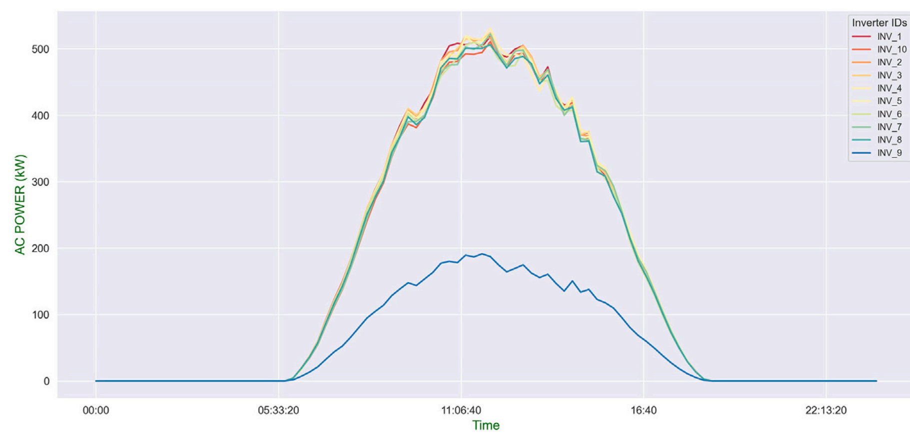


Fig. 7. Identification of under-performing inverter for microgrid PdM

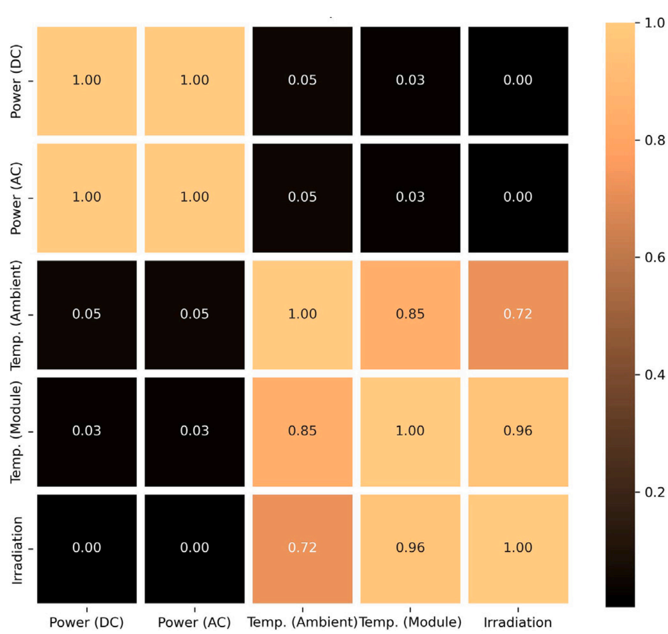


Fig. 8. Correlation heat-map of features for microgrid PdM.

Algorithm 1: Data preparation for the advanced HDL architecture of microgrid PdM.

Input: X, T, T_s

Output: $X_{\text{Train}}, X_{\text{Valid}}, X_{\text{Test}}$

$Data\ Scaling : X_{\text{Scaled}} \rightarrow (X - X.\text{min}())/(X.\text{max}() - X.\text{min}())$

$Dividing\ Data\ into\ Sequence \rightarrow X_{\text{Seq}}$

$[X_{\text{Scaled}}[i : i + T] \rightarrow X_{\text{Seq}}$ for i in range $(\text{length}(X_{\text{Scaled}}) - T + 1)]$

$Split\ Data,\ D_s \rightarrow X_{\text{Train}}, X_{\text{Valid}}, X_{\text{Test}}$

$D_s \rightarrow Train.Test.Split(X_{\text{Seq}}, T_s = 0.15)$

3.3. LSTM layer of the advanced HDL framework for microgrid PdM

LSTM layers could be an excellent avenue for the PdM application in MG systems. It is a type of neural network that is linked to the recurrent neural network (RNN) class. Having a number of layers for processing each time step, this technique has proven to be more effective than the conventional RNN because of possessing a number of layers which can process each time step more efficiently [35]. Moreover, it can retain the long-term dependencies from the diverse data-points from previous time steps. An advanced LSTM network has been tailored in this HDL framework specifically for capturing the dynamic and complicated data patterns from the AC power signals of the MG inverters.

During each time step t, the implemented advanced LSTM layer of the HDL framework processes the input X_t as well as the hidden state H_{t-1} from the prior time step for initiating new hidden state H_t, as can be seen from Fig. 9. The decision for retaining or discarding any information from the prior hidden state and the current input are managed by the input, forget, and output gates. The forget gate (G_t^f) regulates which information to eject from the prior hidden state whereas the input gate (G_t^i) along with the candidate cell state ($\tilde{C}_t$) decide what new information should be added on the current hidden state.

The equations expressing the mathematical operations in different corresponding gates and states with the utilized parameters for this advanced HDL framework have been described as follows:

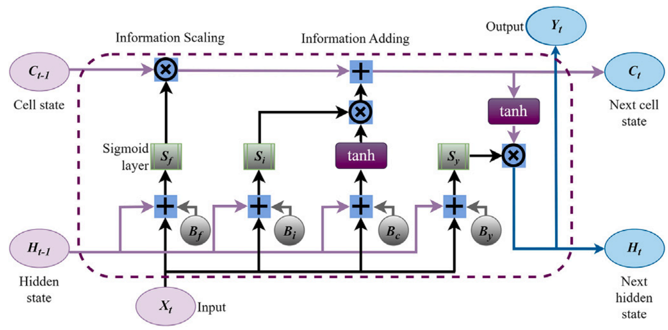


Fig. 9. LSTM layer operation of the advanced HDL framework for microgrid PdM.

$$G_t^f = S_f(M_w^f[H_{t-1}, X_t] + B_f) \tag{3}$$

Here, H_{t-1} indicates the output in time step $(t-1)$, M_w^f and B_f denote the weight matrix as well as the forget gate bias respectively, and S_1 represents the implemented sigmoid activation function for this gate.

$$G_t^i = S_i(M_w^i[H_{t-1}, X_t] + B_i) \tag{4}$$

Here, (M_w^i, B_i) denote the implemented weight matrix as well as the input gate bias respectively.

$$\tilde{C}_t = \tanh(M_w^c[H_{t-1}, X_t] + B_c) \tag{5}$$

Here, tanh represents the hyperbolic tangent activation function utilized at the candidate cell state, (M_w^c, B_c) denote the implemented weight matrix as well as the bias for candidate cell state respectively. The cell state equation is represented as follows:

$$C_t = G_t^f C_{t-1} + G_t^i \tilde{C}_t \tag{6}$$

Here, C_{t-1} is the cell state of the prior time step. In those above equations, the sigmoid activation function has been represented by S_i, the weight matrices as well as the biases of the corresponding gates have been denoted through M_w and B. The hidden state output from the previous time step was represented by H_{t-1}, the cell state and the input at the current time step have been indicated through C_t and X_t respectively.

The processing of information from the current cell state had been decided through the output gate Y_t finally. The new hidden state H_t gets enumerated after that through multiplying the cell state processed by the tanh activation function as well as the output gate. The equations for the output gate and new hidden state utilized for this advanced HDL framework have been described as follows:

$$Y_t = S_y(M_w^y[H_{t-1}, X_t] + B_y) \tag{7}$$

Here, (M_w^y, B_y) represent the implemented weight matrix as well as the output gate bias respectively. The new hidden state can be expressed by the following equation:

$$H_t = Y_t \tanh(C_t) \tag{8}$$

3.4. LSTM-AE architecture of the advanced HDL model for microgrid PdM

For enabling the unsupervised learning as well as extraction of features, an LSTM-AE architecture has been tailored into the advanced HDL framework to discern intricate, relevant-nuanced patterns from the data-points. The auto-encoder layer captures the complex temporal patterns and any subtle deviations in the output AC power of the MG inverters with a robust reconstruction of the input sequences.

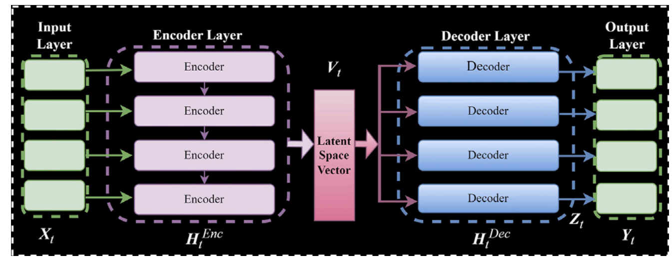


Fig. 10. Auto-encoder architecture of the advanced HDL framework for microgrid PdM.

Fig. 10 illustrates an overview of the implemented autoencoder architecture where the basic components include the input layer, encoder and decoder layer, and finally the output layer. The input layer receives the input data from the MG inverter output power signals which have already been processed through the advanced LSTM layers of the HDL model by capturing both long-term dependencies and modeling of sequential patterns.

The input data are encoded then by the encoder layer into a lower-dimensional space which is also called the latent space vector. The temporal dependencies as well as any long-term patterns from the data-points are extracted. The output from the last encoder layer is the latent space representation of the input data. The mathematical equations for the implemented auto-encoder architecture can be expressed as follows:

$$H_t^{Enc} = \mathbf{E}(H_{t-1}^{Enc}, X_t) \tag{9}$$

$$V_t = H_t^{Enc} \tag{10}$$

where, the input data is X_t, H_t^{Enc} is the hidden state of the encoder layer at time step t, and $\mathbf{E}$ indicates the function for the signals being processed by the advanced LSTM layers. V_t represents the latent space representation of the input data at time t. The latent space representation of the signal is then decoded back into the original input data-points by the decoder layer of the advanced HDL framework. The temporal dependencies and long-term patterns are then reconstructed back from the data by the following equations:

$$H_t^{Dec} = \mathbf{E}(H_{t-1}^{Dec}, Z_{t-1}) \tag{11}$$

$$Z_t = \mathbf{F}(H_t^{Dec}) \tag{12}$$

Here, H_t^{Dec} is the hidden state and Z_t is the output of the decoder layer, $\mathbf{F}$ represents a fully connected layer, and Z_t represents the reconstructed input data at time step t.

The final output of the auto-encoder architecture from the reconstructed signal is generated by the output layer, which should be similar to the input if there are no faults or deviations. The final output (Y_t) of the auto-encoder model at time step t can be represented by the following equation:

$$Y_t = Z_t \tag{13}$$

Algorithm 2 illustrates the overall architecture of the developed auto-encoder model.

Both capturing of long-term dependencies and modeling of sequential data-points have been excelled by harnessing the advanced LSTM layers in the HDL model. Finally, the auto-encoder layer of the advanced HDL algorithm enables the framework to discern the compact representations of normal operating conditions from the anomalous data-points.

Algorithm 2: Auto-encoder architecture of the advanced HDL-based MG PdM framework.

```
Encoder: LSTM followed by dense layer.
for inputs → Input(shape = (T, D)) do
    LSTM(32, activation =' relu')(inputs) → x;
    outputs → Dense(8, activation =' relu')(x);
    Encoder = Model(inputs, outputs);
end
Decoder: LSTM followed by dense layer with 'relu' activation
  function.
for Decoder inputs → Input(shape = (8, )) do
    Dense(32, activation =' relu')(Decoder inputs) → x;
    x = RepeatVector(T)(x);
    Decoder outputs → LSTM(D, return sequences = True)(x);
    Decoder = Model(Decoder inputs, Decoder outputs)
end
```

3.5. Adaptive gradient estimation of MAE

For enhancing the accuracy of the proposed advanced HDL architecture, an adaptive gradient-based optimization technique has been implemented in this work to optimize the error distribution. The error distribution has been optimized by decreasing the MAE rates between the actual and predicted data points. The advantages of both root mean square propagation and adaptive gradient descent strategies have been leveraged in this study in order to update the parameters iteratively to minimize the MAE.

Firstly, for each weight (M_w) as well as bias (B) of the proposed advanced HDL architecture, the parameters get initialized at (M_w^0) and (B^0) respectively. The first (p) and the second moments (q) get initialized to zero ($p_0 = 0, q_0 = 0$). After that, for time step t, the parameters are updated following several stages. The gradient of the MAE loss function (G_t) gets enumerated firstly ($G_t = \frac{\partial \text{mae}}{\partial M_w^t}, \frac{\partial \text{mae}}{\partial B^t}$) with respect to each parameter. The biased first moment (p_t) gets updated after that at the decaying rate (θ_1) using the following equation:

$$p_t = \theta_1 \cdot p_{t-1} + (1 - \theta_1) \cdot G_t \tag{14}$$

The biased second moment (q_t) gets updated then at the decaying rate (θ_2) according to the following equation:

$$q_t = \theta_2 \cdot q_{t-1} + (1 - \theta_2) \cdot G_t^2 \tag{15}$$

After that, the computed first and second moment estimations are bias-corrected (p_t^{corr}) and (q_t^{corr}) respectively through the following implemented equations:

$$p_t^{corr} = \frac{p_t}{1 - \theta_1^t} \tag{16}$$

$$q_t^{corr} = \frac{q_t}{1 - \theta_2^t} \tag{17}$$

Utilizing the bias-corrected moment estimations, the parameters are then updated finally according to the following equations:

$$M_w^t = M_w^{t-1} - \alpha \cdot \frac{p_t^{corr}}{\sqrt{q_t^{corr}} + \epsilon} \tag{18}$$

$$B^t = B^{t-1} - \alpha \cdot \frac{p_t^{corr}}{\sqrt{q_t^{corr}} + \epsilon} \tag{19}$$

Here, the learning rate has been represented by (α), and a constant had been implemented to prevent the division by zero which has been indicated by (ϵ).

3.6. Residual based dynamic threshold framework

For enhancing the PdM capabilities of the HDL algorithm, a residual based dynamic threshold framework has been introduced. Based on the real world microgrid data characteristics, the proposed framework can improve the PdM capabilities through adjusting the threshold point dynamically. In case of any nuanced deviations in the operational conditions, the proposed algorithm's responsiveness gets enhanced to distinguish between potentially critical faults and the normal variations more efficiently during operations with high dependence on complex external factors through this framework:

- Enumeration of Residuals: After training the proposed architecture through implementing the adaptive gradient estimation based optimization method, the converted AC power values ($\hat{z}_t$) from the inverters are predicted by the algorithm. The residuals (s_t) are enumerated to be the absolute differences between the predicted and the actual AC power values (z_t).

$$s_t = |\hat{z}_t - z_t| \tag{20}$$

- Moving Average of the Residuals: For capturing the trend in the prediction errors of the algorithm, the moving average of the residuals has been enumerated. At the time step t, the moving average of the residuals is calculated through the following equation:

$$\bar{s}_t = \beta \cdot s_t + (1 - \beta) \cdot \bar{s}_{t-1} \tag{21}$$

  Here, $\bar{s}_t$ and $\bar{s}_{t-1}$ are the moving averages of the residuals at the time steps t, and $(t-1)$ respectively and β denotes the smoothing operator.
- Standard Deviation of the Residuals: For quantifying the variableness in the prediction errors of the algorithm, the standard deviation of the residuals is calculated through the following equation:

$$\sigma_t = \sqrt{k \cdot (s_t - \bar{s}_t)^2 + (1 - k) \cdot \sigma_{t-1}^2} \tag{22}$$

  Here, σ_t and σ_{t-1} represent the standard deviations of the residuals at the time steps t, and $(t-1)$ respectively and k denotes the weighting factor.
- Enumeration of the Dynamic Threshold: Based on the standard deviation of the residuals as well as the moving averages, the dynamic threshold point at the time step t is then calculated using the following equation:

$$\tau_t = \bar{s}_t + \upsilon \cdot \sigma_t \tag{23}$$

  The threshold point gets set to be a multiple (υ) of the standard deviation (σ_t) above the moving average ($\bar{s}_t$). Here, υ represents the sensitivity of the dynamic threshold framework.
- Identification of Faults: The faults get detected finally based on if the absolute differences between the predicted and the actual AC power values exceed the dynamic threshold point (τ_t) at any time step t according to the following equation:

$$\text{MG Inverter Faults} = \begin{cases} 1 & \text{if } |\hat{z}_t - z_t| > \tau_t \\ 0 & \text{Normal} \end{cases} \tag{24}$$

This residual based dynamic threshold framework integration enhances the model's fault detection capability through remaining flexible while enabling it to be responsive to varying patterns in the converted AC power signals by the inverters. The dynamic tailoring of the threshold points based on the residuals helps the fault detection framework in adapting to changing operational conditions of real-world scenarios, enabling it more robust in terms of detecting faults within complex microgrid operations.

Algorithm 3: Advanced HDL framework for microgrid PdM.

Input: $X = \{x_1, x_2, \dots, x_t, x_N\}$ - Sequence of multivariate MG data variables; $x_t \in \mathbb{R}^p$ represents a p-dimensional vector for the time instance t

parameter: N - Total number of samples, X_i - the actual observed values from the data-points of the AC power signals, Y_i is the predicted values from the advanced HDL framework, $\bar{X}$ is the mean of the actual values, k is the weighting factor, standard deviation of the residual is σ_t

Output: Y_t →Identify encountered faults and trigger alerts for microgrid PdM

1 Identify under-performing inverter by solving:
$AC(t) = a \cdot I(t) \left[1 - b \cdot \frac{T(t)+I(t)}{800(c-20)-25} - d \cdot \ln I(t)\right] \cdot \eta_{\text{inv}}$
2 Solve Eq. (2)
3 Normalize the input data X
4 **for** $i = 1$ *to* N **do**
5 Sample a data point from X
6 Input the data point → Advanced HDL framework:
7 Solve Eqs. (3)–(8)
8 Encode the data-points using: $H_t^{Enc} = \mathbf{E}(H_{t-1}^{Enc}, X_t)$
9 Compress those into latent space vector: $V_t = H_t^{Enc}$
10 Decode and reconstruct the data-points by implementing Eqs. (11)–(13)
11 Calculate: $R^2 = 1 - \frac{\sum_{i=1}^{N}(X_i - Y_i)^2}{\sum_{i=1}^{N}(X_i - \bar{X})^2}$
12 Enumerate: $MAE = \frac{1}{N}\sum_{i=1}^{N}|X_i - Y_i|$
13 Optimize the MAE to the minimum level by solving Eqs. (14)–(19)
14 Calculate the residual values using the formula: $s_t = |\hat{z}_t - z_t|$
15 Enumerate the moving average of the residuals using the formula: $\bar{s}_t = \beta \cdot s_t + (1-\beta) \cdot \bar{s}_{t-1}$
16 Solve: $\sigma_t = \sqrt{k \cdot (s_t - \bar{s}_t)^2 + (1-k) \cdot \sigma_{t-1}^2}$
17 Enumerate the dynamic threshold: $\tau_t = \bar{s}_t + \upsilon \cdot \sigma_t$
18 **if** $|\hat{z}_t - z_t| < \tau_t$ **then**
19 Classify the data point as normal
20 **end**
21 **else**
22 Classify the data point as a fault
23 **end**
24 PdM Alerts:
25 **for** *each time step t* **do**
26 **if** $s_t > \epsilon_{er}$ **then**
27 Emergency Alert
28 **else if** $\epsilon_{sr} < s_t \le \epsilon_{er}$ **then**
29 Serious Alert
30 **else if** $\epsilon_{cr} < s_t \le \epsilon_{sr}$ **then**
31 Careful Alert
32 **end**
33 **end**
34 Return classified input as normality or fault
35 Trigger PdM alerts

3.7. Maintenance alerts

By integrating non-linear patterns from the inverter operations and temporal dependencies along with the dynamic threshold, different alert regions have been generated in this work for the predictive maintenance. The proposed advanced HDL framework is capable of reconstructing normal inverter operations, and associated deviations between the real and reconstructed signals, triggering different alerts for predictive maintenance when the relevant regions get breached.

Based on the deviations between the real and reconstructed AC signals from the inverters with respect to time steps, few alert regions are generated through the advanced HDL framework. The alerts have been highlighted depending on breaching the regions $\epsilon_{\text{cr}}, \epsilon_{\text{sr}}$, and ϵ_{er} implementing distinct colors in terms of the priority of the maintenance operations.

Maintenance alerts have been classified in the proposed advanced framework by the following equation:

$$\text{Maintenance Alerts} = \begin{cases} Careful: & \text{if } \epsilon_{\text{cr}} < s_t \le \epsilon_{\text{sr}} \\ Serious: & \text{if } \epsilon_{\text{sr}} < s_t \le \epsilon_{\text{er}} \\ Emergency: & \text{if } \epsilon_{\text{er}} < s_t \end{cases} \tag{25}$$

Here, careful, serious, and emergency regions are indicated by $\epsilon_{\text{cr}}, \epsilon_{\text{sr}}$, and ϵ_{er}, respectively. Rather than being arbitrarily assigned to static values, maintenance alerts were classified using the framework's dynamic thresholding mechanism. Historical inverter performance was analyzed through residual-based dynamic thresholding under varying external factors such as irradiance, ambient temperature, and module temperature to identify baseline deviation points for alert regions, following steps (14–32) of Algorithm 3. This time-adaptive normalization mechanism allowed the framework to scale deviation patterns dynamically, reducing false alarms during periods of low irradiance and temperature, such as late evening, night, or early morning.

To accurately reflect real-world MG inverter performance, the proposed framework's maintenance alerts were developed and tested using complex historical MG data. These alerts effectively identified inverter performance fluctuations at 15-minute intervals, prioritizing issues to assist MG maintenance operators in making informed decisions. This capability enhances system efficiency by minimizing potential downtime and failures. The framework demonstrated high accuracy when applied to retrospective MG data. Future research will explore real-time implementation, continuous performance monitoring, and automated maintenance scheduling under diverse operational conditions.

4. Results and discussion

The training of the advanced HDL algorithm for MG predictive maintenance, model compilation and evaluation has been described briefly in this section.

4.1. Model training for microgrid PdM

The proposed framework was trained over 100 epochs with a batch size of 10. A structured data-splitting approach was employed to ensure rigorous performance evaluation. The algorithm was trained on 65 % of the dataset, enabling it to learn diverse real-world operational scenarios, including variations in module and ambient temperatures, MG inverter efficiency, irradiance, and AC power fluctuations. To optimize the dynamic thresholding strategy and prevent overfitting, 20 % of the training data was allocated for validation, with early stopping applied. For an unbiased assessment of predictive accuracy, the remaining 15 % of unseen data was reserved for testing.

Fig. 11 illustrates the training as well as the validation of the proposed HDL framework for microgrid PdM incorporating the differences between the predicted values from the model and the real values. After passing through several epochs, a remarkable reduction in losses can be seen in the figure. The trained advanced HDL architecture is implemented afterward that for the model compilation to identify the anomalies in the AC power signals of MG inverters, and generate different alerts for maintenance based on their operations.

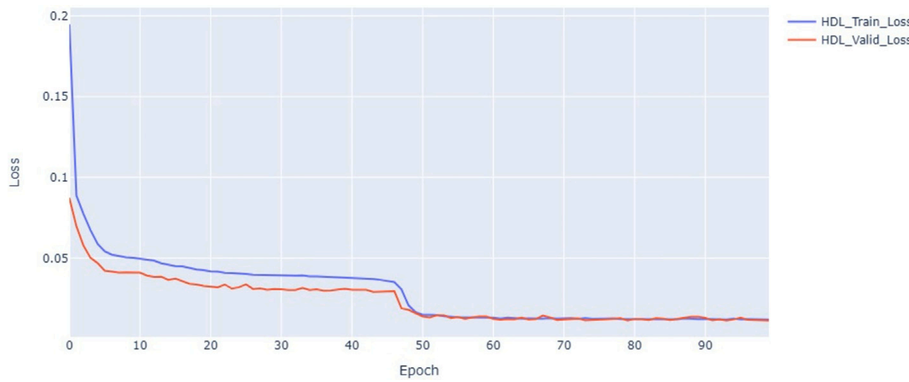


Fig. 11. Training and validation of the advanced HDL framework.

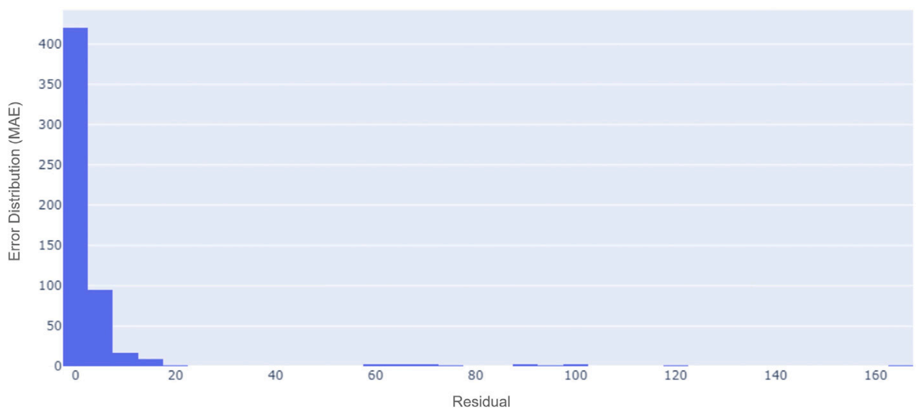


Fig. 12. Gradient-based optimization of MAE distribution function.

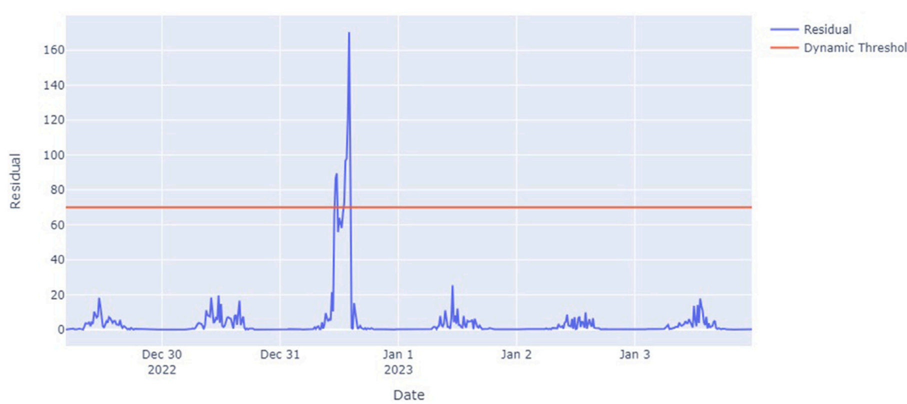


Fig. 13. Residual-based dynamic threshold for fault detection.

4.2. Compilation and evaluation of the advanced HDL model

The developed advanced HDL model is directed towards the parameter space effectively. The error distribution of the algorithm is optimized through a gradient-based minimization of the MAE rates between the actual and predicted data points of the MG inverter power signal from the advanced HDL framework as can be seen from Fig. 12.

Fig. 13 illustrates the integration of the residual-based dynamic thresholding method within the advanced HDL framework. On December 31, 2022, faulty signal peaks—residual values exceeding 160—were identified from the MG inverter outputs. These peaks correspond to faulty or under-performing operations, consistent with the pattern observed in Fig. 12, where error distribution was minimized. Based on this, the algorithm dynamically calculates the residual threshold by analyzing deviations from normal operational behavior. Faulty signal points are then detected, and under-performing operations are classified within residual-based alert regions, as defined by Eqs. (24) and (25).

Figs. 14–17 demonstrate the MG inverter faults detected on December 31, 2022, using the advanced HDL framework. The encountered faults had been identified with the specific inverter number and time-frame of the encountered faults from the real AC signals by the proposed framework denoted through the purple dotted points that occurred on 31/12/22 from the MG dataset. It can be seen that the faults encountered on 31st December 2022 from the time-frame 11.15 am to

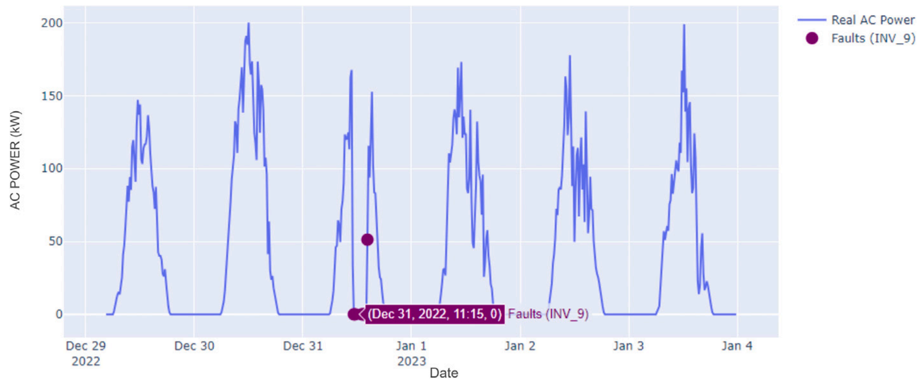


Fig. 14. Detected fault (INV-9) at 11.15 am.

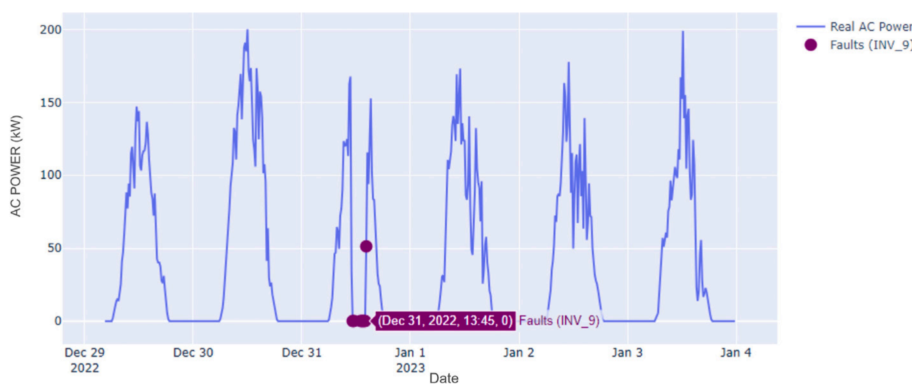


Fig. 15. Detected fault (INV-9) at 1.45 pm.

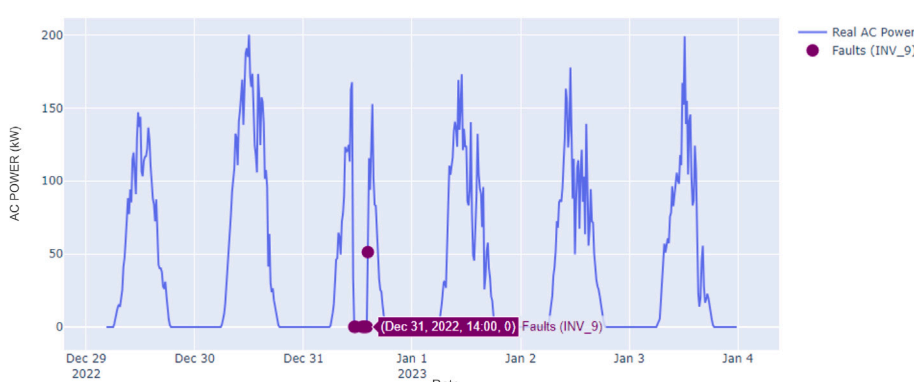


Fig. 16. Detected fault (INV-9) at 2.00 pm.

1.45 pm, then 2.00 pm to 2.15 pm during the peak solar production hours by the inverter 9.

Fig. 18 further shows how the algorithm generates alert regions, focusing on predictive maintenance (PdM) during peak solar production hours (11 AM to 4 PM). It also effectively avoids false alarms during periods of low irradiance and temperature. The alert regions—classified according to residual thresholds defined in steps 24–32 of Algorithm 3—are visually represented using light orange, purple, and red rectangles, indicating careful, serious, and emergency PdM events, respectively.

Finally, the framework issues PdM alerts at 15-minute intervals whenever residual points breach their corresponding alert thresholds, allowing real-time monitoring and response throughout the inverter's operation. Fig. 19 depicts the maintenance alerts for all inverter operations during the maximum sunlight hours based on breaches in the regions. Here, the orange, purple, and red dots indicate the careful, serious, and emergency alerts for PdM respectively. It can be seen that one careful alert (orange dot) was generated for INV-8 at 3.45 pm, and all the careful, serious, and emergency alerts were triggered for INV-9 during the maximum sunlight hours at each time step according to the priority based on the generation performance.

For evaluation, the R-squared (R^2) score as well as mean absolute error (MAE) matrices are implemented in this work to assess the performances of the proposed advanced HDL framework for microgrid PdM. The evaluation matrices are calculated through the equations as follows:

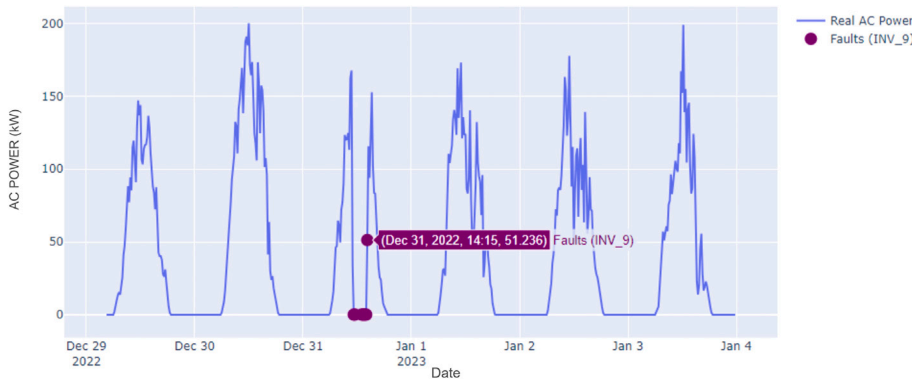


Fig. 17. Detected fault (INV-9) at 2.15 pm.

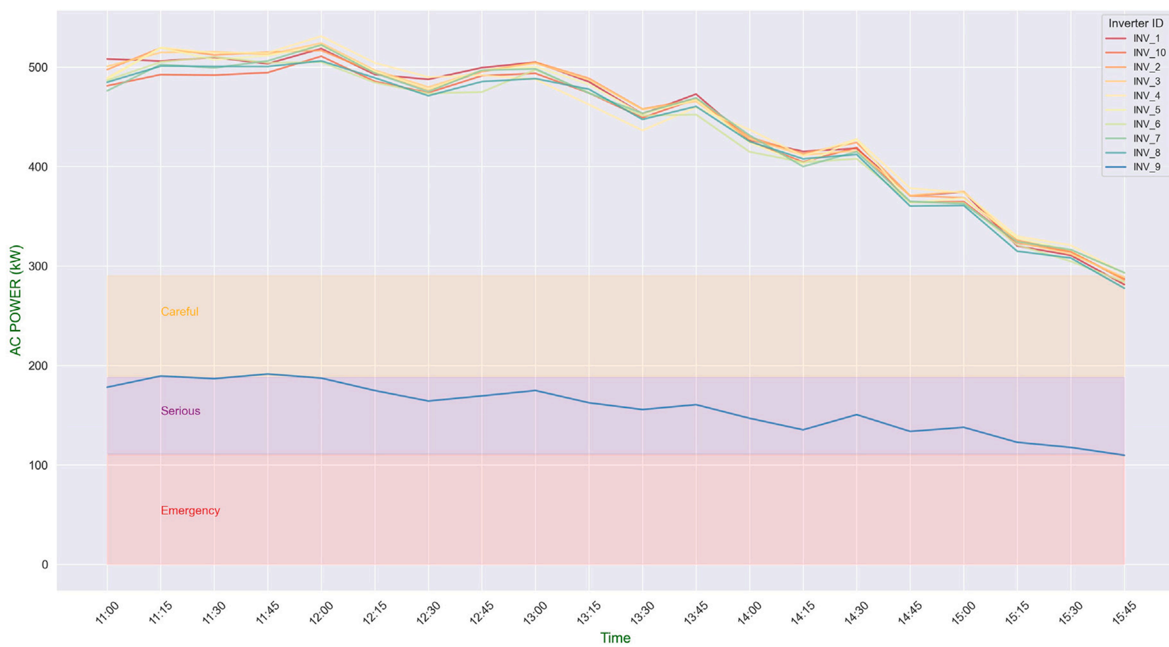


Fig. 18. Priority based PdM alert regions.

$$R^2 = 1 - \frac{\sum_{i=1}^{N} (X_i - Y_i)^2}{\sum_{i=1}^{N} (X_i - \bar{X})^2} \tag{26}$$

$$MAE = \frac{1}{N} \sum_{i=1}^{N} |X_i - Y_i| \tag{27}$$

Where, total number of samples has been denoted by N. X_i indicates the actual values from the data-points of the AC power signals, $\bar{X}$ represents the mean of the actual values, and the predicted values from the advanced HDL framework have been denoted by Y_i.

4.3. Discussion

The developed advanced HDL architecture has shown outstanding performance in the context of detecting MG inverter faults and generating the maintenance alerts for PdM. The proposed model had been implemented with a careful training and evaluation procedures. The advanced HDL framework attained an R^2 value of 0.992 and MAE score of 3.246, respectively. Table 1 enlists the proposed advanced HDL model's performance with respect to the traditional RNN, gated recurrent unit (GRU), and LSTM techniques where it can be seen that the proposed framework outperforms the RNN, GRU, and LSTM models in terms of detecting faults and generating maintenance alerts for the PdM scenarios of MG inverter operations.

The traditional DL-based methods provided a good performance for microgrid PdM scenarios but still have few limitations especially for RNN, during processing the diverse MG data to capture long-term dependencies. Being capable of tackling gradient vanishing concerns, GRU method scored a lower MAE and higher R^2, yielding a better performance than the RNN technique. GRU method could be more competent for predictive maintenance applications with a better ability to capture temporal dependencies from the diverse MG data. LSTM technique performed better providing a higher R^2 and lower MAE score than the RNN and GRU methods which makes it more efficient for microgrid PdM applications.

DL-based methods performed well but still possess few limitations for handling diverse large scale MG data which resonates with the demand for more advanced hybrid approaches including advanced memory capacity along with enhanced capabilities to capture temporal

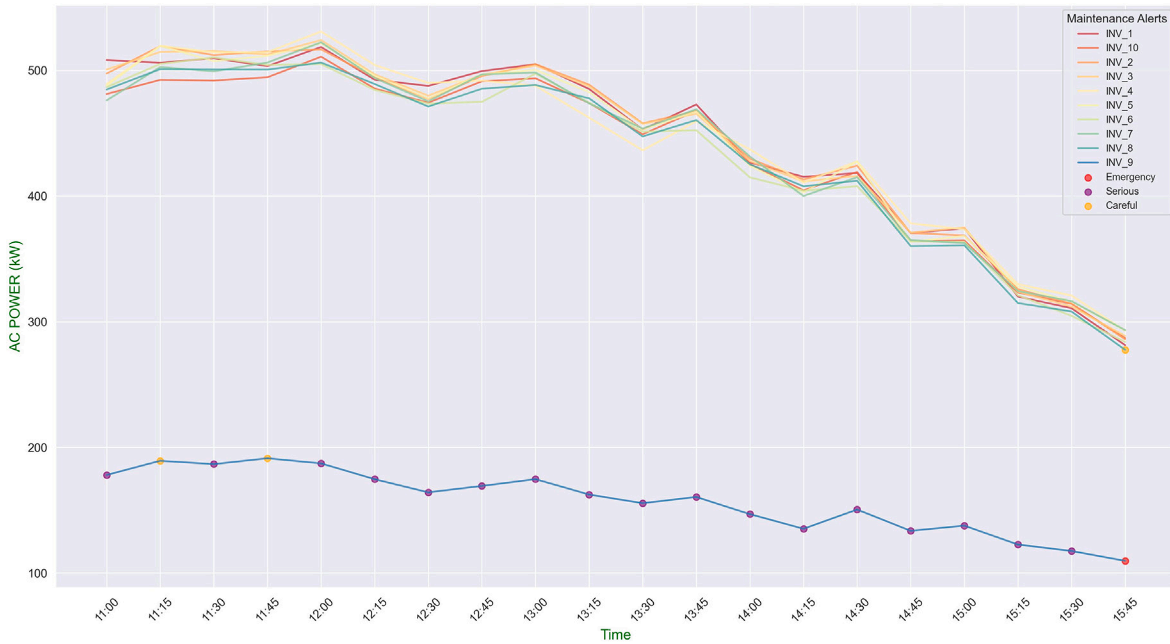


Fig. 19. Triggered alerts for PdM operations.

Table 1
Permormance evaluation of the proposed HDL framework.

Models	R^2 score	MAE value
GRU	0.937	12.545
LSTM	0.949	11.847
RNN	0.911	15.188
Proposed framework	0.992	3.246

patterns. The proposed advanced HDL technique leveraged both advanced LSTM architecture and autoencoders which enabled a remarkable performance through capturing temporal patterns as well as reconstructing the input sequences properly along with learning the compact attributes of normal condition. The developed advanced HDL framework achieved higher performance than other counterparts. Algorithm 3 illustrates the developed PdM framework of the proposed advanced HDL architecture to predict the maintenance needs within MG system.

5. Concluding remarks

The advanced HDL-based framework developed in this work for microgrid PdM achieved an outstanding R^2 score of 0.992 and MAE of 3.246, demonstrating the framework explains 99.2 % of the variance in the data, indicating a noteworthy accuracy in discerning the underlying patterns for identifying faults and generating PdM alerts from the multi-sensor MG data. Moreover, the low MAE score 3.246 demonstrates the precision of the algorithm, as it indicates the average absolute difference between the actual and predicted values, signifying minimal predictive errors.

This highlights the efficacy and robustness of the developed framework in handling multi-sensor, complex MG datasets which can be a significant tool in the context of advancing future research in this emerging domain. This study also progresses the advanced HDL-based avenues for PdM applications in complex MG scenarios. By integrating advanced data analysis, residual-based dynamic threshold framework, optimizing the algorithm's error distribution function, and generating different priority based alerts, the proposed framework can pave the way towards more enhanced PdM techniques for MG networks.

Hybrid advanced DL algorithms have promising applicability but still possess few challenges in the context of generalization and scalability concerns regarding large-scaled diverse MG scenarios. There are some challenges despite the success of this work. One of the crucial challenges that might impact the performance and generalization capability of the algorithm involves the complexity of model design and hyperparameter tuning. Integrating more data from other factors, such as variations in MG topology, module aging, load profiles, cloud cover, and energy sources, can further enhance the generalizability of the algorithm. Moreover, substantial computational resources might be required for practical implications in terms of complex, large-scale MGs for algorithm training and inference. Addressing these limitations, scalability issues, implementation in real-time, and integration of multiple data sources from diverse MG operational scenarios will be explored in future studies.

CRediT authorship contribution statement

M.Y. Arafat: Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **M.J. Hossain:** Writing – review & editing, Supervision, Resources, Project administration, Investigation.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The authors do not have permission to share data.

References

[1] M. Mishra, B. Patnaik, M. Biswal, S. Hasan, R.C. Bansal, A systematic review on DC-microgrid protection and grounding techniques: issues, challenges and future perspective, Appl. Energy 313 (2022) 118810.
[2] A. Gupta, S. Doolla, K. Chatterjee, Hybrid AC–DC microgrid: systematic evaluation of control strategies, IEEE Trans. Smart Grid 9 (4) (2017) 3830–3843.
[3] A. Bedawy, N. Yorino, K. Mahmoud, Y. Zoka, Y. Sasaki, Optimal voltage control strategy for voltage regulators in active unbalanced distribution systems using multi-agents, IEEE Trans. Power Syst. 35 (2) (2019) 1023–1035.

[4] A. Bhatt, W. Ongsakul, J.G. Singh, et al, Sliding window approach with first-order differencing for very short-term solar irradiance forecasting using deep learning models, Sustain. Energy Technol. Assess. 50 (2022) 101864.

[5] T. Wang, C. Zhang, Z. Hao, A. Monti, F. Ponci, Data-driven fault detection and isolation in DC microgrids without prior fault data: a transfer learning approach, Appl. Energy 336 (2023) 120708.

[6] M.Y. Arafat, M.J. Hossain, M.M. Alam, Machine learning scopes on microgrid predictive maintenance: potential frameworks, challenges, and prospects, Renew. Sustain. Energy Rev. 190 (2024) 114088.

[7] P.K. Dash, S.R. Pattnaik, E.N. Prasad, R. Bisoi, Detection and classification of DC and feeder faults in DC microgrid using new morphological operators with multi class AdaBoost algorithm, Appl. Energy 340 (2023) 121013.

[8] W. Yu, T. Dillon, F. Mostafa, W. Rahayu, Y. Liu, A global manufacturing big data ecosystem for fault detection in predictive maintenance, IEEE Trans. Ind. Inf. 16 (1) (2019) 183–192.

[9] A. Jaenal, J.-R. Ruiz-Sarmiento, J. Gonzalez-Jimenez, Machnet, a general deep learning architecture for predictive maintenance within the industry 4.0 paradigm, Eng Appl Artif Intel 127 (2024) 107365.

[10] O. Alshboul, R.E. Al Mamlook, A. Shehadeh, T. Munir, Empirical exploration of predictive maintenance in concrete manufacturing: harnessing machine learning for enhanced equipment reliability in construction project management, Comput. Ind. Eng. 190 (2024) 110046.

[11] O. Dayo-Olupona, B. Genc, T. Celik, S. Bada, Adoptable approaches to predictive maintenance in mining industry: an overview, Resour. Policy 86 (2023) 104291.

[12] H. Zhou, Q. Liu, H. Liu, Z. Chen, Z. Li, Y. Zhuo, K. Li, C. Wang, J. Huang, Healthcare facilities management: a novel data-driven model for predictive maintenance of computed tomography equipment, Artif. Intell. Med. 149 (2024) 102807.

[13] M. Ejlali, E. Arian, S. Taghiyeh, K. Chambers, A.H. Sadeghi, E. Taghiye, D. Cakdi, R.B. Handfield, Developing hybrid machine learning models to assign health score to railcar fleets for optimal decision making, Expert Syst. Appl. 250 (2024) 123931.

[14] M.S. Nazir, F.M. Almasoudi, A.N. Abdalla, C. Zhu, K.S.S. Alatawi, Multi-objective optimal dispatching of combined cooling, heating and power using hybrid gravitational search algorithm and random forest regression: towards the microgrid orientation, Energy Rep. 9 (2023) 1926–1936.

[15] S. Tajjour, S.S. Chandel, A comprehensive review on sustainable energy management systems for optimal operation of future-generation of solar microgrids, Sustain. Energy Technol. Assess. 58 (2023) 103377.

[16] P. Wu, X. Mei, Microgrids energy management considering net-zero energy concept: the role of renewable energy landscaping design and iot modeling in digital twin realistic simulator, Sustain. Energy Technol. Assess. 63 (2024) 103621.

[17] R. Rashidi, A. Hatami, M. Abedini, Multi-microgrid energy management through tertiary-level control: structure and case study, Sustain. Energy Technol. Assess. 47 (2021) 101395.

[18] D.T. Ramotsoela, G.P. Hancke, A.M. Abu-Mahfouz, Practical challenges of attack detection in microgrids using machine learning, J. Sens. Actuator Netw. 12 (1) (2023) 7.

[19] N. Kumari, A. Sharma, B. Tran, N. Chilamkurti, D. Alahakoon, A comprehensive review of digital twin technology for grid-connected microgrid systems: state of the art, potential and challenges faced, Energies 16 (14) (2023) 5525.

[20] N. Bayati, E. Balouji, H.R. Baghaee, A. Hajizadeh, M. Soltani, Z. Lin, M. Savaghebi, Locating high-impedance faults in DC microgrid clusters using support vector machines, Appl. Energy 308 (2022) 118338.

[21] P. Pan, R.K. Mandal, Learning approach based DC arc fault location classification in DC microgrids, Electric. Power Syst. Res. 208 (2022) 107874.

[22] J.O.C.P. Pinto and M. Moreto, Protection strategy for fault detection in inverter-dominated low voltage AC microgrid, Electric. Power Syst. Res. 190 (2021) 106572.

[23] S.F. Zarei, M. Parniani, A comprehensive digital protection scheme for low-voltage microgrids with inverter-based and conventional distributed generations, IEEE Trans. Power Deliv. 32 (1) (2016) 441–452.

[24] S.F. Zarei, H. Mokhtari, F. Blaabjerg, Fault detection and protection strategy for islanded inverter-based microgrids, IEEE J. Emerg. Sel. Top. Power Electron. 9 (1) (2019) 472–484.

[25] R. Bhargav, B.R. Bhalja, C.P. Gupta, Novel fault detection and localization algorithm for low-voltage DC microgrid, IEEE Trans. Ind. Inf. 16 (7) (2019) 4498–4511.

[26] F. Zhang, L. Mu, A fault detection method of microgrids with grid-connected inverter interfaced distributed generators based on the PQ control strategy, IEEE Trans. Smart Grid 10 (5) (2018) 4816–4826.

[27] D.P. Mishra, S.R. Samantaray, G. Joos, A combined wavelet and data-mining based intelligent protection scheme for microgrid, IEEE Trans. Smart Grid 7 (5) (2015) 2295–2304.

[28] J.Q. James, Y. Hou, A.Y.S. Lam, V.O.K. Li, Intelligent fault detection scheme for microgrids with wavelet-based deep neural networks, IEEE Trans. Smart Grid 10 (2) (2017) 1694–1703.

[29] A. Abdali, K. Mazlumi, R. Noroozian, High-speed fault detection and location in DC microgrids systems using multi-criterion system and neural network, Appl. Soft Comput. 79 (2019) 341–353.

[30] S.M. Nosratabadi, R.-A. Hooshmand, E. Gholipour, A comprehensive review on microgrid and virtual power plant concepts employed for distributed energy resources scheduling in power systems, Renew. Sustain. Energy Rev. 67 (2017) 341–363.

[31] L.P. Van, K. Do Chi, T.N. Duc, Review of hydrogen technologies based microgrid: energy management systems, challenges and future recommendations, Int. J. Hydrogen Energy 48 (38) (2023) 14127–14148.

[32] W. Zhang, D. Yang, H. Wang, Data-driven methods for predictive maintenance of industrial equipment: a survey, IEEE Syst. J. 13 (3) (2019) 2213–2227.

[33] D. Zhang, G. Hu, J. Song, H. Gao, H. Ren, W. Chen, A novel spatio-temporal wind speed forecasting method based on the microscale meteorological model and a hybrid deep learning model, Energy 288 (2024) 129823.

[34] D. Guha, R. Chatterjee, B. Sikdar, Anomaly detection using LSTM-based variational autoencoder in unsupervised data in power grid, IEEE Syst. J. 17 (3) (2023) 4313–4323.

[35] Y. LeCun, Y. Bengio, G. Hinton, Deep learning, Nature 521 (7553) (2015) 436–444.