Artificial Intelligence-Based Predictive Maintenance of Microgrids

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Certificate of Original Authorship

I, Md Yeasir Arafat, declare that this thesis is submitted in fulfilment of the requirements for the award of Doctor of Philosophy, in the *School of Electrical & Data Engineering (SEDE)*, *Faculty of Engineering & Information Technology (FEIT)* at the University of Technology Sydney (UTS), Australia.

This thesis is wholly my own work unless otherwise referenced or acknowledged. In addition, I certify that all information sources and literature used are indicated in the thesis. This document has not been submitted for qualifications at any other academic institution.

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Abstract

The increasing complexity of microgrids demands sophisticated strategies for improved maintenance and reliable operation. The integration of artificial intelligence (AI) in microgrids allows for the analysis of system performance, anomaly detection, and malfunction identification, enhancing predictive maintenance capabilities and sustainable decision-making. To improve system reliability and performance, accurate fault identification in microgrids is becoming crucial for enhanced predictive maintenance of microgrids.

The first study presents advanced frameworks for microgrid predictive maintenance by performing a comprehensive correlative analysis of advanced recurrent neural network (RNN) architectures, i.e., RNNs, Long Short-Term Memory (LSTM), and Gated Recurrent Units (GRUs) for photovoltaic (PV) based dc microgrids. An algorithm is developed to detect faulty operations of inverters which is indispensable for ensuring the reliability and sustainability of distributed energy resources (DERs) in modern microgrid systems. The performances of the developed advanced models have been compared with the conventional RNN-based techniques. Results demonstrate strong predictive capabilities of all, with the proposed advanced LSTM method outperforming RNN, GRU, and the traditional techniques.

The second study introduces an intelligent data-driven hybrid fault detection framework for microgrid predictive maintenance utilizing an advanced hybrid deep learning (HDL) architecture, combined with advanced data analysis and a residual-based dynamic threshold technique. An adaptive gradient technique is employed to optimize the loss function of the proposed hybrid algorithm for microgrid predictive maintenance. The results show significant accuracy in fault identification for predicting the maintenance needs within microgrids. This research offers valuable insights for designing and enhancing hybrid algorithms for fault detection in microgrid systems, contributing to advancements in predictive maintenance technology and promoting a resilient and cost-effective microgrid operation.

The third study proposes a smart predictive maintenance framework for addressing the critical research problems of accurately classifying DER operational states with maintenance alerts and assessing the annual capacity degradation for enhanced predictive maintenance capabilities of complex industrial microgrid scenario by coupling a novel power-aware adaptive kernel function

with a hybrid Wiener-GRU degradation algorithm. The overall accuracy of 99% demonstrates the excellent performance of the proposed framework which can allow early identification of performance degradation, enabling proactive scheduling for the maintenance actions which can ensure enhanced reliability, reduced maintenance costs, and improved operational efficiency in complex microgrid networks.

Keywords: Artificial Intelligence (AI), Microgrid (MG), Predictive Maintenance, Inverters, Distributed Energy Resources, Fault Detection, Hybrid Deep Learning, Intelligent Hybrid Degradation Algorithm, DER Capacity Degradation.

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List of Abbreviations

AI	Artificial Intelligence
ANN	Artificial Neural Network
BESS	Battery Energy Storage System
CBM	Condition Based Maintenance
CNN	Convolutional Neural Network
CSP	Concentrated Solar Plant
DCNN	Deep Convolutional Neural Network
DERs	Distributed Energy Resources
DFIG	Doubly Fed Induction Generators
DL	Deep Learning
DN	Distribution Networks
ESG	Environmental, Social, and Governance
FC	Fuel Cell
FN	False Negatives
FP	False Positives
GMM	Gaussian Mixture Models
GPG	Gas Powered Generator
GRU	Gated Recurrent Unit
HDL	Hybrid Deep Learning
IBRs	Inverter Based Resources
IoT	Internet of Things
IQRT	Interquartile Range Technique
LSTM	Long Short-Term Memory
LV	Low Voltage
MAE	Mean Absolute Error
MG	Microgrid
ML	Machine Learning

MLPNN	Multi Layer Perceptron Neural Network
PdM	Predictive Maintenance
PMU	Phasor Measurement Units
PV	Photovoltaic
PVS	Photovoltaic System
RF	Random Forest
RES	Renewable Energy Sources
RNN	Recurrent Neural Network
RTU	Remote Telemetry Units
RUL	Remaining Useful Life
SCADA	Supervisory Control and Data Acquisition
SDGs	Sustainable Development Goals
SoC	State of Charge
SoD	State of Discharge
SoH	State of Health
SPV	Solar Photovoltaic
SVM	Support Vector Machine
TN	True Negatives
TP	True Positives
UN	United Nations
WAMS	Wide Area Monitoring Systems
WT	Wind Turbine

Chapter 1

Introduction

1.1 Background

The increasing demand for renewable energy sources has led to the development of microgrid systems that enable the integration of various renewable energy sources into the power grid [1]. A microgrid is a small-scale power system that can operate independently or in conjunction with the main power grid. The microgrid is comprised of distributed energy resources (DERs) such as solar photovoltaic (SPV) systems, fuel cells (FCs), wind turbines, gas powered generators (GPGs), battery storage that can generate and store electricity.

Several challenges are faced by the main power grid at present regarding the implementation of energy storage devices at the grid level, through integrating complex DER for instance FCs, GPGs, SPVs, and specifically through the utilization of power electronic devices on a large scale at many electric grid levels as well as interconnecting between prosumers and microgrids.

In addition, the power grid might undergo through different disturbances which could result in a fault or even lead to catastrophic damage on any rare circumstances. Harmonics generation, grounding, load variations, wiring issues, and switching transients [2], [3] are some examples of these disturbances. As a result, the significance of real time power grid condition monitoring as well as deployment of predictive maintenance algorithm gets justified by these constraints. Consequently, the development and implementation techniques on power system condition monitoring possessing efficient and ubiquitous communication, identification of problems at the root level, classification of disturbances and fault diagnosis have become significant topics to the engineers and researchers of both academia and industry.

Due to the increasing number of demand as well as implementation of nonlinear loads in the power system, the network of power system is becoming more complex than previous. This issue regarding network complexity could be reduced through utilizing microgrids (MGs) possessing proper predictive maintenance measures. Microgrids are a power supply system (small-scale) that possesses loads, energy storage, and distributed generations (DGs) [4]. In accordance with the revolutionary advancement of

modern technology, in the near future, it is expected that an increasing number of microgrids will be connected to the distribution networks (DN). The prime motto of microgrids consists of supporting the high penetration of renewable energy, improving the reliability of DN, enhancing the generation efficiency in a sustainable power grid, and offering islanding operability [5]. Figure 1.1 depicts the architecture of a microgrid system that comprises of wind turbine (WT), solar photovoltaic (PV) system as the DERs, some local loads, and BESS.

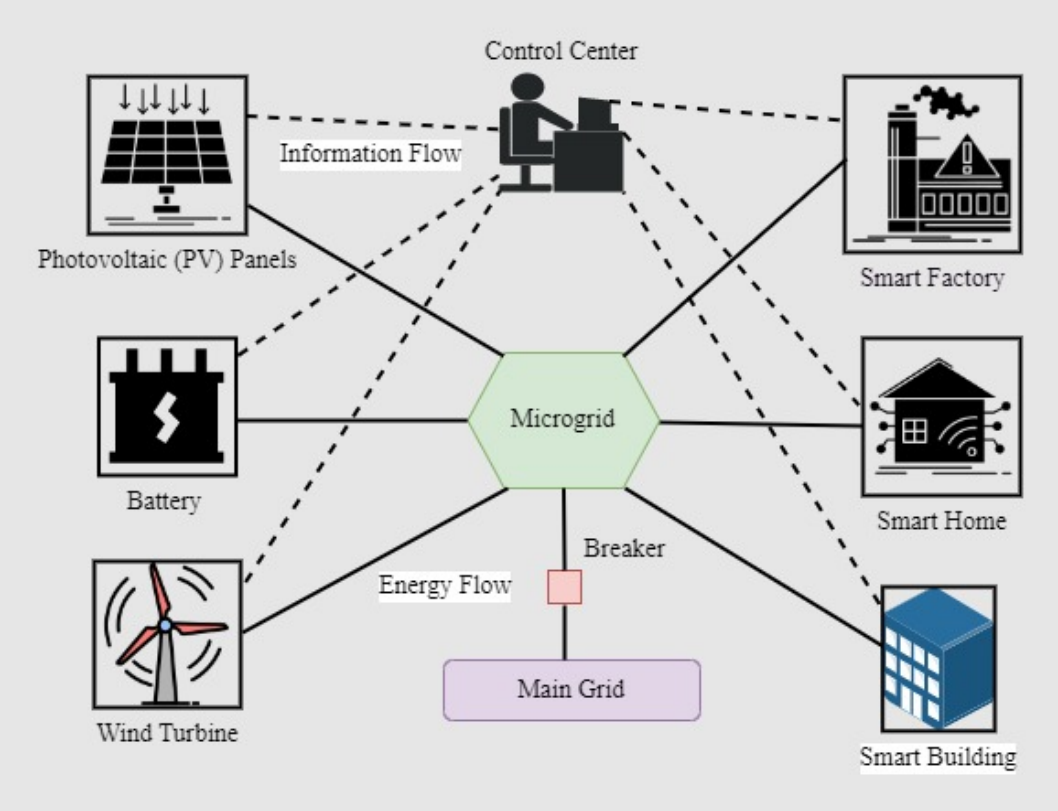


Figure 1.1: **Overview of a microgrid system.**

DERs work as the primary source of providing electricity in a microgrid, encircling several small-scale generation sources. These can comprise solar PVs, wind turbines for generating clean energy. The BESS plays a vital role in the microgrid operation by storing the generated surplus energy during low demand. These systems could be discharged when renewable sources are unavailable, or throughout the peak demand; ensuring a steady power source. Inverters work as the heart of the microgrid system through converting the DC power stored in BESS, and produced by the DERs into AC suitable for the main grid and consumer usage. Inverters also perform a significant role of regulating the frequency and voltage, ensuring a steady and reliable power supply. Consequently, it has become crucial to ensure the efficient, reliable operation of both DERs and inverters within the microgrid network for a sustainable and resilient power flow.

Predictive maintenance has emerged as a significant aspect of microgrid operations as it enables identifying potential equipment failures in advance, reducing downtime, and increasing the overall efficiency of the system. Machine learning-based techniques have a great potential to be effective in improving the accuracy of failure predictions, detecting, and diagnosing faults in real-time, and monitoring

the health and remaining useful life of microgrid components. The integration of these techniques with microgrid components can lead to reduced downtime, improved safety, overall efficiency, and sustainability.

This chapter discusses the background, research motivation & gaps, the main objectives as well as the contributions of this thesis focused on the advanced machine learning-based predictive maintenance applications for microgrid systems. This thesis provides a comprehensive review of the state-of-the-art machine learning techniques that could be used for microgrid predictive maintenance and highlights the gaps and challenges that need to be addressed. Besides, advanced deep learning based models and their correlative performance analysis, intelligent hybrid deep learning based architecture with optimized error distribution function based on advanced data analytics for the predictive maintenance of microgrid inverters, and microgrid DERs power signal analysis based advanced machine learning architecture for classifying the priority based maintenance operations and forecasting of future power capacity based on Wiener degradation model integrated advanced deep learning architecture have been introduced in this thesis. This study also suggests future research directions in the field and frameworks to improve predictive maintenance using machine learning for microgrid industries.

1.2 Research Motivation and Gaps

Significant challenges are emerging because of integrating the microgrid into DN through the dynamic variances of different energy sources and the limitations of operating conditions. Issues like system instability, high losses, and voltage rises can be ignited through improper operation and allocation of microgrid [6]. To ensure the reliable and efficient operation of the microgrid, maintenance is a crucial aspect that needs to be considered. Maintaining the stability and reliability of microgrid systems can be challenging, given the diverse sources of energy and the complexities associated with their integration. Traditional maintenance approaches, such as corrective and preventive maintenance, are insufficient in addressing the maintenance needs of microgrid systems. These methods rely heavily on periodic inspection and scheduled maintenance, which can be costly, time-consuming, and not very effective.

Predictive maintenance is one approach that has gained significant attention due to its ability to predict equipment failure before it occurs. This approach involves using data from various sensors and analyzing it to identify patterns that indicate potential equipment failures. The quality of production as well as control, costs and the downtime of a system or machine could be enhanced through utilizing the contribution of performing predictive maintenance. Predictive maintenance is domain knowledge and models which generally is historic data-based. Related trends, correlations, and behaviour patterns could be predicted through machine learning or statistical models in predictive maintenance in order to get ahead of awaiting failures in advance. Thus, the decision-making process could be enhanced for the maintenance activity mainly to avoid the downtime.

In present times, most of the researched topics on microgrid are focused on the economic dispatching [7], [8]. Research needs to be conducted on the predictive maintenance which is an essential tool for ensuring the reliability and efficiency of microgrids. Machine learning techniques could be a promising

medium in predictive maintenance due to their ability to handle large amounts of data and extract useful information. By using data and machine learning techniques to predict equipment failures, predictive maintenance is capable of allowing for the proactive identification of potential equipment failures, reducing downtime, increasing the overall efficiency of the system, extending equipment life, and improving safety. Additionally, it can lead to significant cost savings by reducing the need for expensive repairs or replacements, and unnecessary scheduled maintenance. Through the integration of sensors and IoT devices, machine learning techniques can further enhance the capabilities of predictive maintenance of microgrids.

Machine learning-based predictive analytic has been applied to various industries, including manufacturing [9], [10], transportation [11], [12], [13], [14], [15], and healthcare [16], [17], [18], [19]. However, its application in the microgrid system is still relatively new and requires further exploration. The research motivation behind the use of machine learning in predictive maintenance of microgrid is to develop effective maintenance strategies that can improve the reliability, performance, and safety of the system while reducing maintenance costs. The use of machine learning algorithms can analyze large amounts of data from various sources, identify potential faults in the system, and adapt to changes in the system, making them more accurate and effective in predicting potential faults. The implementation of machine learning in predictive maintenance of microgrid can lead to significant cost savings, improve the safety of the system, and improve the overall performance of the system. The increasing adoption of renewable energy sources in microgrids has increased the complexity of the system, making the use of machine learning algorithms even more critical in ensuring reliable operation.

1.3 Research Objectives

For addressing the challenges in the intelligent predictive maintenance operations of microgrid inverters and DER, this thesis will focus on the three key objectives as well as the core aims of each objectives as follows:

- **Objective 1:** Carry out a correlative study of key monitoring deep learning models applied to predictive maintenance in the context of microgrid inverters.

  Aims:

  - Highlighting the need for an effective and reliable predictive maintenance framework to ensure the optimal performance of the microgrid.
  - Conducting an extensive analysis of the importance and implementation of deep learning-based techniques for fault detection of microgrid inverters.
  - Exploring the comprehensive overview of the key steps involved in building advanced RNN, GRU, and LSTM-based predictive maintenance framework for microgrid.
  - Analysing different DL-based techniques critically for gaining insights into the strengths and weaknesses of various techniques and selecting the most appropriate one depending on the specific application.

- Exploring their correlative performance in terms of a complex real-world microgrid scenario.

- **Objective 2:** To design an intelligent hybrid framework integrated advanced data analytics for predictive maintenance of microgrid inverters with respect to complex exogenous factors.

  Aims:

  - Exploring the potential of intelligent hybrid DL-based techniques for improving predictive maintenance performance for microgrid inverters.
  - Developing a novel technique that can leverage advanced data analytics to achieve higher accuracy with respect to complex exogenous factors for identifying the maintenance needs of microgrid inverters.
  - Investigating the design considerations and requirements specific to the system parameters for generating priority based predictive maintenance alerts.
  - Evaluating the performance of the proposed intelligent hybrid architecture in comparison to other popular DL techniques for predictive maintenance in microgrid systems.

- **Objective 3:** Designing a smart predictive maintenance architecture for classifying the DER operational states and investigating the future power capacity degradation of microgrid DER over time.

  Aims:

  - Designing a novel classification architecture for classifying the predictive maintenance events of complex microgrid DER by analyzing the power signals.
  - Developing an intelligent hybrid degradation algorithm by integrating Wiener degradation model with advanced GRU architecture.
  - Investigating the future degradation pattern and power capacity loss per year from the DER power signals.
  - Evaluating the performance of the proposed algorithm through implementing on a real-world, public dataset of a complex microgrid network.

1.4 Major Contribution of the Thesis

The purpose of this study is to provide a comprehensive and critical correlative analysis of both advanced and intelligent hybrid machine learning-based predictive maintenance techniques for microgrid network. This thesis presents a comprehensive review of the state-of-the-art machine learning techniques that could be used for microgrid predictive maintenance and highlights the gaps and challenges that need to be addressed. Besides, advanced DL-based algorithms and their correlative performance analysis, intelligent hybrid deep learning based architecture with optimized error distribution function based on advanced data analytics for the predictive maintenance of microgrid inverters, and microgrid DER power signal analysis based advanced machine learning architecture to classify the priority based

maintenance operations and forecast future power capacity degradation based on Wiener degradation model integrated advance DL architecture have been introduced in this thesis.

The findings of the thesis can have significant implications for the development of effective and reliable predictive maintenance frameworks for microgrid components and provide a useful guide for future research and development in this area. The major contributions of this study can be seen from the following key findings:

- This thesis aims in exploring the potential scopes and frameworks of ML-based methods, their innate pros and cons while developing the algorithms, challenges, available resources, data sources and available public datasets in the context of microgrid predictive maintenance which could serve as an excellent starting point for the future research in this emerging domain.
- Designing of advanced DL-based algorithms and their correlative performance analysis with respect to complex exogenous factors for predictive maintenance in the context of microgrid inverters have been performed in this study. This study also explores the advantages and weaknesses of each of the developed frameworks in terms of handling non-linear, temporal patterns of exogenous factors while analyzing and implementing the microgrid inverter power signals into the models.
- Development of advanced hybrid machine learning-based predictive maintenance framework for microgrid inverters along with a comprehensive overview of the key steps involved in building advanced data analysis framework with respect to dynamic exogenous factors and their complex non-linear characteristics to calculate the inverter performances on daily basis and detect the exact malfunction operations for enabling proactive maintenance.
- An intelligent ML architecture based on the power signal analysis of microgrid DERs has been introduced in this thesis to classify the priority based maintenance operations and forecast future power capacity degradation based on Wiener degradation model integrated with advanced DL architecture. This can provide a useful guide for researchers and practitioners who aim to develop intelligent predictive maintenance systems to monitor both the short term performance, maintenance scheduling and long term performance through capacity degradation process for the microgrid components.

1.5 Organization of the Thesis

This thesis has been organized as follows: Chapter 1 presents the research motivation & gaps, objectives of the study, and major contributions of this study. Chapter 2 investigates a comprehensive literature review on the machine learning scopes on microgrid predictive maintenance, potential frameworks and challenges. The importance of implementing advanced and hybrid machine learning-based techniques in the context of predictive maintenance for microgrids has been emphasized in this chapter. This highlights the need for an effective and reliable predictive maintenance framework to ensure the optimal performance of the microgrid operations. In this regard, this chapter aims in exploring

the potential scopes and frameworks of ML-based methods, their innate pros and cons while developing the algorithms, challenges, available resources, data sources and available public datasets in the context of microgrid predictive maintenance which could serve as an excellent starting point for the future research in this emerging domain.

Chapter 3 proposes three advanced DL-based algorithms and their correlative performance analysis with other counterparts with respect to complex exogenous factors for predictive maintenance in the context of microgrid inverters. This study also explores the advantages and weaknesses of each of the developed frameworks in terms of handling non-linear, temporal patterns of exogenous factors while analyzing and implementing the microgrid inverter power signals into the models. This can help gain insights into the strengths and weaknesses of various techniques and to select the most appropriate technique for their specific application in the future studies. Chapter 4 of this thesis presents a comprehensive overview of the key steps involved in building advanced, hybrid machine learning-based predictive maintenance framework for microgrid inverters. The dynamic exogenous factors and their complex non-linear characteristics have been explored through an advanced data analysis framework to calculate the inverter performances on daily basis and find out the exact malfunction operations for proactive maintenance. This can provide a useful guide for researchers and practitioners who aim to develop predictive maintenance systems for microgrid components with respect to complex environmental factors.

Chapter 5 of this thesis introduces microgrid DERs power signal analysis-based advanced ML architecture to classify the priority based maintenance operations and forecast future power capacity degradation based on Wiener degradation model integrated with advanced DL architecture. The performance of the proposed algorithm has been evaluated through implementing on a real-world, public dataset of a complex microgrid network. This can provide an excellent starting point for researchers who wish to explore and contribute to developing more advanced algorithms for microgrid predictive maintenance applications. Chapter 6 finally concludes this thesis with remarks, summary, and future research scopes.

Chapter 2

Literature Review

2.1 Introduction

Predictive maintenance is an essential aspect of microgrid operations as it enables identifying potential equipment failures in advance, reducing downtime, and increasing the overall efficiency of the system. Machine learning-based techniques have a great potential to be effective in improving the accuracy of failure predictions, detecting, and diagnosing faults in real-time, and monitoring the health and remaining useful life of microgrid components. The integration of these techniques with microgrid components can lead to reduced downtime, improved safety, overall efficiency, and sustainability. This chapter investigates a comprehensive literature review on the machine learning scopes on microgrid predictive maintenance, potential frameworks and challenges. The importance of implementing advanced and hybrid machine learning-based techniques in the context of predictive maintenance for microgrids has been emphasized in this chapter. This highlights the need for an effective and reliable predictive maintenance framework to ensure the optimal performance of the microgrid operations. In this regard, this chapter aims in exploring the potential scopes and frameworks of ML-based methods, their innate pros and cons while developing the algorithms, challenges, available resources, data sources and available public datasets in the context of microgrid predictive maintenance which could serve as an excellent starting point for the future research in this emerging domain to improve predictive maintenance operations using machine learning for microgrid industries.

2.2 Background

The power system network is getting complex due to its interdependency with communication and transportation networks, and interconnection of new loads due to electrification of different sectors. This issue regarding network complexity could be reduced through utilizing MGs, possessing proper predictive maintenance measures. MGs are typically a power supply (small-scale) system that consists of loads, energy storage, and DGs. In accordance with the revolutionary advancement of modern technology, in the near future, it is expected that an increasing number of microgrids will be connected

to the distribution networks.

The main contributions of MGs consist of supporting the high penetration of renewable energy, improving the reliability of distribution networks, enhancing the generation efficiency in a sustainable power grid, and offering islanding operability. MGs comprise several main components like distributed energy resources, battery energy storage systems, and inverters that work together for generating, storing, and distributing electrical energy.

DERs work as the primary source of providing electricity in a microgrid system, encircling several small-scale generation sources. These can comprise solar PVs, wind turbines for generating clean energy. The BESS plays a vital role in microgrid operation by storing the generated surplus energy during low demand. These systems could be discharged when renewable sources are unavailable, or throughout the peak demand; ensuring a steady power source. Inverters work as the heart of the microgrid system through converting the DC power stored in BESS, and produced by the DERs into AC suitable for the main grid and consumer usage. Inverters also perform a significant role of regulating the frequency and voltage, ensuring a steady and reliable power supply.

Significant challenges are emerging because of integrating the microgrid into DN due to the dynamic variances of different energy sources and the limitations of operating conditions. Issues like system instability, high losses, and voltage rises can be ignited through improper operation and allocation of microgrid [6]. To ensure the reliable and efficient operation of the microgrid, maintenance is a crucial aspect that needs to be considered. Maintaining the stability and reliability of microgrid systems can be challenging, given the diverse sources of energy and the complexities associated with their integration. Traditional maintenance approaches, such as corrective and preventive maintenance, are insufficient in addressing the maintenance needs of microgrid systems. These methods rely heavily on periodic inspection and scheduled maintenance, which can be costly, time-consuming, and not very effective.

Predictive maintenance is one approach that has gained significant attention due to its ability to predict equipment failure before it occurs. This approach involves using data from various sensors and analyzing it to identify patterns that indicate potential equipment failures. The quality of production as well as control, costs and the downtime of a system or machine could be enhanced through utilizing the contribution of performing predictive maintenance.

Most of the recent researched topics on microgrid are focused on the economic dispatching [7], [8], and energy management [20], [21]. Research needs to be conducted on the predictive maintenance which is an essential tool for ensuring the reliability and efficiency of microgrids. Machine learning (ML) techniques could be a promising medium in MG predictive maintenance due to their ability to handle large amounts of data and extract useful information. By using data and ML techniques to predict equipment failures, predictive maintenance is capable of allowing for the proactive identification of potential equipment failures, reducing downtime, increasing the overall efficiency of the system, extending equipment life, and improving safety. Additionally, it can lead to significant cost savings by reducing the need for expensive repairs or replacements, and unnecessary scheduled maintenance. Through the integration of sensors and IoT devices, ML techniques can further enhance the capabilities

of predictive maintenance of microgrids.

ML-based predictive analytic has been applied to various industries, including manufacturing [9], [10], [22], transportation [14], [15], and healthcare [16], [17]. However, its application in the microgrid system is still relatively new and requires further exploration as there is no recent review work conducted focusing on the ML based predictive maintenance prospects for microgrid, challenges, limitations of the techniques, a general guideline for building this framework, required microgrid data sources and available datasets. The research motivation behind the use of ML in microgrid predictive maintenance is to develop effective maintenance strategies that can improve the reliability, performance, and safety of the system. The use of ML algorithms can analyze large amounts of microgrid data from various sources, identify potential faults in the system, and adapt to changes in the system, making them more accurate and effective in predicting potential faults. The implementation of ML in predictive maintenance of microgrid can lead to significant cost savings, improve the safety of the system, and improve the overall performance of the system. The increasing adoption of renewable energy sources in microgrids has increased the complexity of the system, making the use of ML algorithms even more critical in ensuring reliable operation.

The novelty of this study lies in synthesizing diverse ML procedures in terms of designing microgrid PdM models, proposing a framework for designing ML based predictive maintenance models for microgrid components, highlighting the excellent prospects of ML based microgrid predictive maintenance towards real-world applications, illustrating sources of microgrid data and publicly available data sources of microgrid which can be very supportive specially in testing, developing methodologies for future studies for enhancing microgrid reliability and efficiency. The contributions of this chapter are five-fold through the following key findings:

- This study emphasizes the importance of implementing ML-based techniques in the context of microgrid predictive maintenance. This highlights the need for an effective and reliable predictive maintenance framework to ensure the optimal performance of the microgrid.
- This chapter proposes a comprehensive overview of the key steps involved in building an ML-based predictive maintenance framework for microgrid components. This can provide a useful guide for academia and practitioners who aim to develop predictive maintenance systems for microgrids.
- Different ML-based techniques for predictive maintenance in the context of microgrid components, their pros and cons have been critically analyzed in this study. This can enable the reader to gain insights into the strengths and weaknesses of various techniques and to select the most appropriate technique for their specific application.
- This study explores several public data sets for microgrid and a detailed overview of the microgrid data sources for maintenance. This can provide a starting point for future studies to explore and contribute new data sources for microgrid predictive maintenance.
- This chapter outlines some recommendations for future studies in the field of microgrid predictive maintenance. This includes exploring the compatibility of recently implemented ML techniques

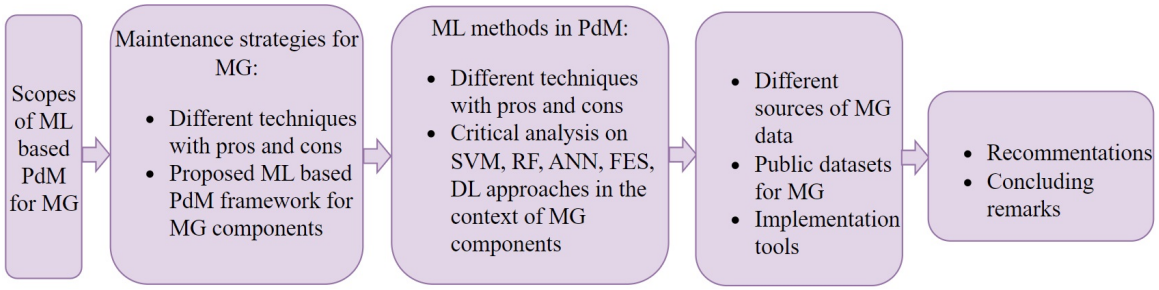


Figure 2.1: **Structural flow diagram of this chapter.**

with microgrid predictive maintenance applications and identifying potential areas for further research.

This analysis can hold noteworthy practical implications. Industries can harness ML-based microgrid predictive maintenance strategies to increase energy reliability as well as minimize operational costs. Different countries and regions can implement supportive policies and regulations through promoting resilient microgrids, resonating with sustainability and climate goals. The research community and policy makers can have significant insights from this study and further contribute by setting standards for reducing emissions and enhancing grid resilience, progressing climate commitments as well as the UN sustainable development goals. Ultimately, this study can pave the way for a cost-efficient, greener, and sustainable energy future.

Fig. 2.1 illustrates the structural flow of this chapter. Methodology of this study has been discussed in Section 2.3. Different maintenance approaches for microgrids, and ML-based predictive maintenance framework for microgrid components have been analyzed in Section 2.4. Section 2.5 presents different ML-based predictive maintenance techniques and critical analysis of each techniques in terms of microgrid predictive maintenance application. Section 2.6 constitutes a detailed overview on microgrid data sources for predictive maintenance. Several public datasets of microgrids, and implementation tools have been discussed in Section 2.7. Finally, this study has been summarized in Section 2.9 with concluding remarks for future research directions.

2.3 Methodology

A systemic approach has been used in the developed methodology for microgrid predictive maintenance. Concentrating on the last five years of research, the preliminary steps incorporated a comprehensive exploration from academic databases. A rigorous analysis has been conducted on those selected studies emphasizing the methodologies, pros and cons. This work contributes to a holistic perspective through synthesizing findings from other research. By exploring key insights on the applicability of ML approaches in microgrid predictive maintenance, the methodology provides a robust understanding not only of the current landscape but also the emerging trends through synthesizing latest articles for exploring the scopes, guiding the future works in this pivotal research domain.

The procedures for searching and selecting articles for this analysis constitute few steps. Fig. 2.2

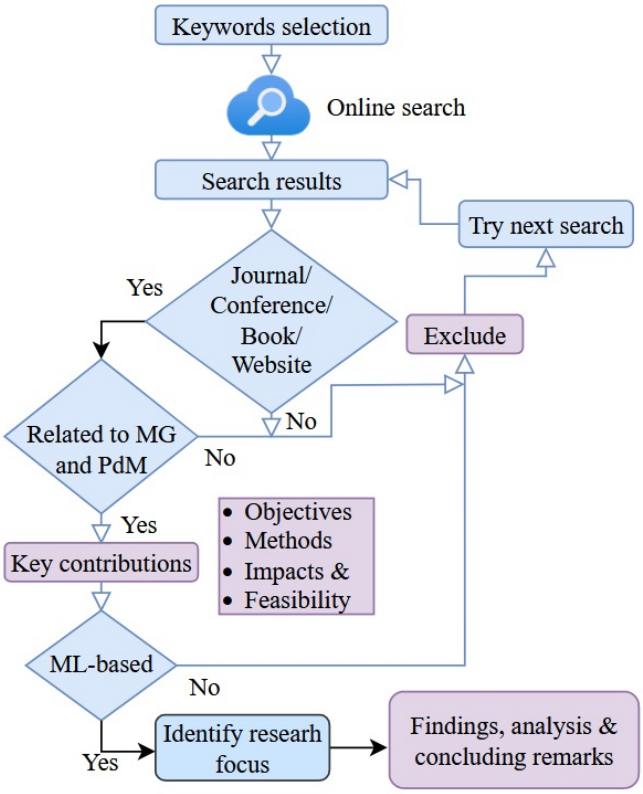


Figure 2.2: **Article search process utilized in this study.**

depicts the keyword-based selection process utilized for this study. Searching procedures involved keywords like "predictive maintenance", "microgrid", "machine learning", and "fault detection". Relevant other review works conducted on microgrids had been chosen as well for comparing the contribution of this study. Table 2.1 illustrates some recently conducted review on microgrids, their focus, and the contribution comparison. Fig. 2.4, and Fig. 2.4 illustrate the information sources, and articles from different publishers utilized for this analysis respectively in percentage.

ML is a technique of designing, creating and implementing of systems or computer-based applications capable of learning the analysis pattern on the basis of input and/or output data. It is mainly based on a core idea which is the machines are given the access of data and utilizing that information,

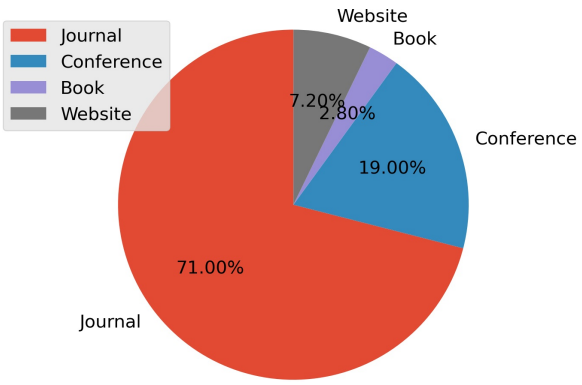


Figure 2.3: **Article sources utilized for this study.**

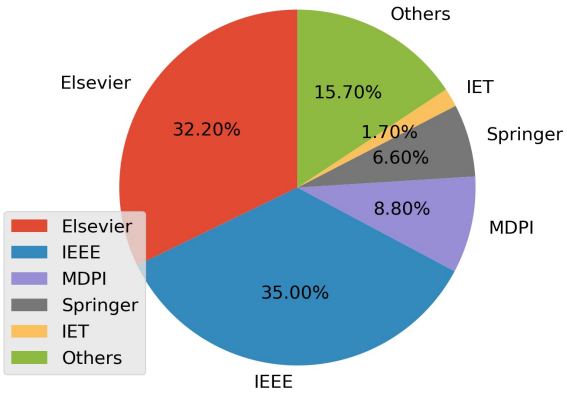


Figure 2.4: **Articles from different publishers utilized in this analysis.**

Table 2.1: Conducted review on microgrids and the survey focus.

Ref.	**Focus**	**ML**	**MG PdM**	**MG data sources**	**Public datasets**
[23]	MG energy management, generation and load forecasting, control	✓	×	×	×
[20]	Renewable energy consumption, and power load forecasting	✓	×	×	✓
[24]	MG digital twin, energy management	×	×	×	×
[21]	Energy management, operation optimization for solar powered MG	✓	×	×	×
[25]	Energy management techniques and standards of MG	✓	×	×	×
[26]	Challenges in cyber-attack identification in MG	✓	×	×	×
[27]	Technical aspect, challenges, and scopes for installing MGs	✓	×	×	×
[28]	Operation and Control Strategies, modelling, islanding detection of MGs	×	×	×	×
[29]	Hydrogen based MG energy management with some experimental platforms	✓	×	×	×
[30]	MG energy management with specific focus on IEEE standards for control and MG operation	✓	×	×	×
[31]	Virtual power plants and different scheduling issues of MGs	✓	×	×	×
[32]	Integration of electric vehicles in MG using deep learning	✓	×	×	×
This study	ML based PdM for MGs, future applicability, potential framework, sources and avilable MG public data	✓	✓	✓	✓

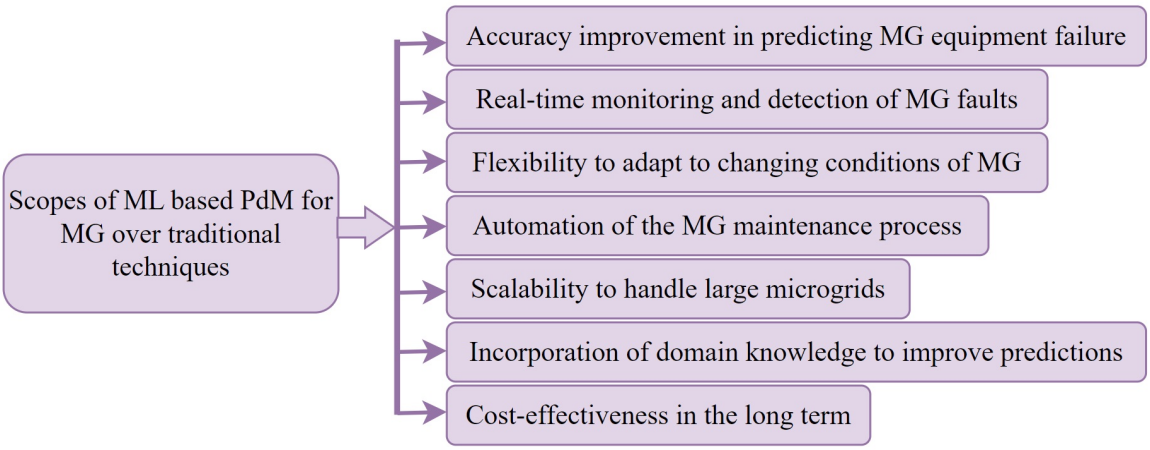


Figure 2.5: **Scopes of ML-based microgrid predictive maintenance.**

they will possess the capability of learning themselves extensively [33]. On the basis of the specific training, the ML algorithms learn through experience or knowledge. After that the models are capable of generalizing on the basis of the interpretation from the wide range of cases and performing actions accordingly. Different other branches have been arisen from data analysis, ranging from pattern recognition and data mining to different predictive analytics. Fig. 2.5 illustrates the scopes for adopting ML based predictive maintenance techniques for MGs over traditional methods.

- **Accuracy improvement in predicting microgrid equipment failure:**

  Improving accuracy in predicting failure is one of the key scopes of using ML for predictive maintenance in microgrids. ML algorithms can analyze large amounts of data and learn from it [34], allowing for more accurate predictions of equipment failure. This is achieved through the use of supervised and unsupervised learning algorithms [35] that can be trained on historical data to predict the probability of microgrid component failure.

  For example, supervised learning algorithms such as Random Forest [36], [37], [38] and Support Vector Machine (SVM) [39], [40], [41] can be trained on historical data to predict the probability of microgrid component failure. The algorithm can then be used to predict the likelihood of microgrid failure based on sensor data. Unsupervised learning algorithms such as K-means [42], [43] and Gaussian Mixture Models (GMM) [44], [45] can be used to identify patterns in the sensor data and detect anomalies that indicate potential failure.

  Additionally, ML models can continuously improve by learning from new data and adapting to changing conditions. This allows the model to improve over time and become more accurate in predicting failure. Whereas, the traditional methods rely on rule-based algorithms and heuristics, which can be prone to errors and may not be able to adapt to changing conditions. These methods may not be able to handle large amounts of microgrid data, which can lead to less accurate predictions of probable failure.

- **Real-time monitoring and detection of microgrid faults:**

  Real-time monitoring and detection of faults [46] is another key attribute of using ML for PdM. ML algorithms can be used to analyze microgrid sensor data in real-time, which allows for the

detection of patterns that indicate a potential fault. This can help to identify potential issues before they become critical and minimize the impact of maintenance on the operation of the microgrid.

For example, ML algorithms can be used to analyze sensor data from generators [47], [48], transformers [49], [50], and other equipment in the microgrid. By analyzing sensor data in real-time, ML algorithms can detect patterns that indicate a potential fault, such as abnormal vibration or temperature changes. This can allow for the early detection of potential failure, which can help to reduce the maintenance impacts on the microgrid operation.

In contrast, traditional methods may not provide real-time monitoring capabilities and may not be able to detect and diagnose faults until they have already occurred. This can lead to power outages and increased maintenance costs.

- **Flexibility to adapt to changing conditions of microgrid:**

  ML algorithms can be easily adapted to changing conditions, which can allow the models to continuously improve and adapt to changing conditions. For example, ML algorithms can be trained on new data, which will allow the models to adapt to changing conditions in the microgrid. This can be achieved through continuous updating of the training data with new sensor data and historical data.

  ML algorithms can be adapted to changing conditions by using techniques such as transfer learning [51], [52] and domain adaptation [53], [54]. These techniques can enable the models to adapt to changing conditions by fine-tuning the models on new microgrid data, rather than retraining the models from scratch.

  Whereas, traditional predictive maintenance methods may require manual adjustments and may not be able to adapt to changing conditions. This can lead to less accurate predictions of microgrid failure and increased maintenance costs.

- **Automation of the microgrid maintenance process:**

  ML algorithms can automate the process of predicting microgrid failure, which can reduce the need for manual intervention and increase overall efficiency.

  For example, ML algorithms can automate the process of predicting failure through analyzing the microgrid sensor data and historical data, and making predictions based on patterns and trends [55] in the data, which can reduce the need for manual input and analysis. Additionally, ML algorithms can be used to optimize the scheduling of maintenance activities [56], [57], which can help to minimize the impact of maintenance on the operation of the microgrid as well.

  Automation of the microgrid predictive maintenance process can also help to reduce the workload of maintenance personnel, allowing them to focus on other tasks. This can increase overall efficiency and productivity, which can lead to cost savings in the long term. In contrast, traditional approaches may require manual input and analysis, which can be time-consuming and prone to errors. This can lead to increased maintenance costs and decreased overall efficiency.

- **Scalability to handle large microgrids:**

Scalability to handle large microgrids can be another scope for using ML for microgrid predictive maintenance. ML algorithms can be used to analyze large amounts of data and therefore can be scaled to handle large microgrids. For example, ML algorithms can be used to analyze sensor data from a large number of devices in a microgrid. By analyzing sensor data in real-time, ML algorithms can detect patterns that indicate a potential fault, allowing for proactive maintenance and reducing the likelihood of power outages.

Scaling ML algorithms for large microgrids can be achieved by using distributed computing techniques [58] such as parallel computing [59], [60] as well as cloud computing [61]. These techniques allow for the processing of large amounts of data in a short amount of time. Additionally, ML algorithms can be optimized for large microgrids by using techniques such as dimensionality reduction [62], [63], feature selection [62], [64], and ensemble methods [65], [66].

Whereas, traditional procedures may not be able to handle large amounts of data from large microgrids. This can lead to less accurate predictions of equipment failure.

- **Incorporation of domain knowledge to improve predictions:**

  ML algorithms can be trained to incorporate domain knowledge [67] provided by experts, which can help to improve the accuracy of microgrid failure predictions. Such as, ML techniques can be trained to incorporate expert knowledge [68], [69] on the typical failure modes of microgrid, which can contribute in improving the accuracy of failure predictions.

  The incorporation of domain knowledge can be done by using techniques such as feature engineering [44], [70], which is the process of creating new features from raw data. This allows to incorporate expert knowledge on the typical failure modes of microgrid, which can help to improve the accuracy of failure predictions.

  In contrast, traditional techniques may not be able to incorporate domain knowledge. Consequently, less accurate predictions of when equipment is likely to fail and increased maintenance costs might happen.

- **Cost-effectiveness in the long term:**

  Implementing ML-based predictive maintenance can reduce microgrid downtime, maintenance cost, and microgrid component replacement, which can lead to cost savings in the long term. For example, by using ML-based predictive maintenance, it is possible to identify potential issues before they become critical and hence the need for equipment replacements can be reduced which can minimize the downtime and maintenance costs.

  Additionally, ML-based predictive maintenance can contribute in optimizing the scheduling of maintenance activities, which can result in reducing the impact of maintenance activities on the microgrid operations. This can help in minimizing the downtime and maintenance costs as well.

  Conversely, traditional methods may not be able to reduce downtime, maintenance costs, and equipment replacement in the long term. This can lead to increased maintenance costs and decreased overall efficiency.

The purpose of this study is to provide a comprehensive and critical analysis of ML-based predictive maintenance techniques in the context of microgrid. The findings can have significant implications for the development of effective and reliable predictive maintenance frameworks for microgrid and provide a useful guide for future research and development in this area. In this analysis, potential sources of error can comprise unavailability of real-time microgrid failure data, assumptions of models that might not have captured real-world complexities accurately, and uncertainties while predicting maintenance requirements. Underlying assumptions can be improved with robust data collection, better model validation compared to real-world scenarios, as well as acknowledging the intrinsic unpredictability of certain events.

2.4 Maintenance Strategies for Microgrids

Different systems are getting way more complex in the present energy sector than previous. Different faults as well as incidents are getting originated from this increasing complexity. All of the operational processes in a system could be troubled in case of the failure of any parts of the system. As a result, maintenance of the machineries or parts of the system is very significant.

Various types of maintenance approaches could be found from the literature. These maintenance techniques can be categorized into three main branches [71] which constitutes corrective maintenance (CM) which is also called run to failure technique, preventive maintenance, and predictive maintenance. All these techniques can be implemented for microgrid maintenance.

In case of corrective maintenance, the microgrid maintenance process is carried out when the critical parts or machinery of the system is at the saturation level or failure. Prolonged losses of energy production can be led through unexpected failures in case of this approach. Moreover, it may result in expensive replacements as well as repairs, or even safety risks at some point since the system reaches to failure.

For preventive maintenances which is also known as planned or time-based maintenances, the microgrid maintenance processes are taken place in accordance with periodic intervals irrespective of the health condition of the components. As a result, the service period of the compromised parts of the system is not completely utilized [72].

With different more complex systems than previous, the present world is experiencing different sorts of faults from this increasing complexity which results in a significant harm to the environment, items, and people. Under such circumstances, the effectiveness of the conventional maintenance procedures such as preventive and corrective maintenance might be largely compromised.

Consequently, an efficient approach is required for upgrading the performance of system reliability. This efficient approach is capable of evolving from time based preventive maintenance to condition-based maintenance. This transition to condition-based maintenance (CBM) is referred as predictive maintenance. Through machine learning, equipment behavior patterns as well as trends could be predicted in predictive maintenance. As a result, the pending failures could be anticipated in advance

which results in an enhanced decision-making outcome in case of maintenance activities that specially helps in minimizing the system downtime [73].

There are several benefits of predictive maintenance over the other maintenance techniques. In the context of microgrid, predictive maintenance can provide several benefits like improved reliability and availability of microgrids, better maintenance planning, increased microgrid equipment life, improved safety, decision making and overall efficiency, better data-driven decisions, reduced downtime of microgrid components, better use of microgrid resources, and improved sustainability. Table 2.2 summarises the pros and cons of each maintenance technique in the context of microgrid components.

Table 2.2: Maintenance techniques in the context of microgrid components.

Method	**Pros**	**Cons**	**Summary**
Preventive-Maintenance	- Can Help prolong component lifespan. - Can minimize the risk of sudden failures.	- Not cost-effective for MG due to scheduled downtime. - Causes superfluous maintenance whereas machineries are still functional.	- Can be suitable for machineries where wear and tear arise gradually, the impacts of failure are acute. - Incompetent where components hardly fail before reaching their expected lifecycle. - Can be suitable for components like transformers, inverters, switchgear.
Corrective-Maintenance	- Lower upfront costs. - Minimal operational interruption until any malfunction occurs.	- Risks of more unexpected failures. - Downtime throughout failures can be expensive.	- Can be suitable for components having low failure chances and the impact is not severe. - Can be suitable for MG components like BESS, inverters, controllers.
Predictive-Maintenance	- Can minimize the downtime and maximize component lifespan. - Decreases overall maintenance costs. - Enhanced component reliability and overall safety.	- Initial investment on monitoring systems - For data analysis, skilled personnel are required.	- Leverages ML into data analytics for making proper maintenance decisions. - Highly effective for any systems where early detection of any potential failure is essential. - Can be suitable for MG components like DERs, BESS, inverters, generators, transformers, controllers, sensors, switchgear.

2.4.1 Predictive Maintenance Framework for microgrid

An ML-based microgrid predictive maintenance framework has been proposed in this study focusing on the key elements of the microgrid. This can provide a structured procedure for deploying ML based predictive maintenance for the microgrid components. Fig. 2.6 depicts the proposed ML-based

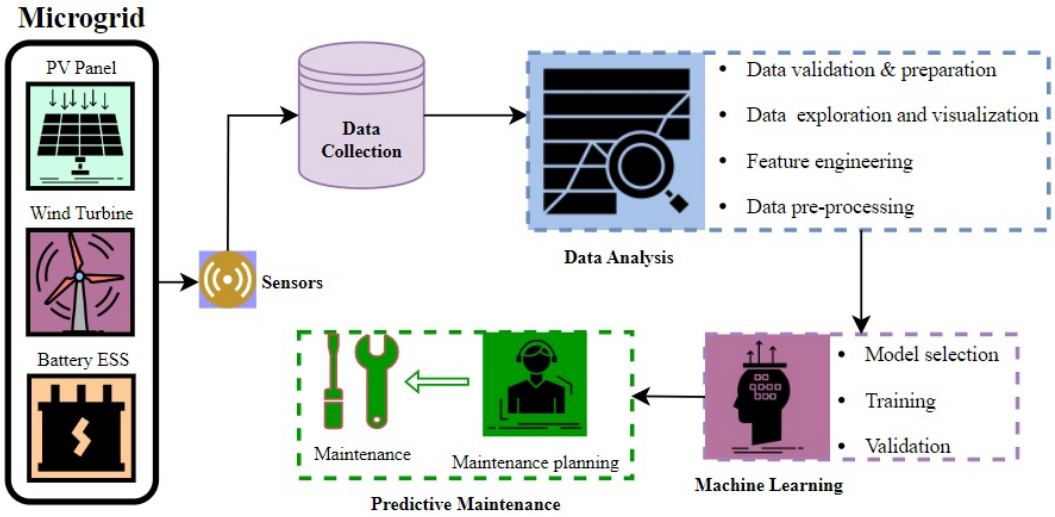


Figure 2.6: **ML-integrated predictive maintenance framework for microgrid.**

predictive maintenance framework for microgrid. The predictive maintenance routine begins with the acquisition of data utilizing different sensors. This can be sensor data from inverters regarding power, temperature; or BESS sensor data possessing charge, discharge; or can be DER sensor data having energy generation and weather conditions.

After that, the main process of the microgrid predictive maintenance framework starts with the data analysis, which includes data validation and preparation, data exploration and visualization, and feature engineering. In this step, the data collected from MG components are validated and prepared for further analysis. Data exploration and visualization are performed to identify any patterns or trends in the MG data that may indicate a fault in the microgrid. Feature engineering involves selecting the relevant features that can be used to train the ML algorithm. Extracted features from this step form the main foundations of developing precise predictive maintenance models.

Next stage is the implementation of the ML algorithms, which includes model selection, training, and validation. The ML algorithm is selected based on the type of data and the specific problem that needs to be solved. Table 2.3 illustrates a systematic workflow on required data, suitable ML methods for designing a predictive maintenance framework for microgrids.

Model training is the process of teaching the ML algorithm to recognize the patterns in the data that indicate a fault in the microgrid. The algorithm learns to differentiate between normal and faulty data by identifying the features that are most important for distinguishing between the two.

Validation needs to be performed then to ensure that the ML algorithm is accurate and reliable. The validation process involves testing the algorithm on a set of data that is different from the data used for training. This helps to ensure that the algorithm can generalize to new data and is not overfitting to the training data. Finally, predictive alerts can be implemented through real-time monitoring integrated with fault detection algorithms.

Then is to perform the maintenance action based on the predictions made by the ML algorithm. Once the algorithm has identified a fault in the microgrid, appropriate maintenance action can be taken

Table 2.3: An overview on designing ML-based predictive maintenance framework for microgrid.

For	**Data**	**Suitable ML models**	**Summary**
Inverters	- Sensor data like voltage, current, temperature - Power flow - Operational data	- LSTM - Hybrid DL models with auto-encoders - Classification - Regression	- Real-time insights into inverter health can be modelled using sensor data. - Temporal patterns can be captured using LSTM, while anomaly detection model identifies inverter faults. - Inverter states can be monitored using operational data where classification models can identify control states, unusual behaviours.
BESS	- Sensor data possessing charge, discharge, temperature - Maintenance records	- LSTM - Classification - Regression - Time-Series Analysis - Hybrid DL models with auto-encoders	- BESS performance can be monitored using sensor data. - Fault classification and maintenance needs can be predicted. - BESS energy flow patterns can be evaluated using time-series analysis, unusual behaviours can be flagged by LSTM.
DER	- Sensor data having power generation, weather conditions - Maintenance records - Load profiles	- Classification - LSTM - Regression - Time-Series Analysis - Hybrid models	- DER efficiency based on environmental factors can be modelled. - Power generation patterns can be identified from time-series analysis i.e., ARIMA can model and predict the power generation trends over time. - Energy output i.e., future generations from PV, wind turbine can be estimated using regression models with historical data and environmental factors.

to prevent further damage or downtime. This may include replacing faulty components, performing repairs, or adjusting the operating parameters of the microgrid. This can help achieve enhanced energy efficiency and grid resilience.

2.5 Machine Learning in Predictive Maintenance

A number of advantages can be achieved through adopting ML strategies in predictive maintenance. It is very beneficial, significant, and cost-effective strategy to the various companies to navigate and detect the faults at the earlier stages [74]. Some critical analysis on different ML-based techniques for predictive maintenance in the context of microgrid has been conducted in this section.

Table 2.4 lists a relative comparison among ML based maintenance techniques for microgrid under real-time scenarios.

Table 2.4: Relative comparison of some existing microgrid maintenance schemes.

Reference	**[75]**	**[76]**	**[77]**	**[78]**
Deployed method	Discrete Wavelet Transform (DWT) and extreme learning machine (ELM) based method	Hilbert transform along with communicating through microprocessor relays	Discrete Fourier Transform as well as DT based differential protection	Wavelet Transform and Decision Tree (DT) based method
Input features	Standard deviations using coefficients from both current & voltage signals extracted through DWT	Superimposed reactive energy enumerated from sampled current & voltage signals	Frequency, amplitude & phase angle of the current & voltage signals	Change in energy, entropy & standard deviation of current signal
Examined test cases	15525	N/A	287	1152
Performed tasks	Fault classification, mode detection & faulty section identification	Faulty location estimation, zone identification & fault detection	Only fault detection	Fault classification & detection
Response time	Less than one cycle (16.6 ms)	73 ms	One & a half cycle (25 ms)	Between 1.5-2.5 cycles (25-41.7 ms)
Real time validation	On OPAL-RT test bed	Was not performed	Was not performed	On OPAL-RT test bed

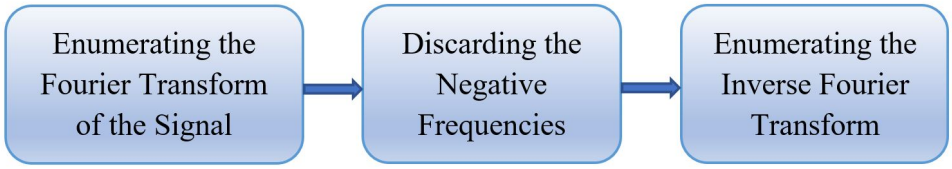


Figure 2.7: **Steps for the Hilbert transform.**

2.5.1 Support Vector Machine (SVM)

SVM applications are generally involved in clustering of input data, classification as well as regression analysis [79]. The SVM algorithm normally pursues the closest means, that it calls, bolster vector. A line is then drawn by the algorithm for interfacing them when the closest means are determined by it. Because of having the high precision, this is very popular ML approach which is being implemented both for the relapse investigation and classification issues.

The SVM technique has been described to be a proven method by many researchers that is well suited in case of dealing with disturbances classification regarding power systems. For extracting the required features, an adaptive approach of chirp mode searching has been utilized in [80]. For the classification of power quality disturbance, a Grasshopper optimization method has been implemented here as well for optimizing the SVM parameters. Another SVM based technique for a practical PV plant which can discriminate between grid fault statuses and islanding, has been carried by [81].

SVM algorithm has been proven to be promising in predicting the remaining useful life (RUL) of a microgrid battery energy storage system. This RUL prediction could have a better performance through implementing the SVM method [82], [83]. The performance of SVM technique has been described [84] to be better than ANN due to the generalizability in terms of dealing with prediction issues.

SVM techniques can contribute in the predictive maintenance of the PV panels, wind turbines in a microgrid system as well. SVM has been described [85] to be capable of implementing small samples, modeling non-linearities, modifying for predicting long-term with faster processing in terms of PV PdM. Moreover, a robust fault detection as well as location identification technique for ac microgrid has been proposed in [39] with combined SVM and Gaussian process regression technique. A classification accuracy of 99.5% has been mentioned here, outperforming than some traditional approaches.

A PdM for wind turbines has been carried by the studies conducted in [86] where for extracting the behavioural patterns of the wind turbine bearings, a vibration signal analysis-based procedure has been conducted. Moreover, for classifying the fault types, different ML based techniques like k-means, SVM, k-nearest neighbour (k-NN) had been implemented.

For the proper classification of the faults, it is necessary to demodulate the vibration signal for extracting the respective features. For this reason, in order to analyse the bearing fault patterns, Hilbert transform has been conducted for demodulating the signal. Fig.2.7 demonstrates the procedures for computing the Hilbert transform.

At the last stage, after implementing the inverse Fourier Transform of the signal, a complex-valued signal was yielded where the Hilbert-transform pair had been formed through a real as well as an imaginary part. After implementing the ML techniques, accuracies of 78.8%, 81.8%, 87%, and 81.8% have been described for the SVM, K-means, k-NN, and Euclidean distance techniques respectively.

One of the main benefits of using SVM for microgrid predictive maintenance is its ability to handle non-linear and complex systems. SVM uses a kernel trick to transform the data into a higher dimensional space where it can be separated by a linear boundary, allowing it to model non-linear decision boundaries. This makes SVM well suited for microgrid systems that have complex and non-linear relationships between the input data and the target variable.

However, SVM has some limitations, such as it can be sensitive to the choice of kernel and the regularization parameter. This can make it difficult to optimize the SVM model for a specific problem. Additionally, SVM can be sensitive to the presence of outliers in the data.

2.5.2 Random Forest

For modeling high dimensional information, random forest could be a suitable technique because of possessing the capability of managing categorical, continuous, binary information of data as well as handling lost values. A massive number of individual decision trees are possessed by RF technique, which are capable of performing as an ensemble [87], as followed by the name random forest. It can be used for performing tasks associated with regression as well as classification. RF techniques have been described as capable of performing a good role in case of lower number of observations or samples than the number of variables [88] .

Within the RF procedure, each tree sets for a class prediction. Finally, the expectation of the algorithm becomes the class having the most votes or decision trees. The models can be made effective accordingly. For most of the scenarios, the accurate model is led by the combination of these massive sets of random decision trees.

There are some key factors where attention should be focused though RF techniques are an assembly of decision trees. First of all, decision trees are being generated through RF where the nodes and rules are generated through decision trees by utilizing the enumeration of index measures as well as the information gain. Secondly, RF algorithms evade the overfitting issue in most of the cases whereas deep decision trees might suffer from it. Because, RF algorithms involve in working along the random subsets of the features. After that smaller trees get built by RF from these random subsets [88], [89].

A work based on RF model has been implemented for generating the predictive technique dynamically by [90]. An upgraded version of the work has been implemented by the study conducted in [91], where a monitoring technique for wind turbines has been conducted. For this purpose, operational data as well as status data had been utilized for designing the RF method where the operational data involved in the wind turbine performances and the status data associated with the activated as well as disactivated alarms. Upgraded data processing speed, automation as well as scalability were described to be the contributions done in [90]. Moreover, in comparison with the predictive accuracy of the

previous study conducted by [91], an enhanced result of 5.54% has been described here.

There had been some other RF based approaches implemented in the literature. A study incorporating Park's vector with RF algorithm has been conducted in terms of the squirrel-cage induction motor in [92] for detecting the short-circuit faults associated with the stator-windings. Moreover, a fault detection procedure for PV arrays has been implemented in [93] based on the RF algorithm. Different monitoring data like temperature, output power and PV array current have been utilized here for identifying the PV array faults.

On the basis of these studies, it could be mentioned that RF technique could be an effective tool for microgrid predictive maintenance. Its ability to handle high-dimensional data, model non-linear relationships, and its ability to improve the accuracy of predictions make it a valuable tool for microgrid predictive maintenance. RF can be used to predict the likelihood of generator failure, predict the likelihood of equipment failure, predict the RUL of microgrid components.

However, the computational cost and sensitivity to outliers should be considered when implementing RF algorithm. Despite these limitations, RF could be a great tool for microgrid predictive maintenance and can be used effectively in conjunction with other ML techniques to increase the overall performance.

2.5.3 Artificial Neural Network (ANN)

ANN methods have a notable implementation for possessing the tendency of processing a wide range of non-linear, random and fuzzy information compared to existing traditional ML approaches. ANN architectures are broadly connected and mostly adopted technique that include fitting systems basically for the processing of unclear data, large scale and complex structures [94].

For the ANN training stage, a learning dataset comprised of various samples of actual cases are the prerequisite [79] where the learning dataset needs to be larger adequately which depends on the complexity as well as structure of the problem of the undergoing case. On the other hand, an overfitting issue might be induced through utilizing larger sized learning dataset and hence the performance of the algorithm might fall because the generalizing capability of the ANN architecture gets decreased accordingly. As a result, establishing the proper balance between the over training and generalization of the model is significant. Fig. 2.8 depicts the basic steps for implementing an ANN based predictive maintenance architecture.

ANN architectures have been implemented by a number of researchers in the power system predictive maintenance. For example, in order to classify and detect the power quality (PQ) disturbances of both single and combined variants depending on both noisy and dynamic environments, this technique has been adopted in many works. A real time disturbance identification model on the basis of ANN architecture has been adopted by studies conducted in [95], [96]. The technique has been described to be capable of classifying single as well as combined PQ disturbances along with real time detection.

Additionally, for processing the PQ attributes, a combined technique of both variational mode decomposition as well as practical mode decomposition implemented with Hilbert transformation process has

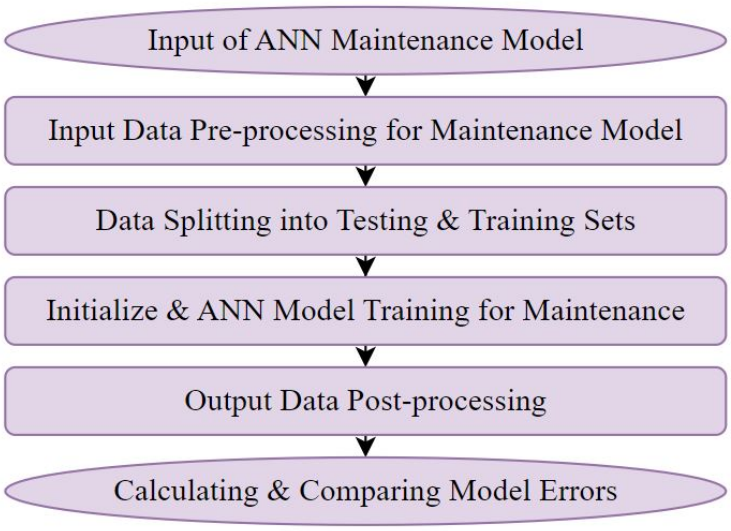


Figure 2.8: **Basic steps for an ANN-based predictive maintenance architecture.**

been adopted in some studies [97], [98], [99]. After that for identifying not only single but also combined PQ features, an online sequential technique with extreme learning model has been utilized. The proposed methodology has been described to be capable of possessing relatively higher classification precision, lower computational complexity, and better performance on anti-noise capability.

Moreover, ANN algorithms can contribute to anomaly detection of the PV panels in a microgrid system. An ANN based predictive maintenance of the PV system has been deployed in [100]. On the basis of the comparison between the predicted and actual or measured ac power production, the anomaly detection algorithm has been implemented here and the ac power has been predicted by the ANN architecture. This study has been described to be capable of achieving a better anomaly detection rate with a predictive detection rate higher than 90%.

In addition, ANN technique can contribute in terms of the predictive maintenance of the wind turbines in a microgrid system. A neural network-based technique for tackling the nonlinear converter model in a doubly-fed induction generators (DFIG) wind turbine has been implemented by [101]. The neural network architecture was developed based on the radial basis function for the identification of the inter-turn short circuits. Another work based on the ANN architecture has been conducted in [102] for specifically monitoring the operational situations of the wind turbine. This technique has been mentioned as capable of recognizing the faults taking place in the critical parts of the WT system. For this purpose, the vibration data have been collected by the researchers here not only under degraded situation but also healthy situation. Then for classifying the characteristics under both healthy and faulty conditions, the predictive analysis had been implemented through an ANN architecture. From the results section, a classification precision of 92.6% has been described by the authors.

These studies demonstrate the effectiveness of ANN for microgrid predictive maintenance. ANNs can be used to predict the likelihood of equipment failure, predict the health and RUL of microgrid components. However, the computational cost and sensitivity to outliers should be considered when implementing ANNs.

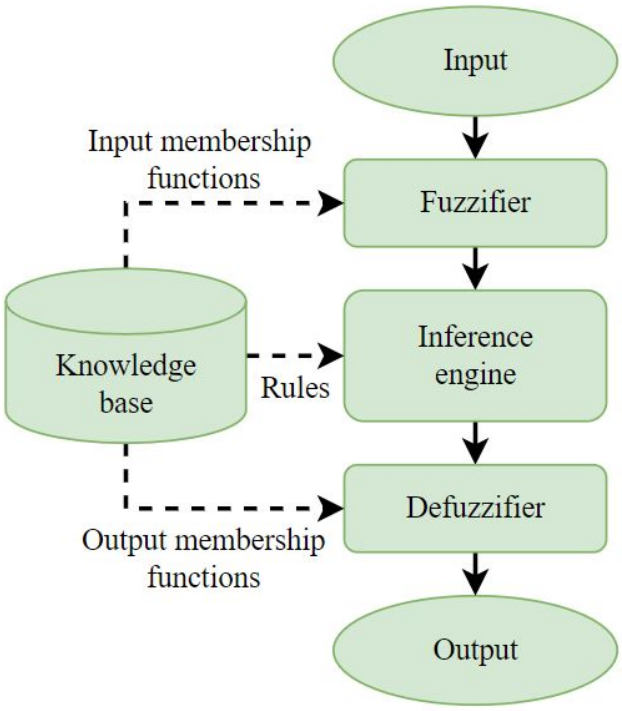


Figure 2.9: **Concept of a Fuzzy Expert System.**

2.5.4 Fuzzy Expert Systems (FES)

Fuzzy logic, being capable of emulating human decision and intelligence, is a type of probabilistic logic which is dissimilar to binary logic. The truth values of the variables of fuzzy logic might vary ranging from zero to one. For coping with the complex problems associated with the domain of search as well as control and decision of the question answering, the higher generalization capability of fuzzy logic is required. A rule based fuzzy logic has been illustrated as a block diagram in Fig. 2.9. Fuzzy rules as well as fuzzy sets are implemented as a basis instead of Boolean sets by the system. Corresponding membership functions along with fuzzy rules possessing the ability of emulating human decision and intelligence comprises a fuzzy set [103].

For the classification and automatic detection purpose of power system faults, fuzzy logic application has been implemented in different studies [104], [105], [106]. Moreover, the GA or ANN based learning capabilities are adopted by adaptive fuzzy logic architecture for adjusting the parameters of the algorithm which can result in an upgraded system performance for monitoring the PQ disturbance parameters [106], [107], [108].

FES can be an efficient tool in terms of microgrid energy storage systems (ESS). A FES based control architecture has been implemented in [109], capable of decreasing the grid fluctuation as well as enhancing the ESS life-cycle in a microgrid. Moreover, a muti-objective FES based microgrid ESS maintenance system has been implemented in [110] where the FES has been deployed with a combined hydrogen as well as battery ESS for ensuring the power demand of the microgrid system. The system has been described to be effective in prolonging the lifespan of the devices.

Another FES model has been deployed in [111] for the predictive maintenance of low-voltage dc microgrids. The proposed approach has been described to be capable of faster fault diagnosis regardless of current magnitude, type of faults as well as the feeding capacity of the power supply in dc microgrids through monitoring of instantaneous current. Another FES integrated predictive maintenance technique of a hybrid microgrid has been implemented in [112]. The proposed method has been described to be capable of intelligent fault identification and diagnisation of microgrids with a higher effectiveness.

One of the main benefits of using FES for predictive maintenance can be their ability to handle uncertainty and imprecision. Microgrid systems often have a large number of sensors that generate data that is uncertain and imprecise. FES can handle such data effectively, making them well suited for microgrid systems. However, FES can be challenging to design and implement, especially when it comes to incorporating domain knowledge. Additionally, they can be computationally expensive and may not perform well when dealing with large datasets.

2.5.5 Deep Learning Approaches

Deep learning comprises of deep belief networks as well as deep neural networks, convolutional neural network (CNN), and RNN. One of the most significant attributes of the DL architecture is possessing the inherent capability of learning optimal features automatically from the input signal [113]. As a result, unlike other feature extraction procedures, excessive time for extracting the features is not required.

The latent powerful applicability of the DL architectures is still under exploration by many studies in the area of power system analysis. These architectures possess a higher possibility of future applicability in estimating, detecting, and predicting different power system issues extensively because of having higher pattern recognition and feature extraction capabilities. Consequently, DL architectures have been adopted in many recent works for addressing and reducing PQ disturbances [114], [115], [116], residential load controlling [117], maintenance of PV panels [74].

DL architectures can contribute to the PV panel predictive maintenance in microgrid systems. For instance, a CNN based DL architecture has been deployed by [118] for the PV panel predictive maintenance where the power curve of a PV panel has been predicted in terms of the neighboring panels on a daily basis. For pointing out the malfunctioning PV panel, the power curve deviation has been analyzed between the observed or actual panel and the predicted curve. The large deviation values indicated the possibility of the malfunctioning PV panels.

DL techniques have been proven to be promising in predicting the RUL of a microgrid BESS. This RUL prediction could have a better performance through implementing the neural network [119] as well as mutated LSTM techniques and could be performed with relatively higher accuracy rate if implemented with a combination of multiple linear regression and RNN [120], where the degradation data could be reflected more efficiently [121].

A new DL architecture for predicting the multi-forward-step voltages of battery systems more ac-

curately, an LSTM technique has been implemented in [122] where the robustness as well as the precision rate of the proposed architecture has been verified through the comparisons among various hyper-parameters. Another improved DL technique has been proposed by [123] capable of describing online capacity changes where a deep convolutional neural network (DCNN) architecture has been implemented for enumerating the battery power portion [124] on the basis of current, temperature as well as voltage prediction during the charging process.

For learning the long-term dependencies regarding the degradation of battery capacity, an LSTM-RNN architecture has been deployed in [125] where the procedure has an adaptive optimization capability through implementing a resilient mean square based back-propagation technique. For addressing the over fitting issue, the dropout procedure has been applied by the authors. An upgraded DCNN architecture has been deployed with integrated and transfer learning based battery capacity [126] estimation. For the data set, daily-cycle data of eight implantable battery cells for 10 years have been implemented for the RUL prediction and 8 sub-models based on DCNN have been trained in accordance with [127].

DL techniques are getting increasingly promising for implementing predictive maintenance applications. With the ability to automatically learn features from large amounts of data, DL methods are expected to play an increasingly important role in microgrid predictive maintenance in the future. Table 2.5 reflects the significant pros and cons of SVM, RF, ANN, FES, and DL techniques in terms of designing ML-based predictive maintenance for microgrid components.

Each of the ML techniques has its own set of complexity, accuracy, merits and demerits, limitations. The limitations of this study can include data quality issues, more comprehensive cost assessments, lack of analysis with detailed environmental impacts as well as more regulatory complexities. Future analysis can involve exploring the scalability of ML methods for accommodating larger and more complex microgrids, performing case studies throughout diverse microgrid settings for assessing the performance and applicability of predictive maintenance models, long-term environmental and economic evaluations, and interdisciplinary tactics to overcome these issues.

2.6 Microgrid Data Sources

A number of interesting and advanced application fields have been paved in power systems through the advancement in data analytics like reliable grid operations and management, load profiling and management, smart-meter analytics, predictive maintenance, energy forecasting, outage management and so forth. For ensuring advanced services in the power grid, microgrid possesses different sensors, control systems, advanced technologies and data transmission. Hence, for carrying out advanced analytics for predictive maintenance, it is very significant to learn about the sources of the microgrid related data. Fig.2.10 illustrates the categorization of microgrid data sources.

Table 2.5: Critical analysis of some ML techniques in terms of designing predictive maintenance for microgrid components.

Methods	Pros	Cons
SVM	• Can be effective in identifying non-linear relationships from multi-dimensional data from microgrids • Less vulnerability to overfitting issue compared to other techniques • Can be suitable for identifying complex patterns from inverter performance, anomaly detection in DERs, BESS health prediction.	• Can have sensitivity to parameter tuning for achieving optimal performance; Complexity may increase with large datasets • Limited interpretability in terms of detecting specific faults • May require deep knowledge while choosing appropriate kernel functions
RF	• Can be robust in predicting battery health, identifying subtle deviations in inverter behaviour, and anomalies from PV, wind turbine power generation datasets. • Can handle high-dimensional DERs, battery, inverter data. • Can be effective in modelling non-linear relationships from microgrid data.	• May require longer times for training large scale BESS, DERs, inverter datasets • Prone to overfitting if not configured properly • Less interpretability and sensitivity to outliers • Complexity may increase in terms of multi-dimensional data from large scale microgrids
ANN	• Can be effective for capturing complex features from inverter data, estimating battery degradation, fault detection from DERs data • Capability of handling high-dimensional microgrid data efficiently • Can be effective in modelling non-linear patterns from inverter, battery, PV or wind turbine datasets	• Vulnerability to overfitting in case of small-scale microgrid datasets • Complex ANN models might require to go through extensive parameter tuning • Substantial data pre-processing as well as cleaning might be required • Less interpretability than other simpler models

FES	• Can be suitable for handling imprecise data from inverters, DERs and modelling the uncertainties in BESS health prediction • Can be robust for systems with qualitative variables like inverter datasets, noisy BESS or DERs data • Can provide interpretability and reasoning for the fault detection of different components	• Less capability in capturing complex non-linear behaviours from the large datasets • May not perform well in case of highly quantitative BESS and DERs data • Knowledge acquisition could be time-consuming, challenging • Domain experts are required for establishing the fuzzy rules • Limited scalability in case of handling large microgrid datasets
DL	• Can be excellent at forecasting battery degradation, modelling non-linear and complex inverter behaviours, complex faults in PV panels and wind turbines • Effective to handle multi-dimensional BESS, inverter data, and capture non-linear relationships from DER data • Capability of learning complex features from BESS data robustly, can be excellent for the anomaly detection in DERs, inverters	• Higher computational complexity along with deep architectures • May require large labelled datasets for training the deep networks • Can be prone to overfitting while having insufficient inverter, BESS or DERs data • Can be Less interpretable than the traditional models due to complexity

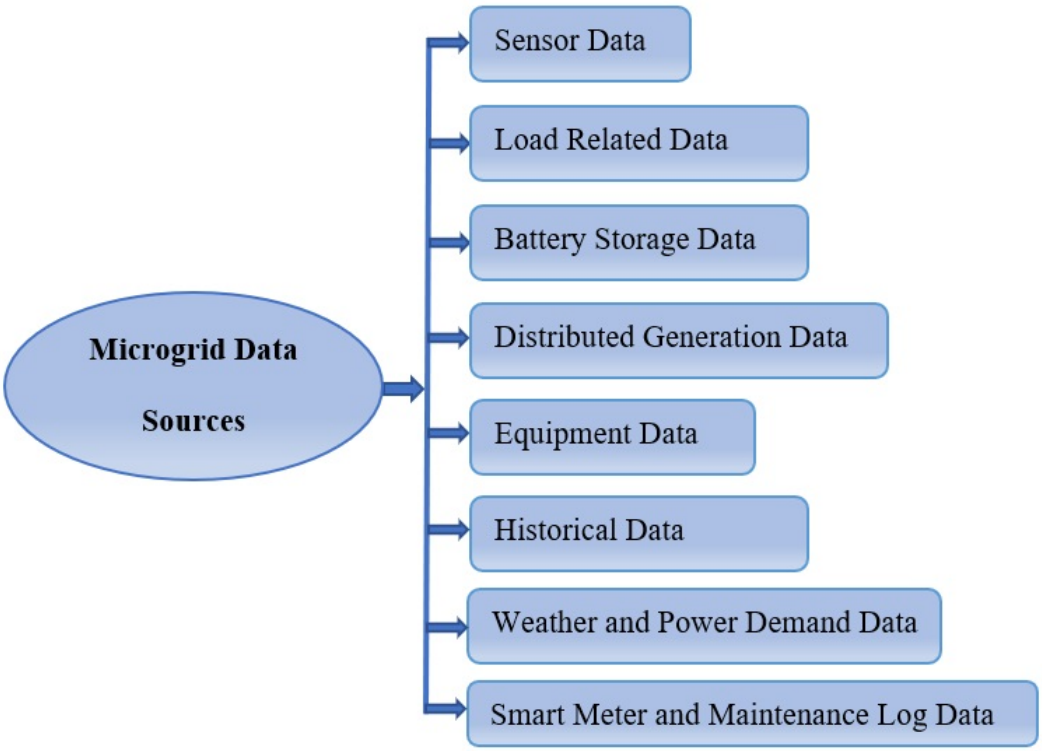


Figure 2.10: **Microgrid Data Sources for Maintenance.**

2.6.1 Sensor data

Different sensors implemented for the operational or maintenance purpose are a feasible data source. Among these wireless networked sensors, cloud storage, phasor measurement units (PMU), IoT, and some specialized monitoring sensors are significant.

Sensor data from equipment such as solar panels, wind turbines, generators, and power distribution systems can be used to train ML models to predict when equipment is likely to fail. This data can include information on temperature, vibration, current, voltage, and other parameters.

One of the key sources of big data utilized in MG are the wireless networked sensors [128]. For instance, for the inspection of PV modules this type of data has been utilized in [129]. This type of data could be comprised of power, solar intensity of each PV module, current, temperature, voltage as well as serial numbers.

The cloud could serve as one of the data sources as well where the data could be collected through meters, smart homes as well as sensors. Some other benefits like fault-tolerant storage, security as well as availability could be facilitated by the cloud [130].

PMUs are sources of fault disturbance recorders. Current, phase angles, frequency, and voltage are mainly logged with response to the time stamp in PMU. It is capable of communicating through the GPS as well. A vast amount of data are generated through the PMU. For instance, about 5.6 Terabytes of data could be generated per year from only forty PMUs [131].

Another source for the data is the IoT [132]. Networked sensors which are embedded in different devices

are represented through the IoT. There are some other sources which are normally the specialized monitoring sensors. These are ceilometer, anemometer, speed, strain, power, stresses and acceleration data collected from bearing sensors, gearbox, blades of the WT [133], outage management systems, frequency disturbance recorders (FDR) as well as wide-area monitoring systems (WAMS) [134].

These sensor data can provide insight into the health and performance of equipment in the microgrid, and can be used to predict when equipment is likely to fail. For example, high vibration levels in a wind turbine can indicate a problem with the gearbox, while high temperatures in a solar panel can indicate a problem with the cooling system.

2.6.2 Load related data

This is normally comprised of various data sources regarding the load management i.e., the smart meters, gas consumption, temperature, cooling or heating, customers life patterns, water status, and consumer questionnaire [135]. This load related data could be an extensive data source. Such as, if data are collected after every 15 minutes, then 2920 Terabytes of data could be generated [136]. From energy consumption data like consumption patterns, the load types can be known. The acquired information of loads could be shared through the consumers as well [137].

2.6.3 Battery storage data

Energy storage systems for microgrid like battery related data are utilized for this purpose. Different data regarding internal states of the battery, state of charge/ discharge (SoC)/ (SoD), voltage, temperature, state of health (SoH), current, terminal voltages, and fault detection data are included by the battery management system [138].

2.6.4 Distributed generation data

The relation regarding the total generated power in terms of the consumption are mainly formed by this generation data set. In comparison with the total required or consumed power by the loads, whether the generated power is adequate or insufficient are represented through this data. Every renewable energy source possesses own data-set generated by it.

WT generation possesses data related to control and monitor depending on various sensor data i.e., implementing temperature sensor PT100 for the gearbox temperature, enclosure temperature, casting temperature, and external air temperature [139]. The wind direction is obtained through the wind vane and wind speed can be calculated by utilizing anemometer. Other WT generation data can be obtained from humidity sensors, rotational speed measurement (i.e., hall effect sensors), electrical current as well as voltage measurements, and tower movement measurements (i.e., accelerometers).

Different data regarding current limit, temperature status, generated power, tilt angles, pump head specifications, mirror dimensions, ultrasonic signals utilized for identifying possible damage as well as orientation of the collector are generated through concentrated solar plant (CSP) [140]. Additionally, some other data related to market demand as well as meteorological information measured through

barometer, hygrometer, cloud cover, pluviometer, pyrometer, anemometer, thermometer, and radiance index are also generated by CSP. Besides, data related to different measurement flows, grid assessment, set points, grid variables, and control commands as well as real-time online data are provided by SCADA [141].

2.6.5 Equipment data

For the monitoring as well as management purposes different data are generated from various equipment i.e., transmission lines, circuit breakers, transformers, substations, switch gears as well as cables [142].

Data regarding short circuit current, transformer dielectric loss, nominal data, manufacturer, polarization index, fault source, resistance, insulation data, fault recorders, description, capacity, connection, load data, cooling system, oil pressure, discharge, release data, tap-change data, moisture content, tripped situations, ground current, and transformer model are included in transformer data [143].

A big data source is generally represented by this equipment monitoring data. Energy management system data i.e., equipment power, voltage, frequency, current can be included in equipment monitoring data. Besides, transformer lubricant or oil status, ventilation, healthy operation are represented by real-time monitoring data as well. Moreover, current as well as voltage waveforms could be utilized for enumerating the power quality like the flicker index, and total harmonic distortion [144].

Switch-gear data possess information regarding discharge level and moisture content. Transmission lines data comprise of leaning of the tower, electrical signal waveforms as well as voltage sag. Substation data constitutes of location, name, type, pollution status, and ID. Besides, circulation current, discharge as well as temperatures are represented in the power cables data [143].

In addition, for the purpose of renewable energy monitoring, remote telemetry units (RTU) are utilized [145]. Besides, equipment diagnostics data could be comprised of data regarding previous faults, voltage dips records, faults descriptions, trip times, previous disturbances, location, transients as well as digital protection data.

2.6.6 Historical data

Historical data [146] on equipment failures and maintenance activities can be used to train ML models to predict when microgrid component is likely to fail. This data can include information on the type of failure, the cause of the failure, and the time and location of the failure. This type of data can provide insight into the common failure modes of equipment in the microgrid, and can be used to predict when similar failures are likely to occur in the future. For example, if a particular type of generator has a history of failing due to overheating, ML models can be trained to predict when that generator is prospecting to failure due to overheating in the future.

2.6.7 Weather and Power Demand data

Weather data [147] can be utilized in modeling ML architectures to predict when equipment or any sub-system is likely to have any failure. This data can include information on temperature, precipitation, wind speed, and other weather conditions.

Power demand data include information on the amount of power being utilized by the microgrid and the power demand at different times of the day [148]. Power demand data can be used to predict when microgrid component is likely to fail due to high power demand, such as generators failing due to overloading.

2.6.8 Smart Meter and Maintenance Log data

Smart meter and maintenance log data can be used in modeling ML architectures to predict when equipment or any sub-system is likely to have any failure. Smart meter data [149] can include information on the energy profile and amount of energy being consumed by individual customers at different times of the day. This data can be implemented for microgrid protection [150] through predicting when any system is likely to fail due to changes in energy demand, such as energy distribution systems failing due to increased demand.

The types of maintenance activities that have been performed throughout the year [151], the dates of the maintenance activities, and the results of the maintenance activities are stored in the maintenance log data. This type of data can provide insight into the effectiveness of maintenance activities and can be used to predict when microgrid component is likely to fail due to a lack of maintenance or inadequate maintenance.

In summary, these are several potential data sources that can be used for modeling ML-based techniques on microgrid predictive maintenance. It is important to note that, data quality, data availability and data accessibility are important factors to consider when implementing ML-based techniques on microgrid predictive maintenance. Data should be cleaned, pre-processed, and transformed to be compatible with modeling and training ML algorithms.

2.7 Public Data Sets for Microgrid

Table 2.5 illustrates some publicly available data sources of microgrid which can be utilized for testing as well as evaluating predictive maintenance techniques. Upcoming studies might find these public data sets supportive specifically in testing, and developing robust methodologies as well as comparing with different procedures implemented in predictive maintenance applications so far under different scenarios.

2.7.1 Implementation Tools

Machine learning techniques have emerged as an essential tool in the field of microgrid predictive maintenance. These techniques can be used to analyze data collected from microgrid equipment and

Table 2.5: Available public data sets for microgrid.

Reference	Dataset description
[152]	OpenAMIData- Contains structured energy data generated by every five minutes possessing time, date, value, and time stamp
[153]	NREL dataset- Geospatial data as well as contains large data sets regarding energy resources like solar, wind, Hydrogen, wave power, geothermal, biomass
[154]	Sinogreenergy- Datasets regarding solar generation have been provided
[155]	DataWorld- Two microgrid datasets regarding levelized cost of electricity (LCOE), and load modelling
[156]	EnergyPlus- Contains dataset for researchers and engineers related to energy consumption in whole buildings
[157]	Liege Microgrid Open Data- PV, microgrid load consumption, and weather data including humidity, precipitation, snow, air temperature, solar irradiation

predict when failure is likely to occur. There are several software platforms that can be used to design and implement ML techniques in microgrid predictive maintenance, such as Matlab, Python and R.

Matlab is a powerful numerical computing platform that is widely used in academia and industry. It has a wide range of built-in functions and toolboxes [158], [159] for data analysis and machine learning. It also has a wide community [160], [161] in terms of users and developers.

Python is an open-source programming language that is widely used in the field of data science and machine learning. It has a large number of libraries and frameworks for machine learning, such as scikit-learn, PyTorch, TensorFlow and Keras [162]. It has a large community [163] of users and developers to learn from and get help from.

R is another open-source programming language that is designed for data analysis and visualization. It has a large number of libraries and frameworks for machine learning, such as caret [164] and mlr [165]. R is also known for its powerful visualization capabilities, which makes it an ideal tool for data exploration and understanding.

In summary, each of these platforms has its own strengths and weaknesses. Therefore, it is important to consider the specific needs of the application and the resources available when choosing a software platform for designing and implementing ML techniques in microgrid predictive maintenance.

2.8 Conclusion

The possibility of future equipment failures while operation can be avoided by monitoring the equipment health through predictive maintenance. Data from different equipment sensors are collected and

then predictive algorithms are then implemented on the basis of those data. One of the most significant contributions of predictive maintenance is that which piece of equipment needs to be replaced or repaired in future can be identified.

The contributions of this analysis lie in proposing a framework for designing ML-based predictive maintenance models for microgrid components, synthesizing diverse ML procedures in terms of designing microgrid predictive maintenance models, exploring sources of MG data and publicly available datasets, in-depth analysis of future prospects based on latest adopted ML techniques from literature which can be very supportive specifically in testing, developing methodologies for future studies with enhanced operational efficacy, grid resilience, and reliability. These insights can help develop sophisticated engineering plans for designing more robust microgrid systems with better energy system regulations. Besides, ML based microgrid predictive maintenance strategies can extend component lifespans and hence lead to substantial cost savings. This can help promoting responsible grid management, enhancing energy sustainability, and minimizing carbon emissions which resonate with Environmental, Social, and Governance (ESG) initiatives.

ML-based predictive maintenance techniques like SVM, RF, ANN, FES, and DL offer diverse advantages, they can vary in terms of complexity and practical implementation. Challenges comprise of limited availability of failure data in real-life scenarios, modeling interpretability, data labeling, and handling large datasets. Future research should be focused on designing hybrid models, data integration in real-time, integrating weather data while model building since generations from the DERs highly depends on weather conditions, and more robust feature engineering for selecting the most significant features from high volume of data which can improve the accuracy of the potential failure detection of microgrid components in the model. This can help provide continuous innovative solutions for ensuring their sustainability, reliability, and resilience in the context of evolving greener energy landscapes.

Chapter 3

Advanced Deep Learning Based Predictive Maintenance of Microgrids: A Correlative Analysis

3.1 Introduction

This chapter presents advanced frameworks for microgrid predictive maintenance by performing a comprehensive correlative analysis of advanced RNN architectures, i.e., RNNs, LSTM, and GRUs for PV-based dc microgrids. Key contributions of this analysis are development of advanced architectures based on RNN, GRU and LSTM, their correlative performance analysis, and integrating adaptive threshold technique with the algorithms to detect faulty operations of inverters which is indispensable for ensuring the reliability and sustainability of DERs in modern microgrid systems. The proposed models are trained and evaluated with a dataset of diverse real-world operational scenarios and environmental conditions. Moreover, the performances of those advanced models have been compared with the conventional RNN-based techniques. The achieved decremental MAE scores from 12.102 (advanced RNN) to 10.182 (advanced GRU) to 8.263 (advanced LSTM) and incremental R^2 scores from 0.941 (advanced RNN) to 0.958 (advanced GRU), and finally to 0.971 (advanced LSTM) demonstrate strong predictive capabilities of all, while the proposed advanced LSTM method outperforming other counterparts. This study can contribute to the emerging technology for predictive maintenance of MGs and provide significant insights into the modeling and performance of RNN architectures for improving fault detection in microgrid systems. The findings can have noteworthy implications to enhance the efficiency and resilience in microgrid systems, thereby evolving the renewable energy technologies in power sector and contributing to the sustainable and greener energy landscape.

3.2 Background and Contribution

The modern energy landscape is experiencing a profound transformation, following an unprecedented shift towards sustainability with the unification of renewable energy sources (RES) into power systems at present. In this dynamic context, dc microgrids are emerging as a pivotal advancement in this modern energy infrastructure, providing an efficient platform towards the seamless integration of these large number of RES and loads within the broader network of ac grids [166]. These dc microgrid systems can play a significant role in achieving technological innovation in power systems with promising improvements in terms of energy resiliency, efficiency as well as economic viability [167], [168].

Remarkably, the appeal of dc microgrids is increasing for their unique features, including improved efficiency, reduced losses and immunity to the harmonics and synchronization issues frequently plaguing ac grids [169], [170]. The ability to overcome these limitations places dc microgrids at the forefront of this evolving energy paradigm, offering a versatile resolution in the context of the integration of DERs to facilitate the transition towards sustainable, resilient power systems. SPV systems stand out in this context as an outstanding generation source within the spectrum of RES by contributing to the evolution of microgrid systems through harnessing the abundant, clean, and renewable energy from the sun [169], [171]. The scalability and cost-effectiveness of SPV generations have fueled its recent widespread deployment, placing it a top role in the global push towards the renewable energy adoption. Nevertheless, the variable and intermittent attribute of solar energy, influenced by diverse factors like solar irradiation and ambient temperature, brings many inherent challenges, mainly in terms of maintaining the stability of the power output from these SPVs into microgrid systems.

ML methods have emerged as a powerful tool in recent times in order to detect and respond to different types of power system faults, offering the potential of enhancing predictive maintenance and upgrading the resilience of the microgrid system. The application of ML-based data-driven [172] predictive maintenance models is getting widely adopted by different industries such as healthcare [16], transportation [15], and manufacturing [9], [10]. Nevertheless, its implementation on microgrid systems is still a relatively new area which requires further exploration.

Besides, most of the latest researched areas regarding microgrid are based on energy management [21], and economic dispatching [7]. Study has been conducted by [24] on microgrid digital twin focused on the energy management of microgrid. Another work [26] explored the microgrid challenges regarding cyber attack detection. Study conducted in [173] investigated digital twin technology for the capacity estimation of battery energy storage of MGs. A convolutional-LSTM based model has been explored in [174] for predicting the voltage stability of microgrid. Research conducted by [31] discussed various DERs scheduling issues on microgrid, Monte Carlo simulation integrated genetic algorithm technique based on sensor networks has been investigated in [175] for microgrid risk assessment, and [29] explored different experimental platforms for the energy management of hydrogen-based microgrids.

A protection technique for low-voltage ac microgrid based on voltage sags, current magnitudes as well as direction of active power flow was proposed in [176] using MATLAB/Simulink platform, which shown a good performance specifically for low impedance faults. Another study [177] explored high

and low resistance dc faults based on the relay ground current and inductor voltage for low-voltage microgrid network using PSCAD/EMTDC platform. In addition, [178] investigated a protection strategy for islanded microgrid incorporating short-circuit fault identification using PSCAD/EMTDC platform. Study conducted in [179] investigated microgrid fault identification under both high and low impedance operating conditions based on power quality control technique using PSCAD/EMTDC platform. There are limited studies based on advanced ML techniques for microgrid predictive maintenance specifically on fault detection of microgrid inverters in the present literature.

Recently, the susceptibility to anomalies within the power system escalates as microgrid architectures have become more complex by integrating diverse DERs and inverters. Inverters, functioning as the essential components of microgrid systems, play an utmost role in terms of converting the dc power generated by RES into ac power compatible with grid integration as well as end-user consumption. Anomalies or faults, characterized by the deviations from the expected or normal measurements, can manifest because of various factors such as inverter faults, load fluctuations, or system oscillations. The detection of faults has become vital for ensuring safe and resilient power supply [180], [181]. For ensuring uninterrupted and reliable energy flow, developing advanced ML-based predictive model focusing on inverter fault detection for microgrid applications has become crucial.

Besides, deep learning methods are gaining a great attention in recent times [182]. Having powerful feature vectors with higher dimension and deeper network structure, DL-based architectures can be excellent avenue for predictive analytics-based fault detection applications compared with traditional ML techniques. Because, the learning algorithms of traditional ANN-based techniques converge slowly and in terms of fault detection, these traditional techniques have poor interpretability [183]. Motivated by the enormous potential of DL in the realm of microgrid operations, this study explores the application of advanced RNN-based DL architectures as well as their comparative performances in order to identify anomalies from the power signals of dc microgrid inverters. The goal of this work lies in providing a comprehensive correlative analysis of these methods, illuminating their respective strengths in terms of microgrid predictive analytics based fault detection. The contributions of this chapter are threefold through the following key points:

- **Advanced DL-based predictive maintenance algorithms for microgrid:** For identifying microgrid inverter anomalies under different real-world exogenous factors, three advanced architectures based on RNN, GRU and LSTM have been presented in this article. The loss function of the advanced algorithms has been leveraged for optimizing the error rates which enhances the generalizability of the algorithms and capabilities of capturing both short and long term temporal dependencies from the complex microgrid data-points. The adaptability of those techniques to the changing patterns of inverter power signals gets increased consequently. As a result, the overall efficacy of the anomaly detection algorithms gets enhanced.

- **Advanced RNN-based correlative analysis:** In the context of microgrid inverter fault detection, a correlative study among advanced RNN-based DL architectures has been introduced in this research work. For capturing the temporal dependencies as well as patterns in the inverter data-points, each of the advanced DL architectures has been leveraged, providing a

comprehensive evaluation of the performances of the implemented and conventional approaches in terms of identifying anomalies from microgrid inverter data.

- **Adaptive threshold integration:** An adaptive threshold-integrated anomaly detection procedure has been implemented with the advanced DL architectures. Based on the statistical properties of the prediction errors of the deployed DL architectures, the threshold level gets adjusted by the proposed technique. Consequently, the sensitivity to anomalies of those models gets enhanced, which enables an efficient detection of deviations from the microgrid inverter power signals.

The following presents the remaining structure of this work. Section 3.3 describes the problem statement. Methodology of this study has been presented in Section 3.4. Section 3.5 describes the findings with simulation results. The discussion with a correlative analysis of the results has been presented in Section 3.6. Finally, the article has been concluded in Section 3.7 with remarks.

3.3 Problem Statement

A new era has emerged in the spectrum of sustainable energy through the rapid adoption of RES into MG systems specifically by the promising SPVs as the DER. Nevertheless, this magnificent transformation in power systems comes with challenges. Specifically, for ensuring the resilient and efficient power generation and distribution through MGs which are equipped with [184] diverse inverter-based resources (IBRs), it is crucial to monitor the inverter performances through anomaly detection. Figure 3.1 depicts the overview of a dc MG system possessing BESS, some local loads, and SPVs as the DER.

One of the key challenges of the microgrid DERs specifically SPVs is the inherent highly dependency on environmental aspects like ambient temperature and irradiation. Any fluctuations impacting by these aspects may cause faults or anomalies in terms of the ac output power yielded from the inverters. Besides, different system complexities and load fluctuations can amplify the possibilities of anomalies. To ensure the stability of the system and prevent any unexpected power losses, maintaining the operational efficacy and reliability of microgrid inverters is significant. Consequently, to enhance the longevity and stable operation of microgrid architectures, the significance of detecting these inverter anomalies effectively is paramount.

For addressing these exclusive challenges risen through the dynamic nature of modern microgrid systems, the conventional techniques are not effective enough to identify microgrid inverter anomalies proactively for maintaining the system performance and reducing downtime. Conventional techniques are not capable of adapting to diverse fault scenarios and evolving conditions in case of real-world modern microgrid scenarios [185]. The overall system efficiency and power quality are directly impacted by these inverter performances within the microgrid network. Anomalies or faults encountered in microgrid inverters can be identified by analyzing the fluctuation patterns of the ac power, that are influenced greatly by few factors.

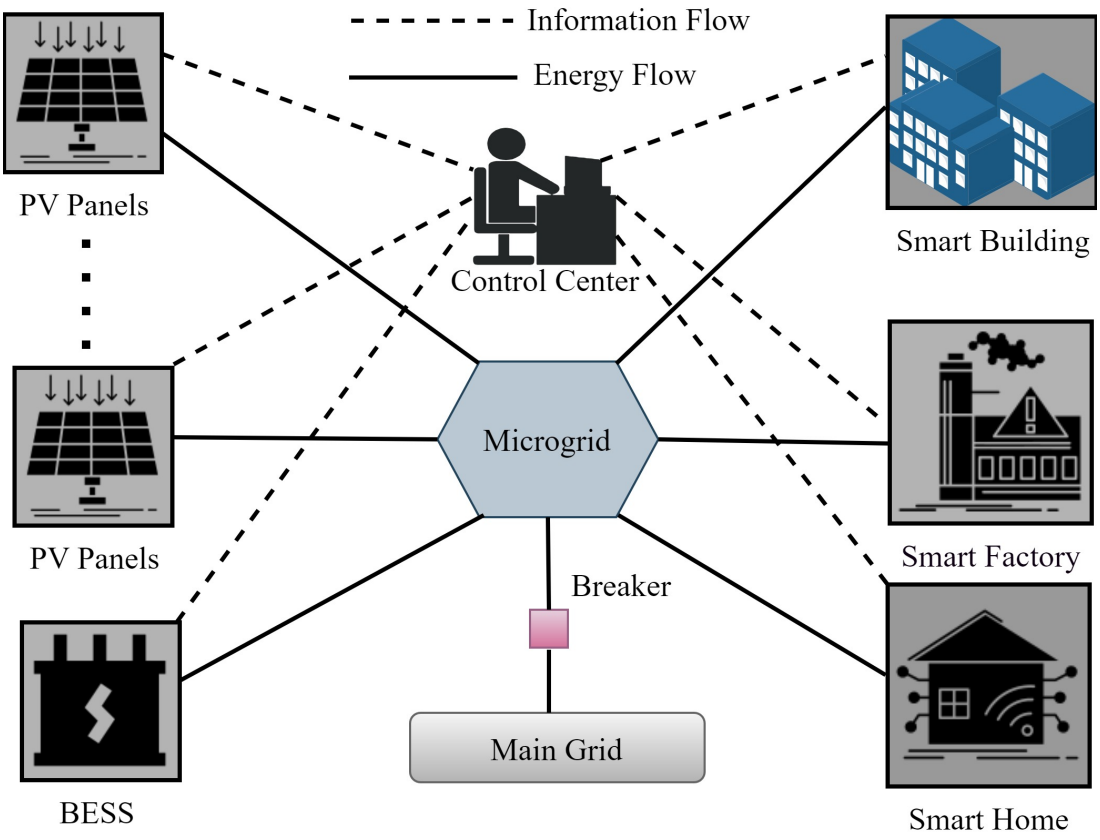


Figure 3.1: Illustration of a dc microgrid network.

The non-linear power characteristics of SPVs, and temporal dependencies are the most critical factors. Consequently, the inverter output ac power is dynamic, which is highly influenced by time-series dependencies such as variations in the temperature and irradiation patterns. Conventional techniques [186] might not be able to identify the intricate temporal dependencies and external factors present in modern microgrid networks and might not be effective enough without explicit domain knowledge. These limitations emphasize the modeling of more advanced techniques that possess adaptive detection capabilities along with addressing these nuanced patterns in the microgrid inverter performances.

Having inherent memory capabilities, advanced techniques based on RNN, GRU, and LSTM can be tailored to learn these complex temporal dependencies. Nevertheless, the implementation of these models for correlative performance analysis in predictive maintenance applications for dc microgrids still remains unexplored. For identifying the intricacies encountered in terms of MG inverter fault detection, the integration of advanced RNN-based DL architectures such as RNN, GRU, and LSTM can be a promising avenue. Moreover, there is no recent study of comprehensive comparative analysis focused on these DL techniques in the context of fault detection scenarios of microgrid inverters in the present literature. Furthermore, study [187] describes that in terms of power grid applications, the performance comparisons of LSTM and GRU architectures are still an unexplored research area.

By exploring an in-depth analysis focused on the advanced RNN-based fault detection architectures, this study aims to bridge this gap. This research work focuses on evaluating the efficacies of the advanced RNN-based DL architectures, compared with the conventional methods in the context of fault

detection scenarios of microgrid inverters under different operational conditions through implementing real-world data. The findings from this research work can provide significant insights regarding the pros and cons of the techniques which can pave the way for developing advanced maintenance strategies in future for the continuation of more resilient and efficient evolution of dc microgrid systems.

In this advanced RNN, GRU, and LSTM-based correlative analysis, the critical environmental factors that affect the output ac power from inverters have been utilized in the feature vector $X(t)$ for modeling these algorithms where $I_{irr}(t), T_m(t), T_a(t)$, and $P_{AC}(t)$ represent the irradiance, module, ambient temperatures, and ac power respectively:

$$X(t) = [I_{irr}(t), T_m(t), T_a(t), P_{AC}(t)] \tag{3.1}$$

For identifying the temporal dependencies properly, the historical patterns of the vector have been fed into the algorithms:

$$\mathbf{X} = [X(t), X(t-1), X(t-2) \ldots, X(t-n)] \tag{3.2}$$

The predicted output power ($AC_{\text{Predicted}}$) has been modeled by implementing the advanced RNN, GRU, and LSTM algorithms according to the following equation where f is the learning function for the temporal sequence and θ_t indicates the optimized model parameters of the advanced algorithms.

$$AC_{\text{Predicted}}(t) = f(\mathbf{X}; \theta_t) \tag{3.3}$$

3.4 Proposed Methodology

A brief overview on the utilized data set and data processing for this study, proposed advanced RNN-based DL architectures: RNN, GRU, and LSTM integrated with an adaptive threshold-based approach has been introduced in this section to identify anomalies from the dc microgrid inverters. Figure 3.2 illustrates the proposed structure of the advanced DL-based correlative analysis on microgrid inverter fault detection.

3.4.1 Data set

A real-world dataset incorporating a dc microgrid has been implemented for this comparative study. The data had been collected for 30 days from December 2022 to January 2023 with timestamp of 15 minutes interval. Reflecting the intrinsic challenges in real world scenarios, this dataset comprises diverse operational conditions. Capturing the dynamics of a complex real world dc microgrid, key attributes of environmental parameters such as irradiation (W/m^2), ambient and module temperatures ($^\circ C$), and electrical parameters such as produced dc power (kW) from the DER and converted ac power (kW) from the inverters had been recorded.

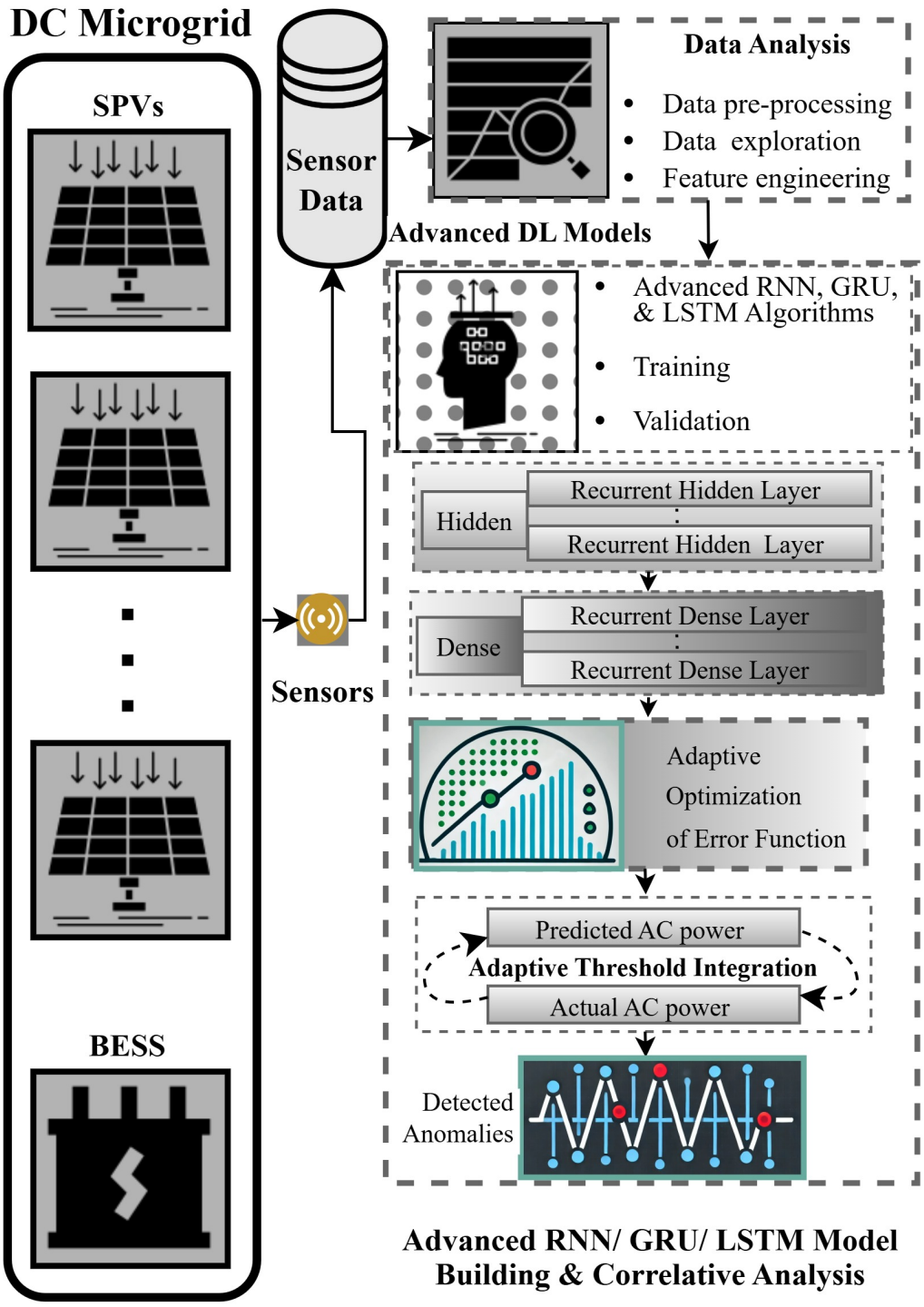


Figure 3.2: Overview of the proposed work.

Python programming language has been implemented for this correlative analysis. Python 3.10, Intel Core i7-1185G7, 3.00 GHz processor on 11th Gen machine with 16 GB RAM, 64-bit OS with kernel version 22H2 and build 19045.5487 specifications have been used while developing the algorithms. Different Python libraries and frameworks like Pandas, Matplotlib, TensorFlow, scikit-learn, NumPy, and Keras have been utilized, which enabled tasks like data cleaning, data visualization, statistical analysis, and model building and implementation.

3.4.2 Data Processing

For improving the performance of the algorithms, it is crucial to choose the most important features from the data [188]. For finding the most significant features from this dataset, a statistical technique has been implemented. For calculating the linear associations among various features within the dataset, the correlation analysis has been performed. The correlation coefficient (γ_{RZ}), indicating the linear association between two features R and Z, has been enumerated using the following equation:

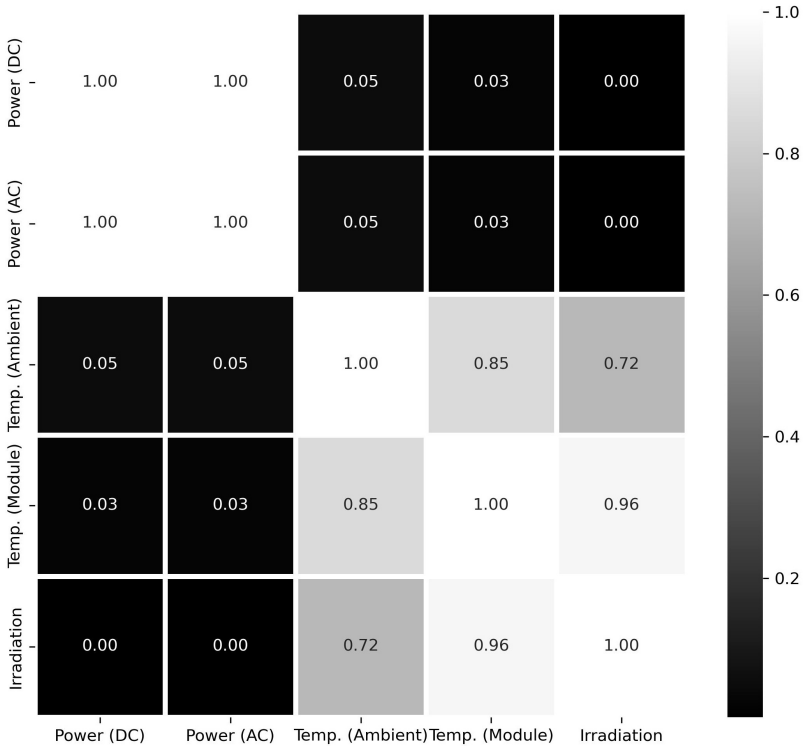


Figure 3.3: Correlation Heat-map of Features.

$$\gamma_{RZ} = \frac{\sum (R_i - \bar{R})(Z_i - \bar{Z})}{\sqrt{\sum (R_i - \bar{R})^2 \sum (Z_i - \bar{Z})^2}} \tag{3.4}$$

Here, R_i and Z_i indicate the individual data points of features R and Z, $\bar{R}$ and $\bar{Z}$ denote the means of R and Z respectively.

The correlations (γ_{XY}) from each pair of features X and Y from the dataset have been computed. This analysis helps find the redundant features from dataset. A high positive value ($\gamma \approx 1$) indicates a high linear association between the features. Figure 3.3 illustrates the correlation (γ_{XY}) coefficients among each pair of features. From the figure, it can be seen that ($\gamma_{\text{DC, AC}} = 1$), which indicates the strongest positive correlation between the features ac and dc powers. As a result, the dc power feature has been omitted during model training. This helps reduce the complexity by improving the model interpretability as well as performance while minimizing multi-collinearity.

After this, data with the selected features has been prepared for training the advanced DL models as can be seen from Algorithm 3.1. Data (X) was scaled and then divided into sequences (T) with test size (T_s).

Algorithm 3.1: Data Preparation for the Developed Advanced DL Algorithms.

Input: X, T, T_s

Output: X_{Train}, X_{Valid}, X_{Test}

1 *Scale Data* : $X_{\text{Scaled}} \rightarrow (X - X_{\min})/(X_{\max} - X_{\min})$

2 *Divide into Sequences* $\rightarrow X_{\text{Seq}}$

3 $X_{\text{Seq}} \leftarrow [X_{\text{Scaled}}[i : i + T]$ for i in range $(length(X_{\text{Scaled}}) - T + 1)]$

4 *Split into* $\rightarrow X_{\text{Train}}, X_{\text{Valid}}, X_{\text{Test}}$

5 $X_{\text{Train}}, X_{\text{Valid}}, X_{\text{Test}} \rightarrow Train.Test.Split(X_{\text{Seq}}, \text{T}_s = 0.2)$

3.4.3 Advanced RNN Architecture

RNN is a type of DL architecture which includes internal memories that enable capturing the sequential dependencies from the data through recurrent connections. Temporal orders of the input sequences are considered in the RNN architectures, enabling them to be a suitable candidate for processing sequential information [189]. In the context of anomaly detection in microgrid inverters, an advanced RNN architecture has been leveraged in this study for predicting the deviations from the ac power signals.

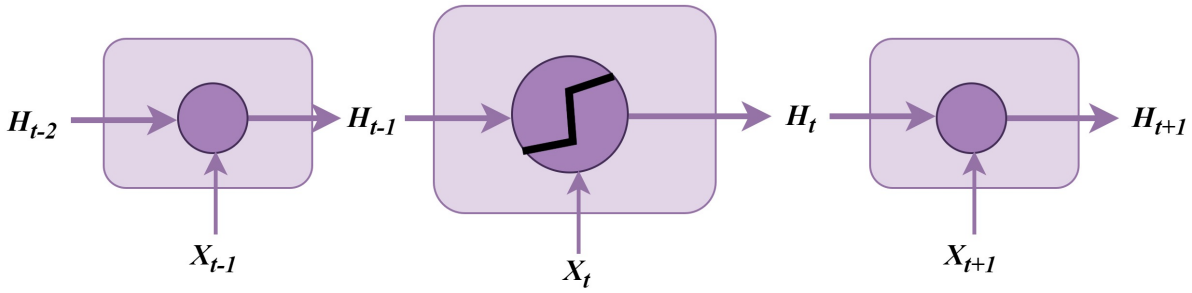


Figure 3.4: Advanced RNN Layer for Microgrid predictive maintenance.

Figure 3.4 illustrates the internal architecture of the implemented advanced RNN model for the microgrid inverter fault detection. The equation for the implemented advanced RNN algorithm integrated with ReLU activation function is:

$$H_t = \text{ReLU}(M_{ih} \cdot X_t + M_{hh} \cdot H_{t-1} + b_h) \tag{3.5}$$

Here, for the time step t, the input and the updated hidden state are indicated by X_t, and H_t respectively. Previous hidden state is represented by H_{t-1} for the time step $(t-1)$. Hidden layer bias is b_h, and the utilized weight matrices are denoted by M_{ih} and M_{hh} for input-to-hidden and hidden-to-hidden layers, respectively. ReLU indicates the rectified linear unit activation function implemented in the algorithm. Y_t indicates the model output at the time step t as follows:

$$Y_t = H_t \tag{3.6}$$

3.4.4 Advanced LSTM Architecture

LSTM technique can be an excellent approach in the context of microgrid inverter fault detection. This is a version of neural network which is connected to RNN family. Having a number of layers for processing each time step, LSTM architectures have proven to be more efficient than the traditional RNNs [190]. LSTM is capable of retaining long-term dependencies of data from many time steps before, making it well-suited for time-series data like inverter power analysis. Figure 3.5 illustrates the internal architecture of the implemented advanced LSTM model for the microgrid inverter fault detection.

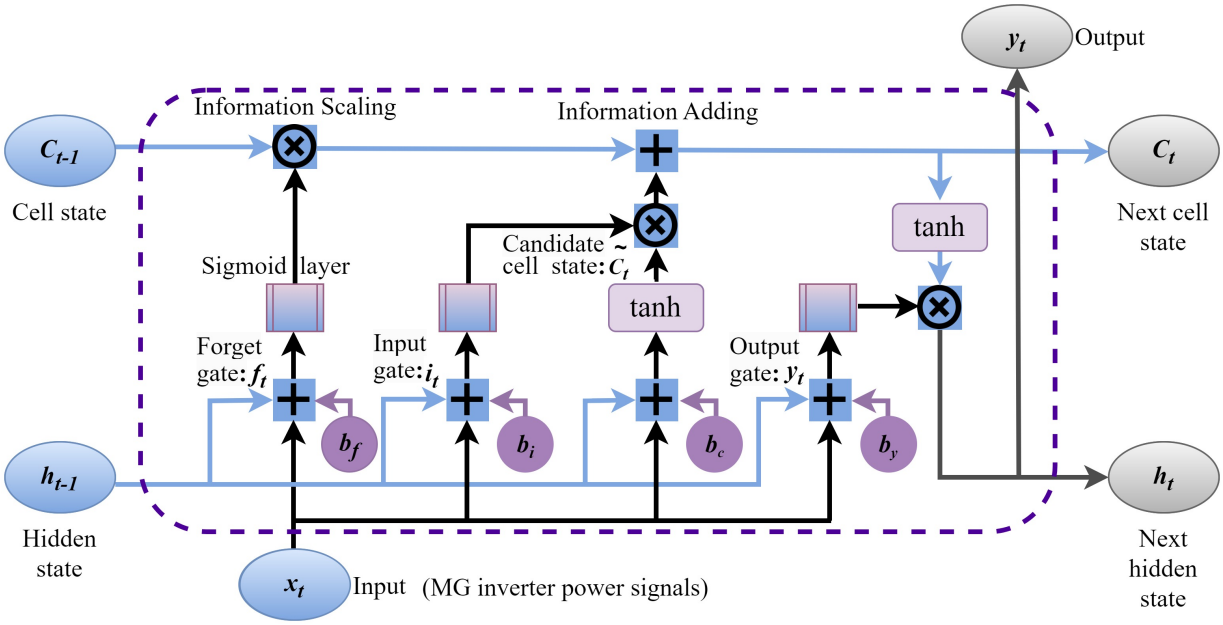


Figure 3.5: Advanced LSTM Cell Operation for Microgrid Predictive Maintenance.

Here, at each time step t, the input (x_t) and hidden state (h_{t-1}) get processed by the advanced LSTM cell from previous time state to generate a new hidden state (h_t). The forget, input, and output gates are responsible for deciding what information to discard or retain from previous hidden state (h_{t-1}) as well as the current input. Forget gate (f_t) decides what information to drop from previous hidden state, while input gate (i_t) and the candidate cell state $\tilde{C}_t$ determine which new information to add to the current hidden state. Corresponding equations utilized for this advanced LSTM architecture are described as follows:

$$f_t = \sigma_1(M_f[h_{t-1}, x_t] + b_f) \tag{3.7}$$

Here, h_{t-1} denotes the output in time step $(t-1)$, M_f and b_f represent the weight matrix and the bias, and σ_1 indicates the sigmoid activation function.

$$i_t = \sigma_2(M_i[h_{t-1}, x_t] + b_i) \tag{3.8}$$

Here, (M_i, b_i) denote the weight matrix and the bias.

$$\tilde{C}_t = \tanh(M_c[h_{t-1}, x_t] + b_c) \tag{3.9}$$

Here, for the candidate cell state, (M_c, b_c) indicate the weight matrix and the bias, and tanh is the hyperbolic tangent activation function.

$$C_t = f_t C_{t-1} + i_t \tilde{C}_t \tag{3.10}$$

Here, C_{t-1} indicates the previous cell state.

In these equations, σ_i represents sigmoid activation function, (M, b) represent the weight matrix and the bias respectively, for the corresponding gates and state. Finally, which information to process from current cell state gets determined by the output gate (y_t), and the next hidden state (h_t) is computed by multiplying the cell state passed through the tanh activation function and the output gate. The corresponding equations of the output and next hidden state (h_t) of this advanced LSTM layer are as follows:

$$y_t = \sigma_3(M_y[h_{t-1}, x_t] + b_y) \tag{3.11}$$

$$h_t = y_t \tanh(C_t) \tag{3.12}$$

3.4.5 Advanced GRU Architecture

GRU is a part of RNN and variant of LSTM architecture. In the context of microgrid inverter fault detection, GRU is capable of both capturing long-term dependencies and addressing gradient vanishing issues. Moreover, in terms of processing smaller dataset, GRU could be a more appropriate technique than LSTM which has been reported in the study conducted in [191]. Figure 3.6 illustrates the basic structure of the proposed advanced GRU architecture which has been leveraged for detecting the microgrid inverter faulty operations. For governing the model operations, this advanced GRU architecture possesses a number of equations as well as parameters which have been defined as follows:

$$U_t = \sigma_u(M_u \cdot [H_{t-1}, X_t] + b_u) \tag{3.13}$$

$$R_t = \sigma_r(M_r \cdot [H_{t-1}, X_t] + b_r) \tag{3.14}$$

$$\tilde{H}_t = \tanh(M_h \cdot [R_t \cdot H_{t-1}, X_t] + b_h) \tag{3.15}$$

$$H_t = (1 - U_t) \cdot H_{t-1} + U_t \cdot \tilde{H}_t \tag{3.16}$$

$$Y_t = \sigma_o(M_o \cdot H_t + b_o) \tag{3.17}$$

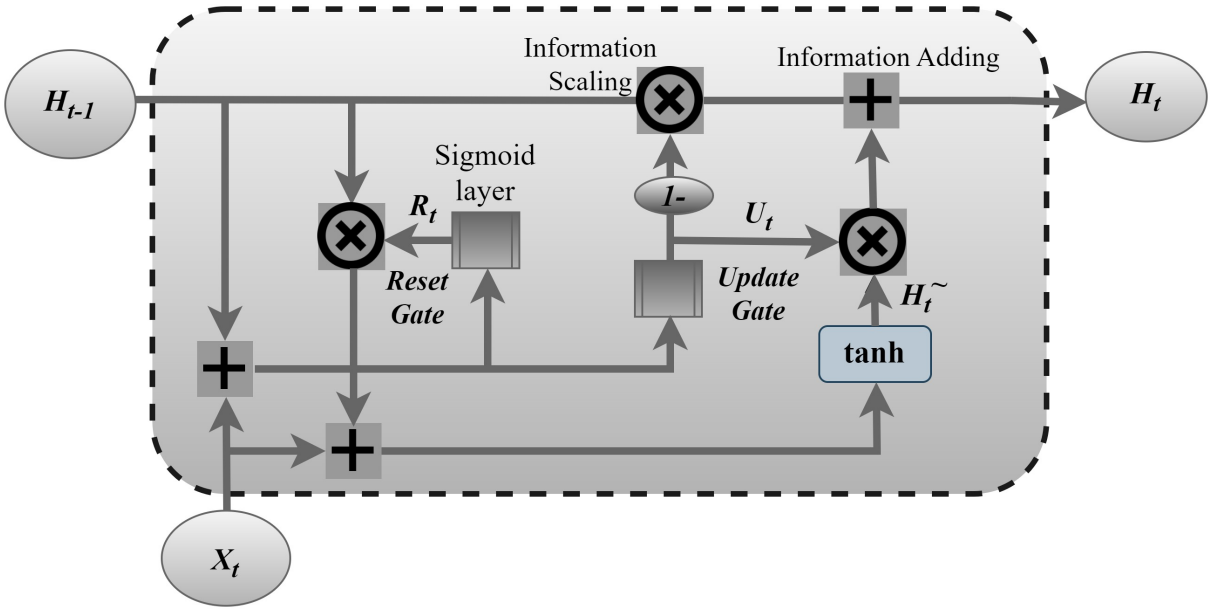


Figure 3.6: Advanced GRU Layer Operation for Microgrid Predictive Maintenance.

Here, for time step t, X_t and Y_t indicate the input and output vectors; the update and reset gates, candidate and latest hidden states are represented by U_t, R_t, and $\tilde{H}_t$, H_t, respectively; σ_i denotes the sigmoid activation function; H_{t-1} denotes the previous hidden state obtained from the previous time step $(t-1)$; the vector concatenation between H_{t-1} and X_t has been indicated through $[H_{t-1}, X_t]$; b_u, b_r, b_h, b_o are the corresponding bias vectors, and M_u, M_r, M_h, M_o are the respective weight matrices for update and reset gates, hidden state of candidate and the output.

3.4.6 Adaptive Optimization of Error

For training the learning parameters of the implemented advanced DL architectures, adaptive stochastic techniques can be outstanding solutions. This can be computationally effective optimization technique [192] with less memory requirements for finding the optimal points and can be core of various engineering applications. An adaptive stochastic optimization technique has been implemented in the advanced DL algorithms for optimizing the error functions. It adapts the learning rates for each parameter during training, providing an effective optimization strategy in scenarios with changing data distributions or model parameters.

In mathematical terms, the adaptive learning rates are calculated using two moving averages: exponentially decaying averages of both past gradients (d_t) and past squared gradients (r_t). The decay rates regarding these moving averages get controlled by the parameters α_1 and α_2. The model parameters (θ) of this adaptive stochastic technique are then updated based on the following equations:

$$d_t = \alpha_1 \cdot d_{t-1} + (1 - \alpha_1) \cdot L_t \tag{3.18}$$

$$r_t = \alpha_2 \cdot r_{t-1} + (1 - \alpha_2) \cdot L_t^2 \tag{3.19}$$

Here, the gradient of the loss at time step t is represented by L_t with respect to the parameters. After that, the moving averages get bias-corrected through the following implemented equations:

$$\hat{d}_t = \frac{d_t}{1 - \alpha_1^t} \tag{3.20}$$

$$\hat{r}_t = \frac{r_t}{1 - \alpha_2^t} \tag{3.21}$$

Here, α_1^t and α_2^t are the bias-corrected parameters. The model parameters then get updated finally using the following equation:

$$\theta_t = \theta_{t-1} - \frac{\eta}{\sqrt{\hat{r}_t} + \epsilon} \cdot \hat{d}_t \tag{3.22}$$

Here, the learning rate is indicated by η, and for preventing the division by zero, a small constant has been applied which is denoted by ϵ.

3.4.7 Adaptive Threshold for Microgrid Fault Detection

In this work, a scenario has been considered where S_c denotes the differences between real ac power (AC_{Real}) and the predicted output ($AC_{\text{Predicted}}$) as follows:

$$S_c = |AC_{\text{Real}} - AC_{\text{Predicted}}| \tag{3.23}$$

An adaptive threshold (T_h) based anomaly detection procedure has been implemented which can be enumerated based on the statistical analysis of S_c. The mean and standard deviation of S_c have been utilized to identify the anomalous data points from the ac signal as follows:

$$T_h = \mu + k \cdot \sigma \tag{3.24}$$

Here, μ, and σ indicate the mean and standard deviation of S_c, respectively; k is a constant regarding the sensitivity of T_h. With the T_h value enumerated, faults can be detected based on whether the S_c value of the ac signal exceed this adaptive threshold point by the following equation:

$$\text{Fault} = \begin{cases} 1 & \text{if } S_c > T_h \\ 0 & \text{Normal} \end{cases} \tag{3.25}$$

This adaptive threshold approach allows for a dynamic identification of anomalies based on the statistical properties of the prediction errors. It's crucial to fine-tune the value of k based on the characteristics of the implemented data and the algorithm parameters.

3.5 Results

In this section, the process of model training, compilation as well as evaluation for this study have been discussed briefly with results.

3.5.1 Model Training

This step includes feeding the training data to the advanced DL algorithms as well as updating the parameters iteratively till the DL architectures converge to minimum error. For all the models, 100 epochs with batch size 10 have been utilized. To handle the overfitting issue, a 0.2 validation split was employed, allocating 20% of the training data for validation purposes during model training and enhancing the generalizability of the advanced algorithms to new data.

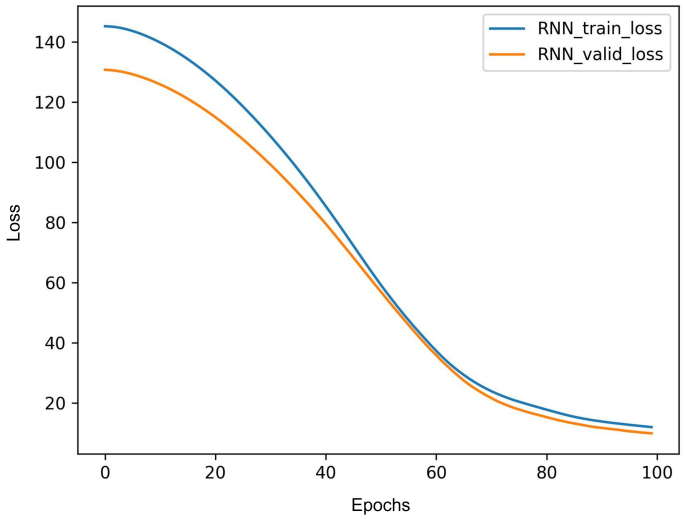
Figure 3.7 depicts the training and validation of the DL architectures capturing the differences between model predictions and real values. A significant decrease of errors can be observed through the adaptive stochastic optization of the error functions from Fig. 3.7(a) for advanced RNN, Fig. 3.7(b) for advanced GRU, and Fig. 3.7(c) for advanced LSTM after several epochs (x-axis). The trained architectures are then implemented in model compilation for detecting microgrid inverter faults from the real ac signal.

3.5.2 Model Compilation and Evaluation

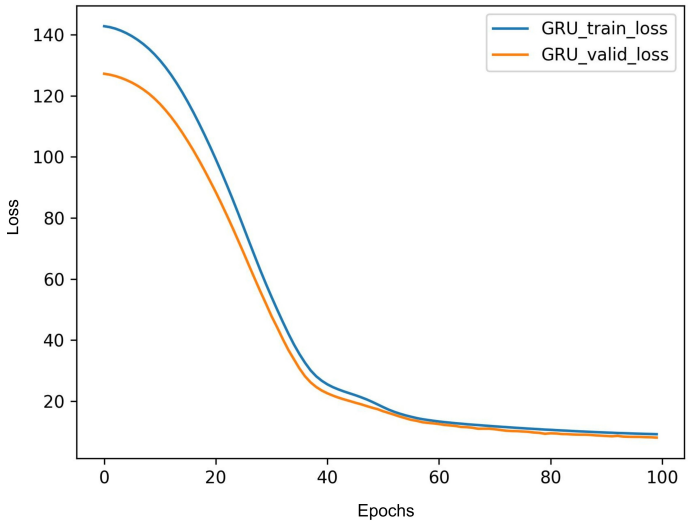
The implemented advanced RNN, LSTM, and GRU architectures are guided into the parameter space efficiently by the implemented adaptive stochastic optimization technique which helps to achieve an enhanced adaptability to changing patterns of inverter's ac power signals during fault detection. For identifying the anomalous points from the inverter's ac output power, the proposed adaptive threshold technique is implemented. Figure 3.8 illustrates the identification of the anomalous data points by integrating the adaptive threshold technique by the algorithm for each of the advanced DL architectures between the actual and predicted ac power.

The threshold levels of the implemented advanced DL frameworks get adjusted dynamically based on the statistical properties of the optimized prediction errors of the DL architectures. The highlighted stars are the potential anomalous data points from the real ac power signal identified by the advanced algorithms based on the adaptive threshold. The threshold lines can be seen at different positions that were adjusted dynamically by the algorithms. In Fig. 3.8(a), for the advanced RNN model, the dynamic threshold (black line) is lower than the advanced LSTM and GRU models. Hence, it captured more data points to be faulty on 22, 24, 30 and 31 December which have been highlighted in red stars by the algorithm. In Fig. 3.8(b), for the advanced GRU model, the threshold (green line) is a bit higher than the advanced RNN model and it identified a bit less data points than the advanced RNN model but a bit more data points than the advanced LSTM model to be faulty (highlighted black stars) on 22, 24 and 31 December.

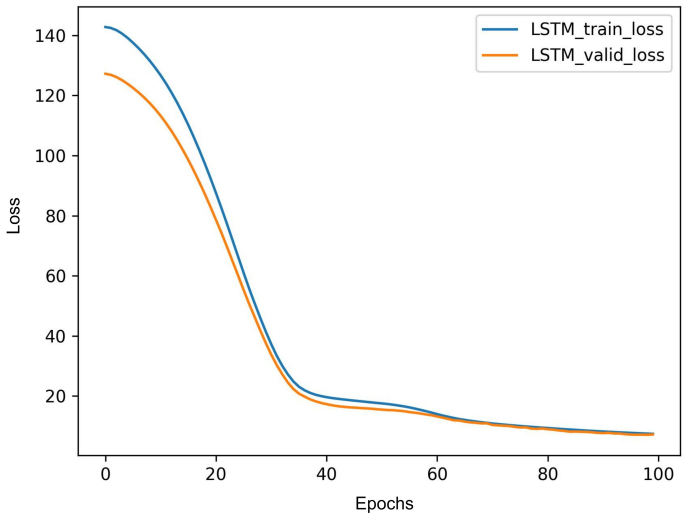
In Fig. 3.8(c), for the advanced LSTM model, the threshold (black line) had been adjusted by the algorithm dynamically at a bit higher point than the advanced RNN and GRU models, and identified a bit less data points from the real ac power signal to be faulty (highlighted purple stars) on 22, 24



(a)

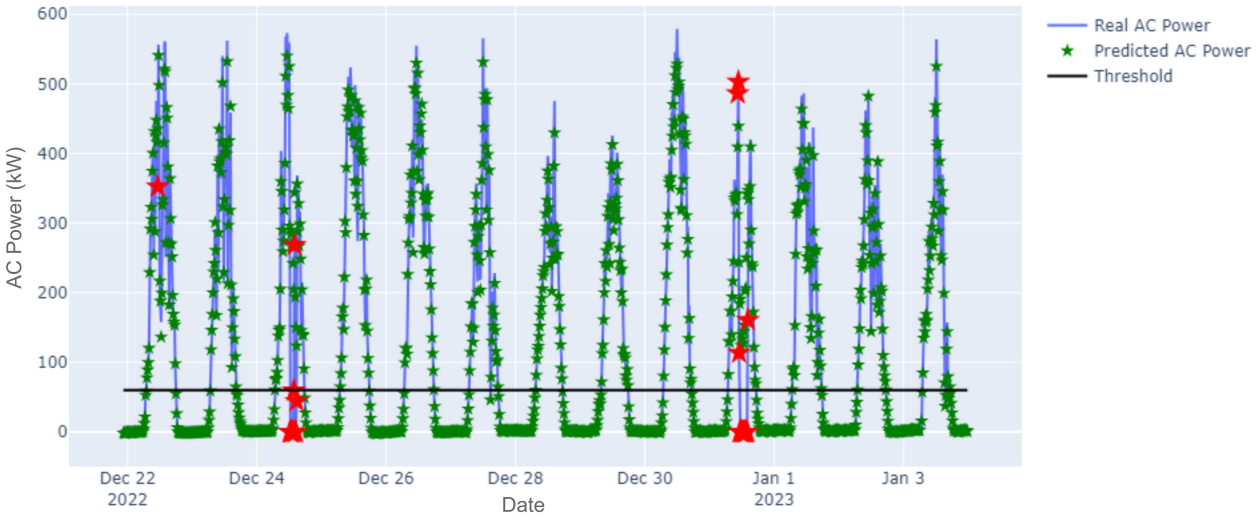


(b)

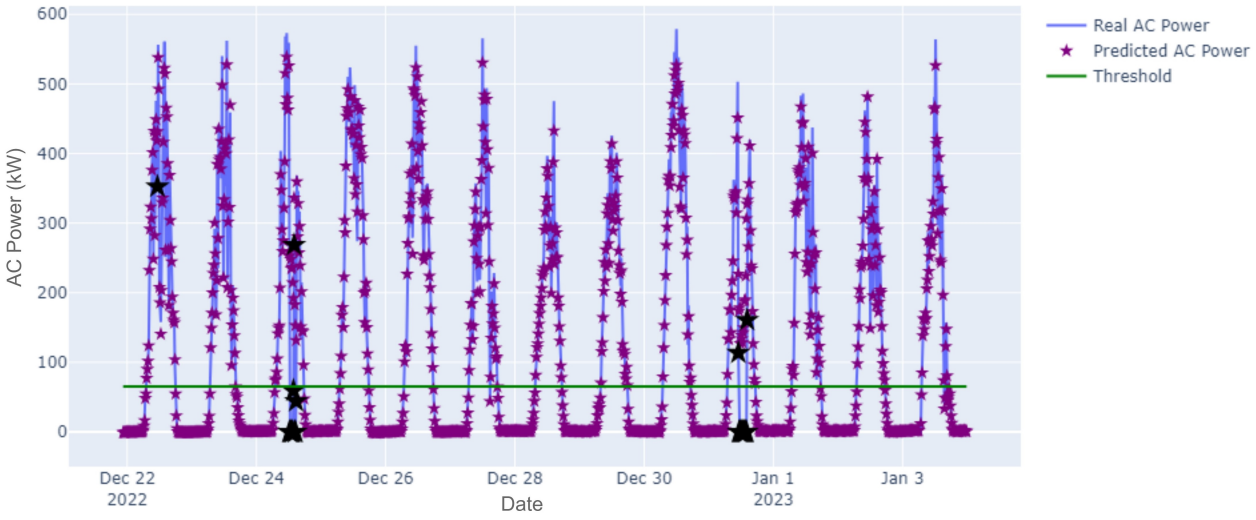


(c)

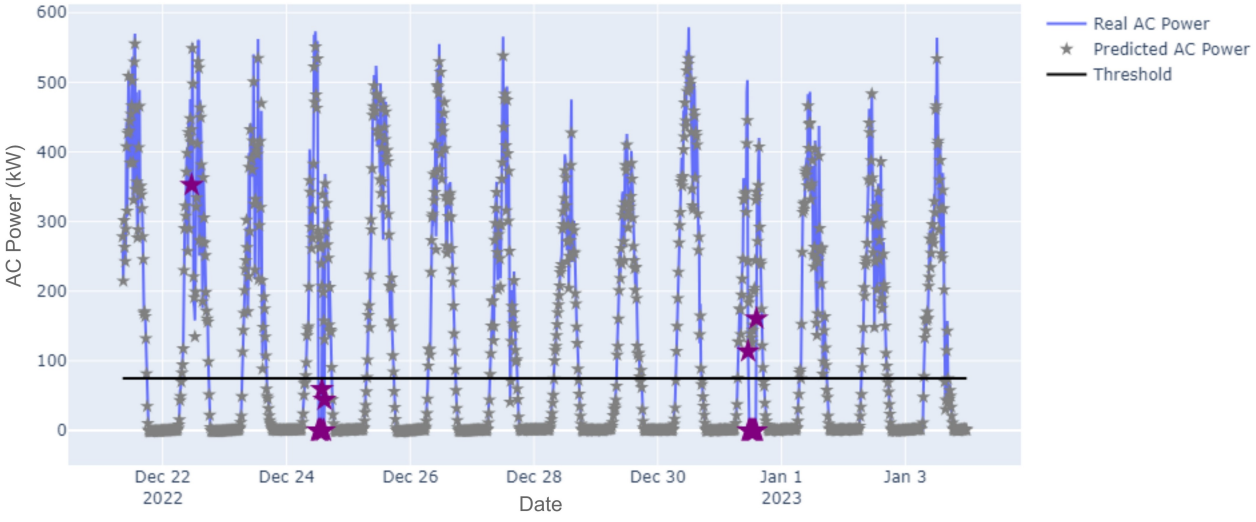
Figure 3.7: Training, Validation Loss of the advanced DL Algorithms: (**a**) Advanced RNN method. (**b**) Advanced GRU method. (**c**) Advanced LSTM method.



(a)

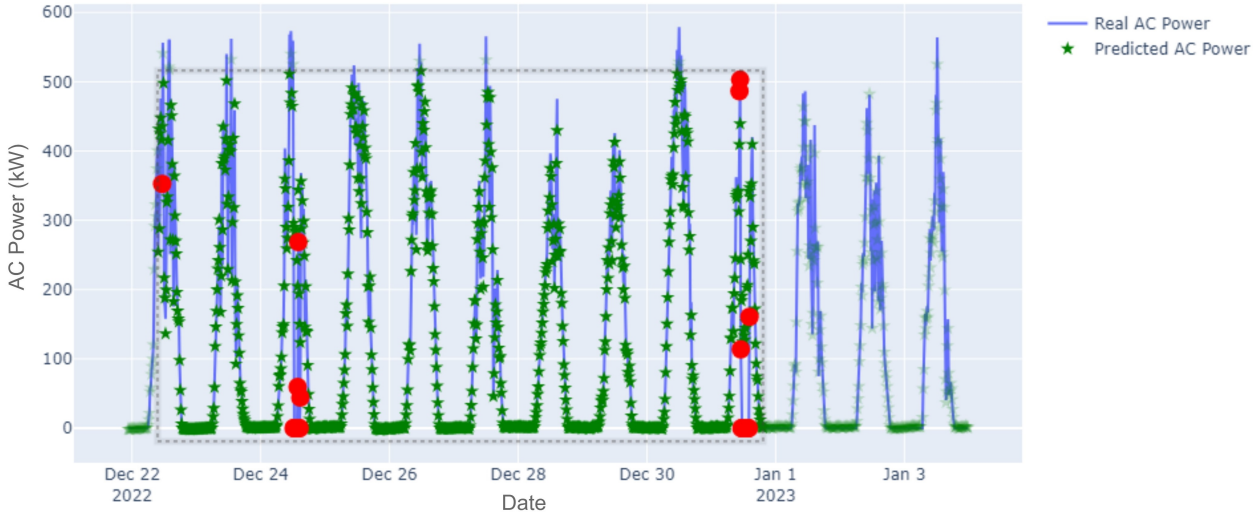


(b)

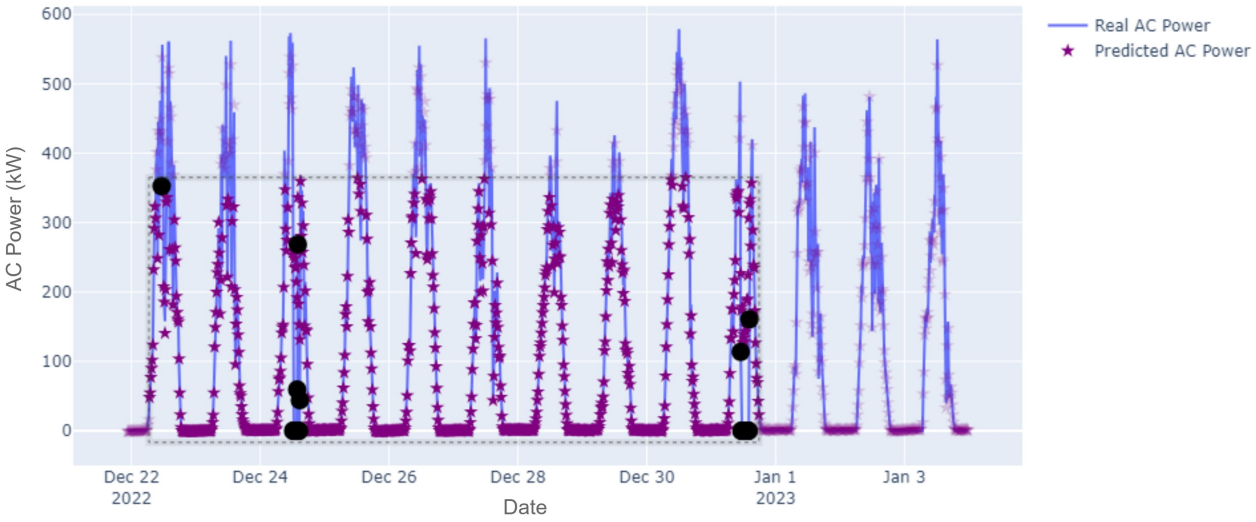


(c)

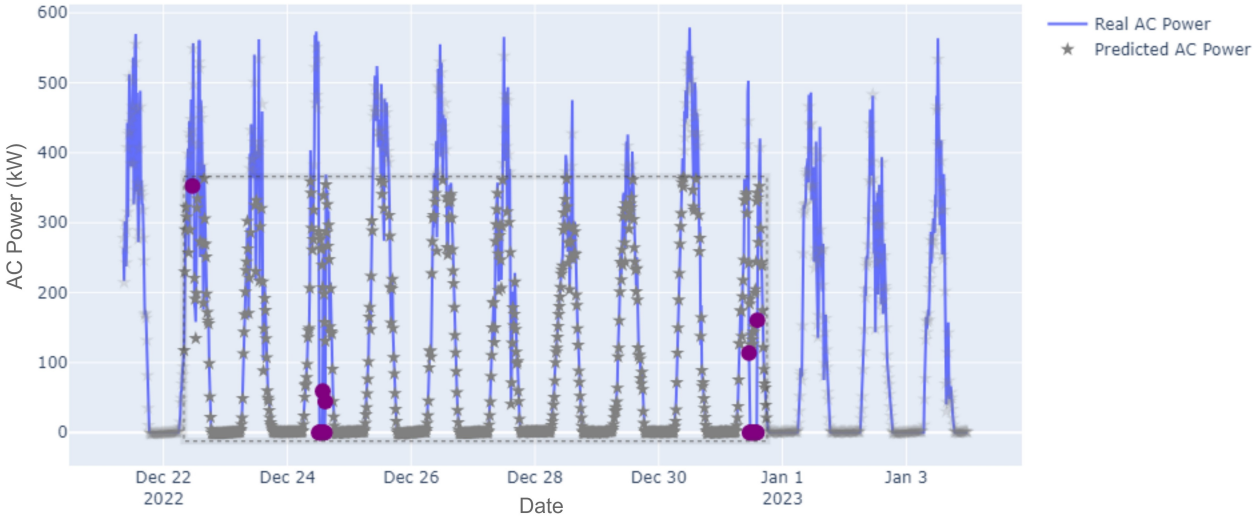
Figure 3.8: Adaptive Threshold Integrated Method With: (**a**) Advanced RNN model. (**b**) Advanced GRU model. (**c**) Advanced LSTM model.



(a)

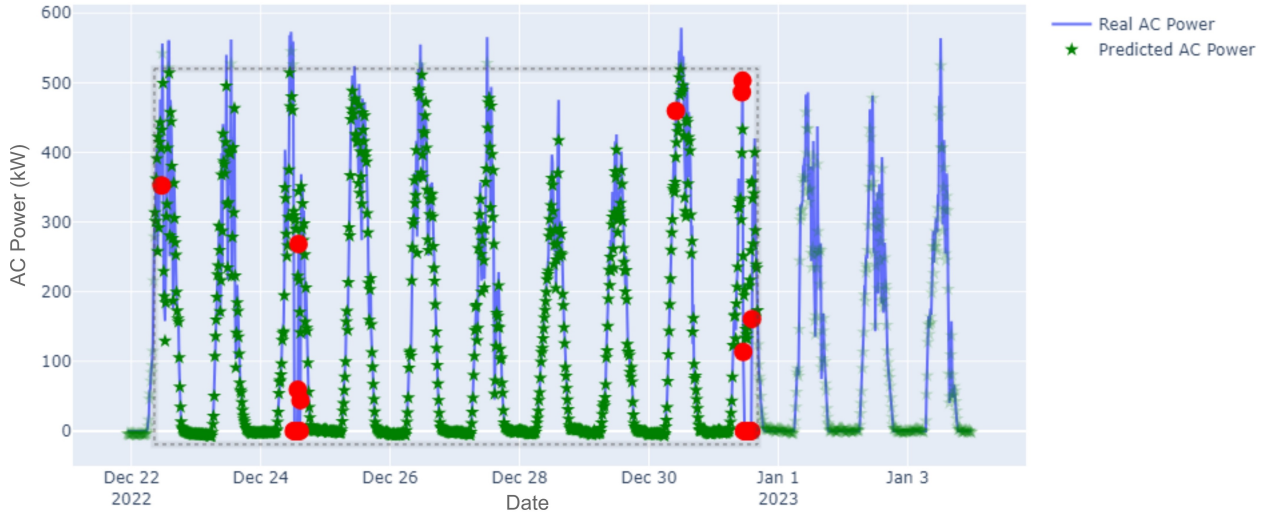


(b)

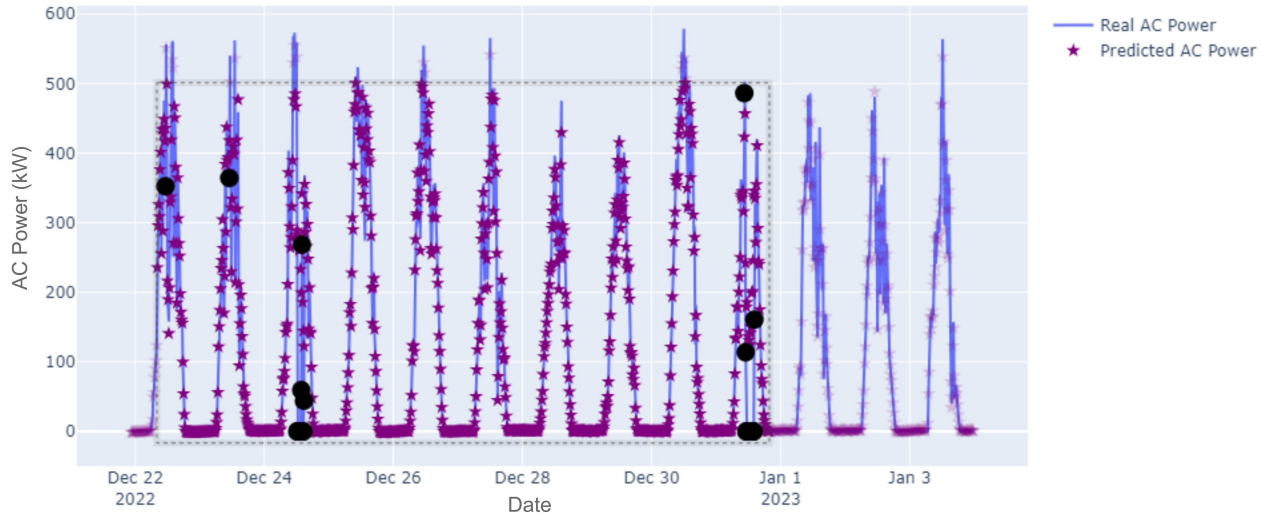


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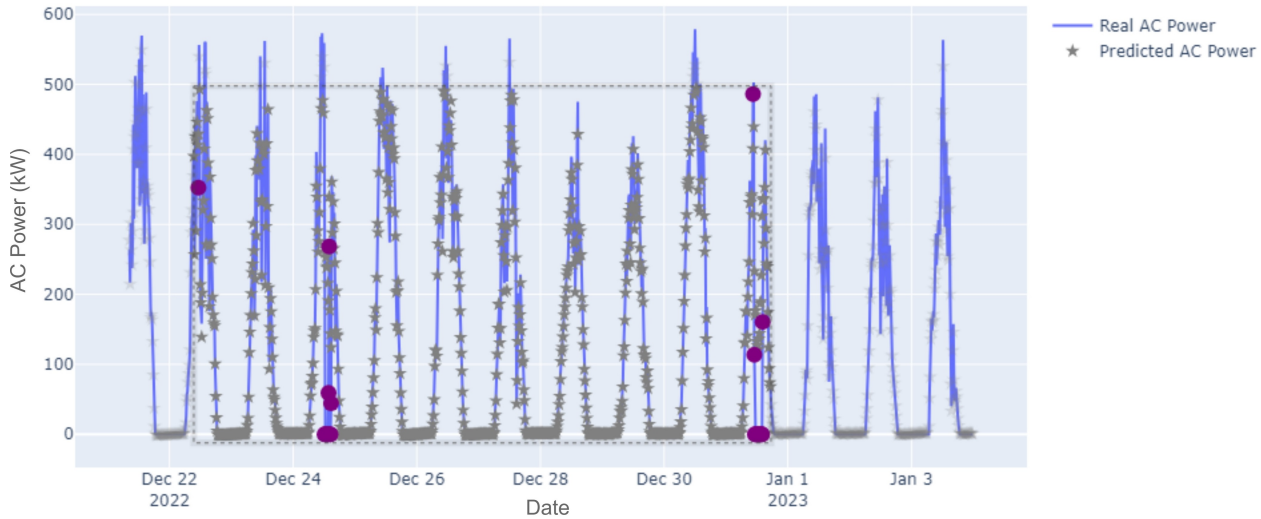
Figure 3.9: Identification of MG Inverter Faults by the Proposed: (**a**) Advanced RNN architecture. (**b**) Advanced GRU architecture. (**c**) Advanced LSTM architecture.



(a)



(b)



(c)

Figure 3.10: Detected MG Inverter Faults by the: (**a**) Conventional RNN Method. (**b**) Conventional GRU Method. (**c**) Conventional LSTM Method.

and 31 December than other counterparts.

Figure 3.9 and 3.10 illustrate the detected inverter faults from the proposed advanced and traditional DL methods, respectively. For the adaptive threshold integration, the sensitivity to anomalies of those models becomes enhanced, enabling efficient detection of deviations from the microgrid inverter power signals. The models identified the faults denoted by dotted points which were encountered on 22th, 24th, and 31st December, 2022 from the dataset.

For evaluating the performances of the implemented DL methods, the R-squared (R^2) and MAE matrices have been utilized for this analysis. The matrices have been enumerated through the following equations:

$$R^2 = 1 - \frac{\sum_{i=1}^{N}(Y_i - \hat{Y}_i)^2}{\sum_{i=1}^{N}(Y_i - \bar{Y})^2} \tag{3.26}$$

$$MAE = \frac{1}{N}\sum_{i=1}^{N}|Y_i - \hat{Y}_i| \tag{3.27}$$

Here, N indicates the total number of samples; Y_i, and $\hat{Y}_i$ denote the real values from the ac signal and the predicted values by the models, respectively; $\bar{Y}$ indicates the mean of the real values.

3.6 Discussion

The implemented advanced DL techniques shown better performances than the conventional methods in terms of detecting microgrid inverter anomalies. Each of the implemented architectures went through a careful training and evaluation. The developed advanced LSTM architecture demonstrated a correlative superiority over other methods in terms of both prediction accuracy and deviation from real values. The proposed advanced LSTM, GRU, and RNN model achieved R^2 scores of 0.971, 0.958, and 0.941, MAE scores of 8.263, 10.182, and 12.102, respectively; whereas the traditional LSTM, GRU, and RNN methods achieved R^2 scores of 0.949, 0.937, and 0.911, MAE scores of 11.847, 12.545, and 15.188, respectively. Table 3.1 enlists the performances of the DL architectures in terms of detecting microgrid inverter faults. The findings from here demonstrate a progressive correlative improvement from conventional to developed advanced RNN to GRU and LSTM method in the context of error reduction as well as prediction accuracy.

A satisfactory performance was achieved from the advanced RNN method with R^2 score of 0.941 and MAE scores of 12.102. Nevertheless, it possesses some limitations while capturing long-term dependencies from the sequential microgrid data. Because of less capability of tackling gradient vanishing issues than other two counterparts while processing long sequences, it's performance was affected when retaining and compiling long-term dependencies from the microgrid inverter power signals. This resonates with the need for models that have improved memory capabilities and possess better capturing capabilities of temporal patterns, which are very significant in terms of discerning subtle deviations from the output ac power trends with respect to the external factors.

Having capabilities of handling gradient vanishing issues, the advanced GRU architecture provided better performance of a higher R^2 value: 0.958 and lower MAE: 10.182 than the advanced RNN and traditional LSTM, GRU, and RNN methods. This enhanced performance was achieved through the architectural improvement with two gating mechanisms for an enhanced regulation of information flow. The relevant past information regarding irradiation, temperature variations, and output ac power were retained whereas the redundant data were discarded through the update gate. Consequently, the sequential temporal dependencies of the microgrid inverter power outputs with complex environmental factors were better processed by this method. With a better capturing capability of temporal dependencies in the time series data, this model can be more efficient in the context of microgrid fault detection.

The advanced LSTM method outperformed with the lowest MAE: 8.263 and highest R^2 value: 0.971, compared to other DL counterparts. Advanced LSTM architecture incorporated gating mechanisms as well as cell states, allowing most enhanced memory retention and discarding of redundant information. The inherent gradient vanishing problem of standard RNN was handled by the cell state mechanism through retaining the long-term dependencies into the model. Consequently, the significant historical patterns which impact the output ac power with variations due to environmental factors like irradiance, temperatures were better preserved than other methods. This allows an enhanced reduction of noise sensitivity as well as output ac power fluctuations which can be caused by external factors or transient faults. As a result, this method was capable of differentiating between normal deviations in power generation with the external factors and real anomalies more precisely, enhancing the predictive maintenance capabilities thereby.

In the context of predictive maintenance, a lower MAE score demonstrates more precise identification of anomalies, indicating reduction of both false negatives which cause missed faults and false positives which cause unnecessary maintenance triggers. The advanced LSTM algorithm outperformed other counterparts with the lowest MAE. Besides, the incremental enhancement of R^2 scores from 0.941 (advanced RNN) to 0.958 (advanced GRU) to 0.971 demonstrates that the advanced LSTM model is more accurate than other DL methods in terms of modeling intricate temporal dependencies from the microgrid inverter performance with respect to the external factors. From the correlative performance analysis, it can be said that the advanced LSTM algorithm can be more robust with the capabilities of capturing both short and long-term dependencies from the complex data-points for identifying

Table 3.1: Correlative Permormance Evaluation of Different DL Models

Methods	R^2 Score	MAE
Advanced RNN	0.941	12.102
Advanced GRU	0.958	10.182
Advanced LSTM	0.971	8.263
Conventional RNN	0.911	15.188
Conventional GRU	0.937	12.545
Conventional LSTM	0.949	11.847

anomalies in microgrid applications to minimize unexpected failure risks and ensure consistent power flow through the microgrid network to improve overall system efficiency and stability.

3.7 Conclusions

This correlative study advances the DL-based avenues for the inverter fault detection in microgrid applications by conducting a comprehensive correlative performance analysis on advanced and conventional RNN, GRU, and LSTM architectures. The proposed adaptive threshold-based technique enhanced the performance of the anomaly detection algorithms through adjusting the threshold point dynamically. Both adaptability of the model to changing patterns and training efficacy were improved through the implementation of adaptive stochastic optimization technique. The achieved incremental enhancement of R^2 scores from 0.941 (advanced RNN) to 0.958 (advanced GRU), and finally to 0.971 (advanced LSTM) suggest that the advanced LSTM model is more accurate and robust than other counterparts in minimizing prediction errors while processing intricate temporal dependencies from the microgrid inverter power signals with respect to complex environmental factors. The applicability of these DL methods is promising, but still has challenges in terms of generalization through diverse microgrid scenarios for an enhanced malfunction diagnosis to improve overall microgrid energy efficiency by minimizing downtime. Besides, some limitations of this research consist of computational complexity, data dependency as DL architectures highly depend on historical high-quality data and in the case of missing values or inconsistencies in the data set the prediction accuracies can be affected, and some factor variability as in this analysis some other factors such as SPV module aging, microgrid topology variations, cloud cover variations were not considered, which can affect the performance of microgrid inverters over time. Developing more advanced hybrid architectures considering these limitations, with more enhanced interpretability and error reduction capabilities with IoT setups can be an excellent avenue for real-time implications of diverse large-scale microgrid scenarios. Future studies can focus on exploring real-time implementation, enhancing robustness with respect to intricate external factors, integration of multiple data sources through diverse DER scenarios, and addressing scalability concerns while deploying on large-scale, diverse microgrid setups.

Chapter 4

Advanced Hybrid Deep Learning Based Framework for Microgrid Inverter Predictive Maintenance

4.1 Introduction

The increasing complexity of microgrids 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 generating 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 generating maintenance alerts according to the performances over time is becoming crucial for enhanced predictive maintenance of microgrids. This study introduces an intelligent data-driven hybrid framework for microgrid predictive maintenance utilizing a hybrid deep learning architecture, combined with advanced data analysis and a residual-based dynamic threshold technique. The loss function of the proposed hybrid algorithm has been optimized for enhancing microgrid predictive maintenance. The results show significant accuracy in predicting the maintenance needs within microgrids. This chapter can offer valuable insights for designing and enhancing hybrid algorithms for advanced maintenance in microgrid systems, contributing to advancements in predictive maintenance technology and promoting a resilient and cost-effective operation of microgrids.

4.2 Background and Contribution

A new era of proficiency and resilience in sustainable energy systems has emerged through the integration of microgrids into modern power systems. Microgrids are attracting significant research interest due to their advantages in terms of stability, controllability, economic efficiency, and reliabil-

ity [193]. In today's evolving energy landscape, microgrids are advancing by seamlessly integrating diverse DERs and loads within the extensive networks of ac grids [166]. Through the rapid growth of DERs in distribution systems, specifically the SPV generations are contributing in transforming the conventional passive networks [194] into more active entities, for example microgrids. Being the key sources of energy in microgrids, DERs encircle a number of small-scale generation sources. In this context, the SPVs stand out being a promising generation source of microgrids by capturing the abundant availability of renewable and clean solar energy from sun [195]. SPV systems are experiencing a boom [196] in power systems at present. The recent widespread adoption of this technology has been fueled by their cost-effectiveness and scalability. Yet, the diverse intermittent attributes of SPV systems cause major protection concerns. For addressing these protection concerns and enhancing the operational reliability within microgrid network, fault detection in microgrid predictive maintenance has become an essential tool [188] and is one of the most significant challenges which demands the greatest research attention [197]. Besides, highly dependence of SPV systems on environmental factors i.e., irradiation and temperatures cause many challenges, specifically in the context of desired output power into microgrid systems which demands for more advanced fault detection, and maintenance alert over time based frameworks for an enhanced predictive maintenance of microgrids.

Fault detection is one of the most critical steps of predictive maintenance for getting rid of any potential catastrophic failures [198].For detecting and responding various faults in power system, machine learning based techniques are emerging as a robust solution, extending the potential of upgrading predictive maintenance and improving the microgrid system resiliency. Various industries are widely implementing these data-driven ML-based predictive maintenance applications for instance in manufacturing [199], [200], mining [201], healthcare [202], and transportation [203]. However, the implementation of ML-based predictive maintenance frameworks for microgrid systems is still a relatively new field that demands further investigation. Moreover, most of the recent research works on microgrid systems are mainly focused on the economic dispatching [7] as well as energy management [21], [204], [205].

Besides, research has been performed by [26] on microgrid challenges, specifically focused on cyber attack detection. Another study was conducted in [24] focusing the digital twin technology specifically for microgrid energy management. For dc microgrid clusters, a support vector machine integrated classification technique has been presented in [206] for high-impedance faults. A multi-layer perceptron neural network (MLPNN)-based classification method for locating dc arc fault for dc microgrids has been proposed by [207] 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 [197] for detecting the feeder faults. A study in [176] 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 [208] 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 microgrid test systems on the PSCAD/EMTDC platform. Further research in [178] expanded on microgrid protection techniques, analyzing islanded microgrid scenarios with short-

circuit faults using PSCAD/EMTDC. Similarly, [177] employed PSCAD/EMTDC to detect high- and low-resistance dc faults in LV microgrids based on inductor voltage and relay ground current. Additional research [179] examined microgrid faults under varying impedance conditions using a power quality control scheme.

Machine learning based approaches have also been explored. In [78] a decision tree and wavelet transform-based method was developed to classify microgrid faults with 97% accuracy on a dataset of 3,860 samples. Another ML technique integrating wavelet transforms in [209] achieved an overall classification accuracy of 97.76% in test cases. A data-driven approach has been presented in [196] for locating short-circuit line faults that occur in dc microgrids by utilizing a tranfer 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 [210] for detecting different low impedance line faults for low voltage dc microgrids. Besides, study conducted by [31] explored different scheduling issues of microgrid DERs, and [29] presented various experimental platforms for hydrogen-based microgrids focused on energy management. In the current literature, there is no study conducted on advanced HDL architectures regarding microgrid predictive maintenance with respect to exogenous factors, specially on fault detection and continuous monitoring through maintenance alerts over time integrated frameworks for microgrid inverters.

With the integration of different DERs and inverters, microgrid structures are becoming more complex recently. As a result, the vulnerability to faults and malfunctions is escalating within the power system. Being the core of the microgrid 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 microgrid systems, developing advanced hybrid ML-based techniques for fault identification integrated with microgrid inverter continuous performance monitoring by generating maintenance alerts over time has become essential. Besides, deep learning techniques with their deeper network layers and powerful feature vectors having higher dimensions [211] 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 [212]. 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 microgrid 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 Predictive Maintenance:** 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 microgrid operations. The developed data analysis technique establishes a strong foundation for model training, which can enhance the accuracy and interpretability of the predictive maintenance framework for microgrid inverters, ultimately improving predictive maintenance capabilities within the microgrid network.

- **Advanced HDL Architecture Based Predictive Maintenance for Microgrid:** 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 microgrid inverters with respect to exogenous factors. Additionally, the 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 predictive maintenance effectiveness within the microgrid 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 microgrid inverters, which can lead to delayed responses and false alarms in the presence of critical, fluctuating data points. Proposed technique enhances predictive maintenance 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 microgrid operation.

By advancing predictive maintenance 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 predictive maintenance capabilities, enhancing system resilience, reliability, and efficiency which resonates with UN's sustainable development goals.

The remainder of this study is structured as follows: Section 4.3 summarizes the problem statement of the study. Section 4.4 provides a detailed overview of the proposed methodology. Section 4.5 presents

the results and discussion of the advanced HDL framework. Finally, Section 4.6 concludes the work with summary and concluding remarks.

4.3 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 been 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 microgrid network. Because, it is the prerequisite for ensuring the efficient and stable generation and distribution of power through microgrid networks that are equipped with a variety of inverter based resources. Therefore, monitoring the performances of inverters throughout microgrid 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 predictive maintenance competency can be enhanced significantly within the microgrid network. Figure 4.1 illustrates a clear overview of a microgrid network which includes SPVs as the DER, BESS, and several local loads.

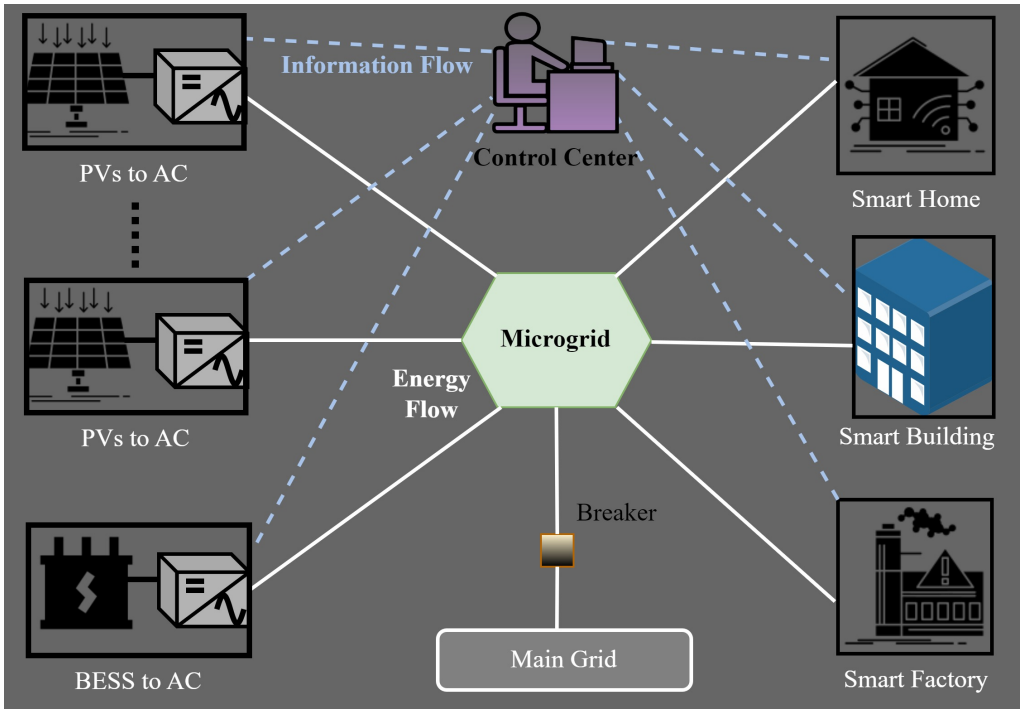


Figure 4.1: Microgrid System Overview.

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 may result in abnormalities or faults in the context of the produced ac powers by the microgrid inverters. Consequently, it is essential to find out if there are any irregular limitations due to the external factors or it is the malfunctioning inverters.

The successful identification of these abnormalities is crucial for enhancing the stable performance as well the resiliency of microgrid system.

A combined DL-based architecture with other efficient techniques can be more robust in identifying the nuance pattern deviations from microgrid inverter ac output signals. Besides, there is a research gap in implementing advanced HDL frameworks in the current literature in terms of predictive maintenance in microgrid applications. Moreover, in power grid applications, implementing advanced DL models, their performance comparison [187] still remain an unexplored research topic.

In case of the recent real-world, dynamic microgrid operational scenarios, ML-based traditional algorithms are not efficient enough to identify the variety of nuanced failure scenarios and varying patterns. Furthermore, traditional 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 of developing advanced hybrid models possessing adaptive predictive maintenance capabilities that can address these varying nuanced patterns from the microgrid 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 microgrid inverters under complex and dynamic operational scenarios is getting essential to enhance the microgrid predictive maintenance 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 microgrid 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 predictive maintenance plans for the uprising adoption of microgrid systems, directing to a greater resilient and efficient green energy landscape.

4.4 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 microgrid data. The advanced HDL model is capable of capturing both spatial and temporal dependencies which has been leveraged in the context of microgrid systems where there are numerous external factors which can impact the performance of the inverters for example any sudden changes in temperature, irradiation or any other factors. An overview of the implemented microgrid dataset in this research, an advanced data analysis procedure incorporating different data

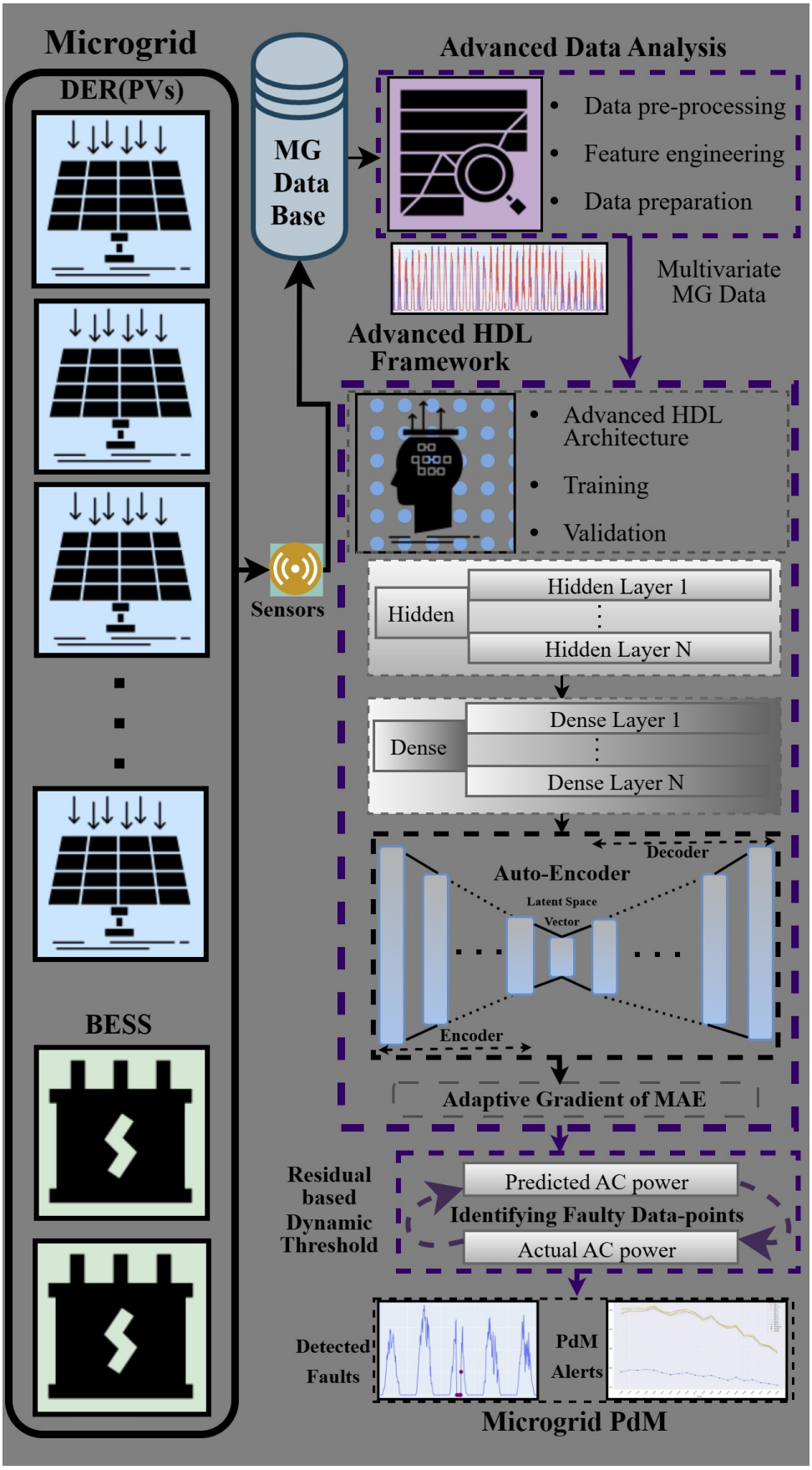


Figure 4.2: Proposed Advanced HDL Framework for Microgrid Predictive Maintenance.

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 for identifying the faults as well as generating predictive maintenance alerts from the microgrid inverters. Figure 4.2 illustrates the proposed structure of the advanced hybrid DL framework for microgrid predictive maintenance.

4.4.1 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 in 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.

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 predictive maintenance.

4.4.2 Advanced Data Analysis

For designing an accurate and robust predictive maintenance 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 microgrid inverters. An advanced data analysis technique has been designed integrated with this HDL framework to determine the potential problem in the microgrid system. The advanced data analysis technique has been described in this subsection followed by several procedures.

Temperature Assessment

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

Figure 4.3 illustrates the module and ambient temperature analysis carried throughout 1 month during the day. Here, it can be seen that 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.

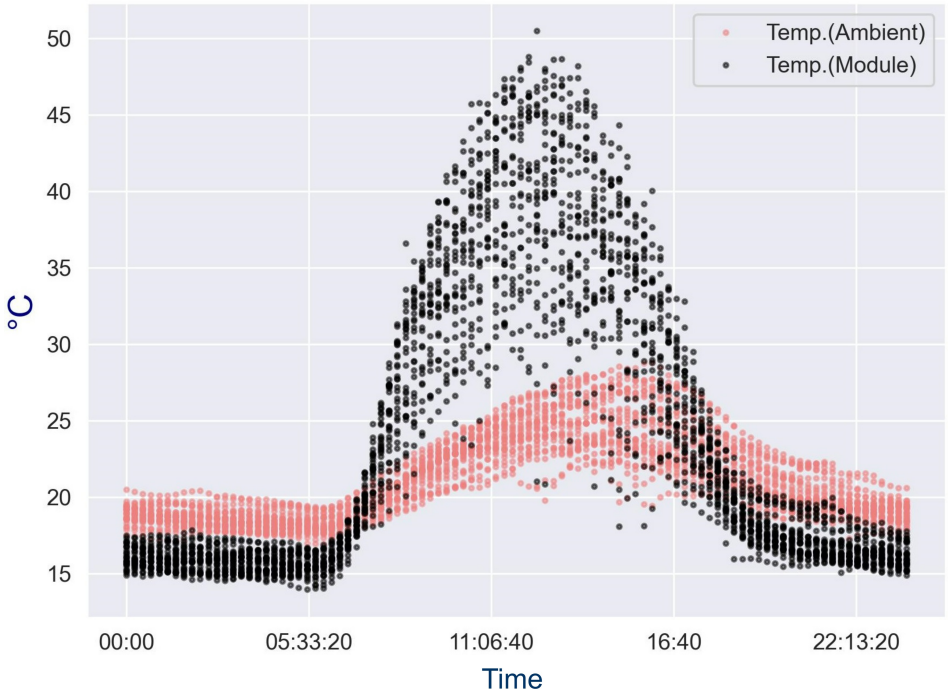


Figure 4.3: Temperature Assessment of the Microgrid Data.

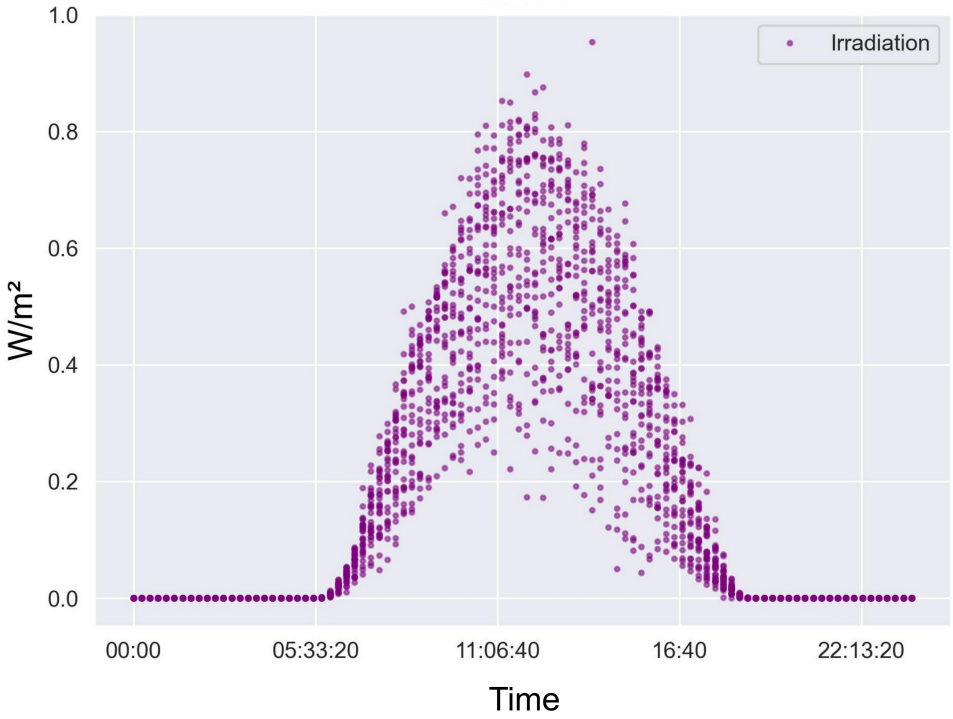


Figure 4.4: Irradiation Analysis from the Microgrid Data.

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.

Figure 4.4 depicts the irradiance or sunlight intensity captured through the arrays during the day. It can be seen that the irradiation index is ranging around 0.6 to 0.9 during the maximum sunlight hours and there had been no drastic fall or zero values observed from the data which means the system should be receiving adequate sunlight intensity without any significant obstruction, dust, or shading.

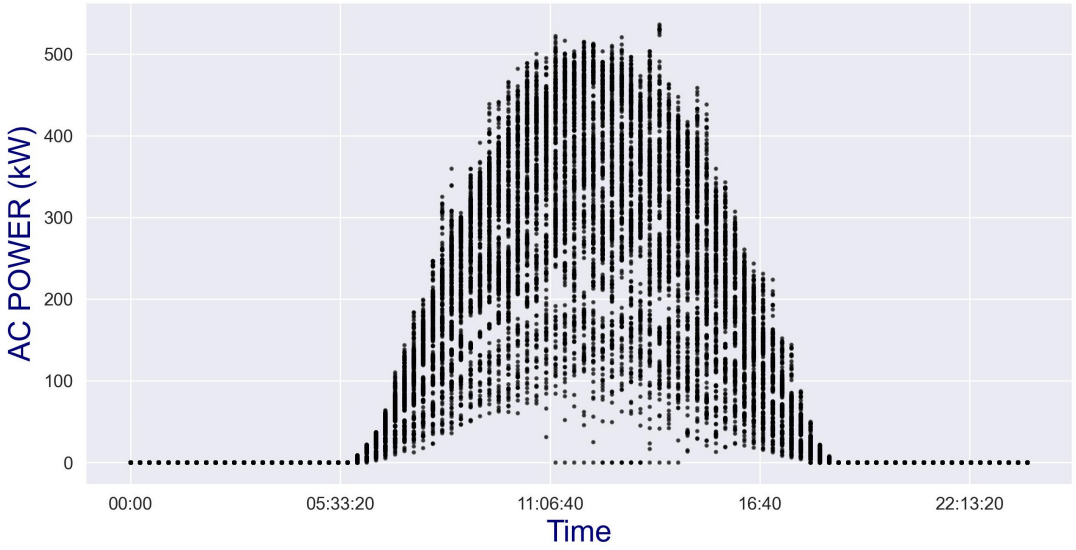


Figure 4.5: AC Output Power Analysis.

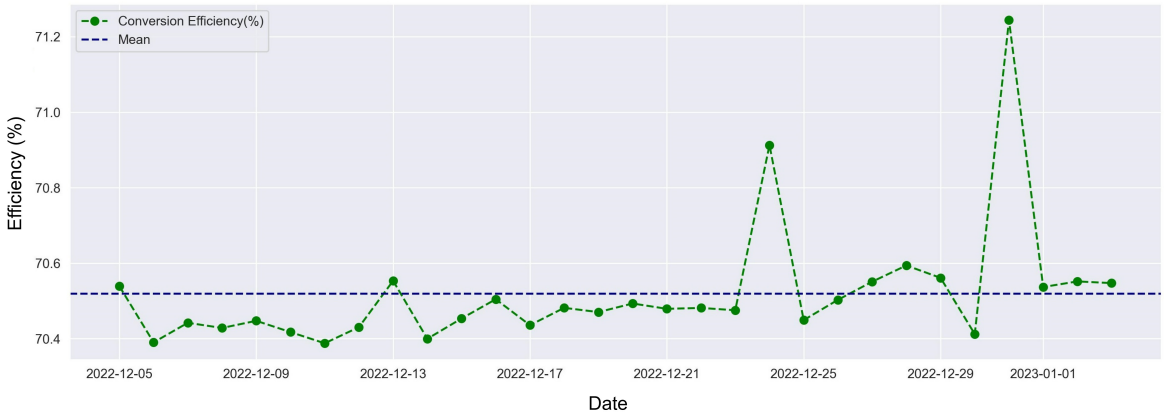


Figure 4.6: Conversion Efficiency Analysis.

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. Figure 4.5 illustrates the converted ac power by the microgrid inverters. It can be seen that almost all of the inverters are converting regular output power during the maximum sunlight hours. But there had 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 microgrid system.

Moreover, the power conversion efficiency has been analyzed on a daily basis all throughout 30 days

where the conversion trend was downward for most of the times with respect to the average efficiency (70.51%) as can be seen from Figure 4.6.

Under-performing Inverter Identification

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

$$AC(t) = a \cdot I(t) \left[1 - b \cdot \frac{T(t) + I(t)}{800(c - 20) - 25} - d \cdot \ln I(t)\right] \cdot \eta_{\text{inv}} \tag{4.1}$$

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.

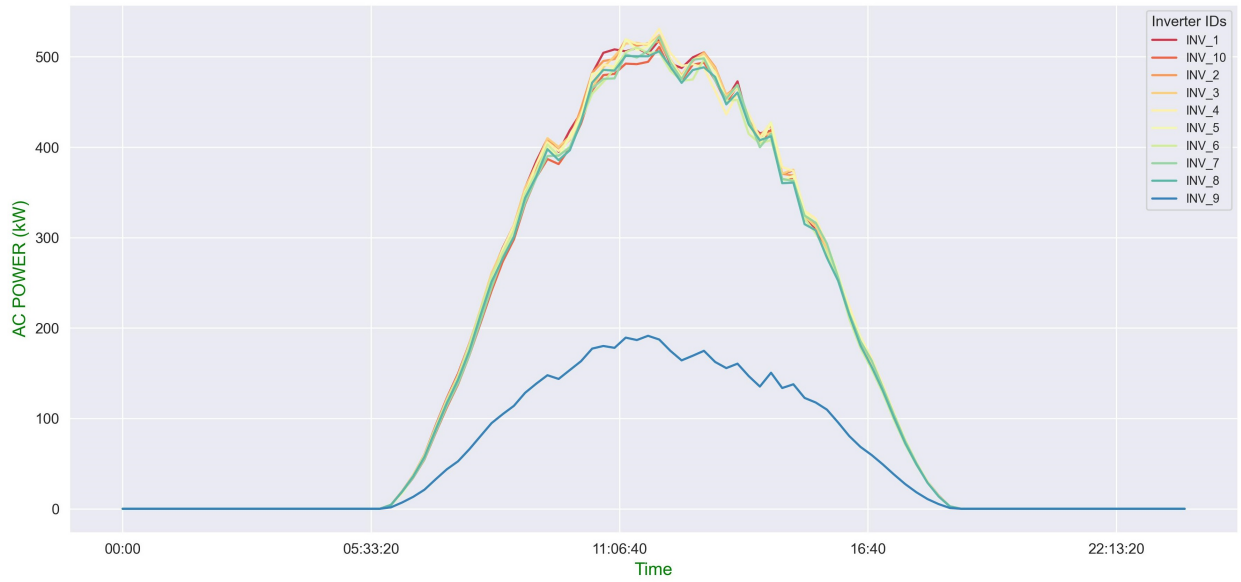


Figure 4.7: Identification of Under-performing Inverter for Microgrid Predictive Maintenance.

Figure 4.7 depicts the individual inverter performances in the microgrid system in terms of converting the produced power to ac. During the maximum sunlight hours, almost all the inverters are performing similar 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 generating maintenance alerts will be investigated in depth in the next stages of this advanced HDL framework.

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 [188] in order to minimize the training complexity and enhance

the predictive maintenance 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 linear association between a pair of features such as U and V, has been enumerated using the following equation:

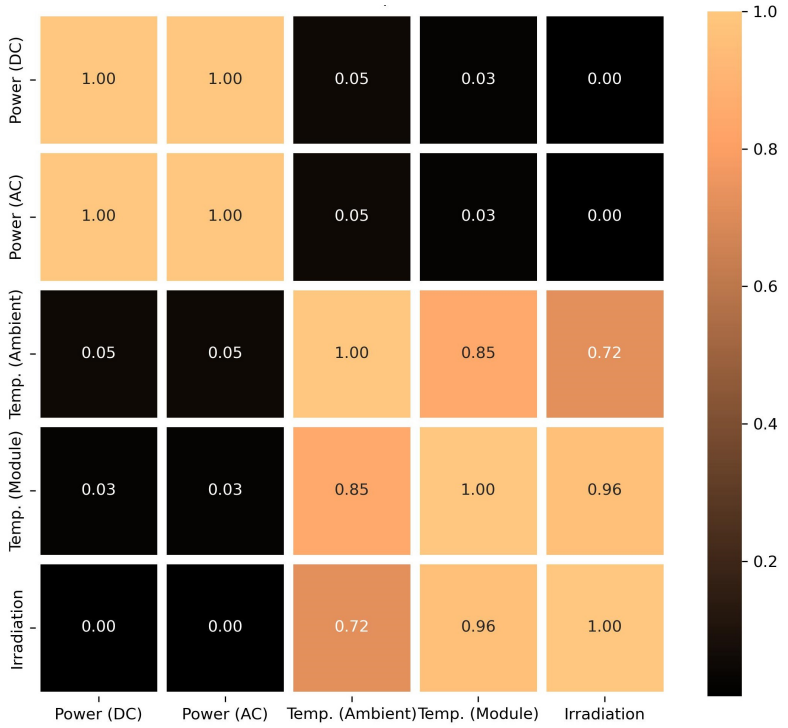


Figure 4.8: Correlation Heat-map of Features for Microgrid Predictive Maintenance.

$$\gamma_{UV} = \frac{\sum (U_i - \bar{U})(V_i - \bar{V})}{\sqrt{\sum (U_i - \bar{U})^2 \sum (V_i - \bar{V})^2}} \tag{4.2}$$

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 from the dataset. The redundant features can be identified from the dataset using this analysis. The linear association within the features is high in terms of a higher positive value ($\gamma \approx 1$). Figure 4.8 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 4.1:

Algorithm 4.1: Data Preparation for the Advanced HDL Model for Microgrid PdM.

Input: X, T, T_s

Output: X_{Train}, X_{Valid}, X_{Test}

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

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

3 $[X_{\text{Scaled}}[i : i + T] \rightarrow X_{\text{Seq}}$ for i in range $(\text{length}(\text{X}_{\text{Scaled}}) - T + 1)]$

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

5 $D_s \rightarrow Train.Test.Split(X_{\text{Seq}}, T_s{=}0.15)$

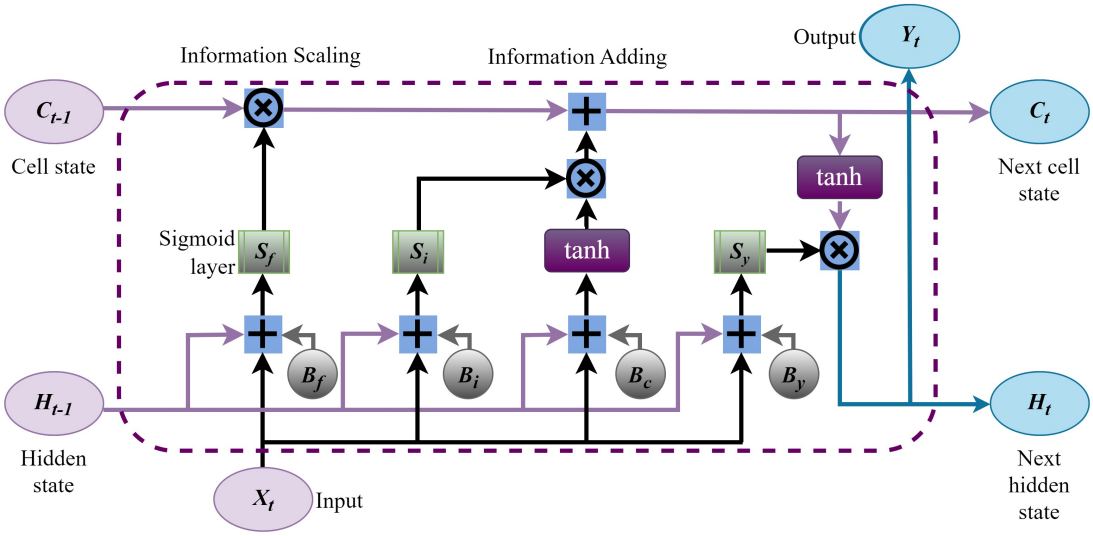


Figure 4.9: LSTM Layer Operation of the Advanced HDL Framework for Microgrid PdM.

4.4.3 LSTM Layer of the Proposed Advanced HDL Framework for Microgrid Predictive Maintenance

LSTM layers could be an excellent avenue for the predictive maintenance application in microgrid systems. It is a type of neural network that is linked to the 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 [190]. 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 microgrid 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 Figure 4.9. 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:

$$G_t^f = S_f(M_w^f[H_{t-1}, X_t] + B_f) \tag{4.3}$$

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.

$$G_t^i = S_i(M_w^i[H_{t-1}, X_t] + B_i) \tag{4.4}$$

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

$$\tilde{C}_t = \tanh(M_w^c[H_{t-1}, X_t] + B_c) \tag{4.5}$$

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:

$$C_t = G_t^f C_{t-1} + G_t^i \tilde{C}_t \tag{4.6}$$

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:

$$Y_t = S_y(M_w^y[H_{t-1}, X_t] + B_y) \tag{4.7}$$

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:

$$H_t = Y_t \tanh(C_t) \tag{4.8}$$

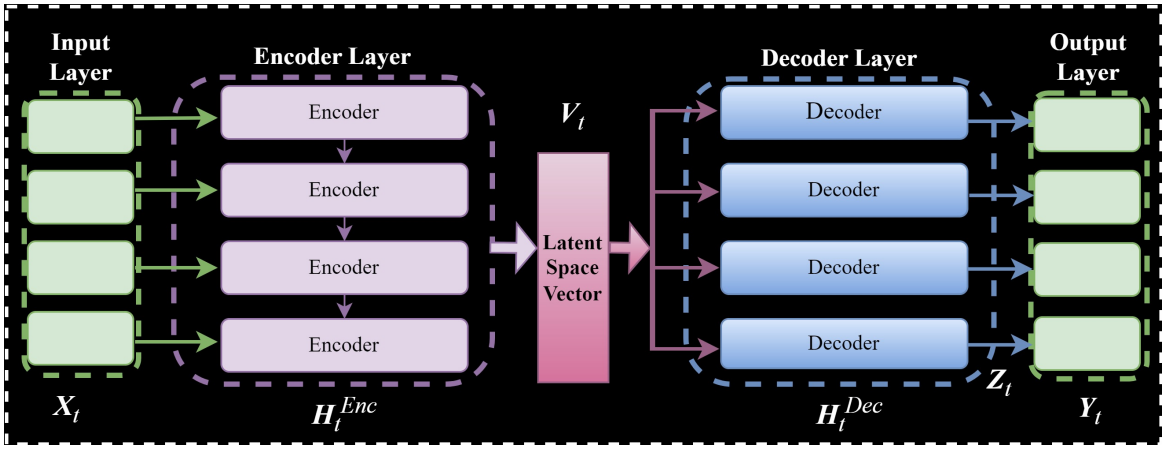


Figure 4.10: Auto-encoder Architecture of the Advanced HDL Framework for Microgrid PdM.

4.4.4 LSTM-AE Architecture of the Proposed Advanced HDL Model for Microgrid Predictive Maintenance

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 of the HDL framework captures the complex temporal patterns and any subtle deviations from the output ac power of the microgrid inverters with a robust reconstruction of the input sequences.

Fig. 4.10 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 microgrid inverter output power signals which already have 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:

$$H_t^{Enc} = \mathbf{E}(H_{t-1}^{Enc}, X_t) \tag{4.9}$$

$$V_t = H_t^{Enc} \tag{4.10}$$

where, the input data is X_t, H_t^{Enc} is the hidden state of the encoder layer of the advanced HDL framework 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:

$$H_t^{Dec} = \mathbf{E}(H_{t-1}^{Dec}, Z_{t-1}) \tag{4.11}$$

$$Z_t = \mathbf{F}(H_t^{Dec}) \tag{4.12}$$

Here, H_t^{Dec} is the hidden state and Z_t is the output of the decoder layer at time step t, $\mathbf{F}$ 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 as 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:

$$Y_t = Z_t \tag{4.13}$$

Algorithm 4.2 illustrates the overall architecture of the developed auto-encoder model:

Algorithm 4.2: Auto-encoder Configuration of the Proposed Advanced HDL Framework.

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

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

4.4.5 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 for optimizing the error distribution. The error distribution has been optimized through 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:

$$p_t = \theta_1 \cdot p_{t-1} + (1 - \theta_1) \cdot G_t \tag{4.14}$$

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

$$q_t = \theta_2 \cdot q_{t-1} + (1 - \theta_2) \cdot G_t^2 \tag{4.15}$$

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:

$$p_t^{corr} = \frac{p_t}{1 - \theta_1^t} \tag{4.16}$$

$$q_t^{corr} = \frac{q_t}{1 - \theta_2^t} \tag{4.17}$$

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

$$M_w^t = M_w^{t-1} - \alpha \cdot \frac{p_t^{corr}}{\sqrt{q_t^{corr}} + \epsilon} \tag{4.18}$$

$$B^t = B^{t-1} - \alpha \cdot \frac{p_t^{corr}}{\sqrt{q_t^{corr}} + \epsilon} \tag{4.19}$$

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).

4.4.6 Residual Based Dynamic Threshold Framework

For enhancing the predictive maintenance capabilities of the developed advanced 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 predictive maintenance capabilities through adjusting the threshold point dynamically. In case of any nuanced deviations in the operational conditions, the proposed algoritm'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).

$$s_t = |\hat{z}_t - z_t| \tag{4.20}$$

- 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:

$$\bar{s}_t = \beta \cdot s_t + (1 - \beta) \cdot \bar{s}_{t-1} \tag{4.21}$$

  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 proposed advanced hybrid algorithm, the standard deviation of the residuals is calculated through the following equation:

$$\sigma_t = \sqrt{k \cdot (s_t - \bar{s}_t)^2 + (1 - k) \cdot \sigma_{t-1}^2} \tag{4.22}$$

  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:

$$\tau_t = \bar{s}_t + v \cdot \sigma_t \tag{4.23}$$

  The threshold point gets set to be a multiple (v) of the standard deviation (σ_t) above the moving average ($\bar{s}_t$). Here, v 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:

$$\text{Microgrid Inverter Faults} = \begin{cases} 1 & \text{if } |\hat{z}_t - z_t| > \tau_t \\ 0 & \text{Normal} \end{cases} \tag{4.24}$$

This residual based dynamic threshold framework integration enhances the model's fault detection capability through remaining flexible while enabling it 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.

4.4.7 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:

$$\text{Maintenance Alerts} = \begin{cases} Careful: & \text{if } \epsilon_{\text{cr}} < s_t \leq \epsilon_{\text{sr}} \\ Serious: & \text{if } \epsilon_{\text{sr}} < s_t \leq \epsilon_{\text{er}} \\ Emergency: & \text{if } \epsilon_{\text{er}} < s_t \end{cases} \tag{4.25}$$

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 (14–31) of Algorithm 4.3. 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. Algorithm 4.3 illustrates the developed predictive maintenance framework of the proposed advanced HDL architecture to predict the maintenance needs within microgrid system:

Algorithm 4.3: Advanced HDL framework for microgrid predictive maintenance.

Input: $X = \{x_1, x_2, \ldots, x_t, x_N\}$ - 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: $Y_t \rightarrow$ Identify encountered faults and trigger alerts for microgrid PdM

Identify under-performing inverter by solving:

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

Solve equation (2)

Normalize the input data X

for $i = 1$ *to* N **do**

- Sample a data point from X
- Input the data point $\rightarrow$ Advanced HDL framework:
- Solve equation (3) to (8)
- Encode the data-points using: $H_t^{Enc} = \mathbf{E}(H_{t-1}^{Enc}, X_t)$
- Compress those into latent space vector: $V_t = H_t^{Enc}$
- Decode and reconstruct the data-points by implementing equation (11) to (13)
- Calculate: $R^2 = 1 - \frac{\sum_{i=1}^{N}(X_i - Y_i)^2}{\sum_{i=1}^{N}(X_i - \bar{X})^2}$
- Enumerate: $MAE = \frac{1}{N}\sum_{i=1}^{N}|X_i - Y_i|$
- Optimize the MAE to the minimum level by solving equation (14) to (19)
- Calculate the residual values using the formula: $s_t = |\hat{z}_t - z_t|$
- Enumerate the moving average of the residuals using the formula: $\bar{s}_t = \beta \cdot s_t + (1-\beta) \cdot \bar{s}_{t-1}$
- Solve: $\sigma_t = \sqrt{k \cdot (s_t - \bar{s}_t)^2 + (1-k) \cdot \sigma_{t-1}^2}$
- Enumerate the dynamic threshold: $\tau_t = \bar{s}_t + v \cdot \sigma_t$
- **if** $|\hat{z}_t - z_t| < \tau_t$ **then**
  - Classify the data point as normal
- **end**
- **else**
  - Classify the data point as a fault
- **end**
- PdM Alerts:
- **for** *each time step* t **do**
  - **if** $s_t > \epsilon_{er}$ **then**
    - Emergency Alert
  - **else if** $\epsilon_{sr} < s_t \leq \epsilon_{er}$ **then**
    - Serious Alert
  - **else if** $\epsilon_{cr} < s_t \leq \epsilon_{sr}$ **then**
    - Careful Alert
- **end**

end

Return classified input as normality or fault

Trigger PdM alerts

To accurately reflect real-world microgrid inverter performance, the proposed framework's maintenance alerts were developed and tested using complex historical microgrid data. These alerts effectively identified inverter performance fluctuations at 15-minute intervals, prioritizing issues to assist microgrid 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 microgrid data. Future research will explore real-time implementation, continuous performance monitoring, and automated maintenance scheduling under diverse operational conditions.

4.5 Results and Discussion

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

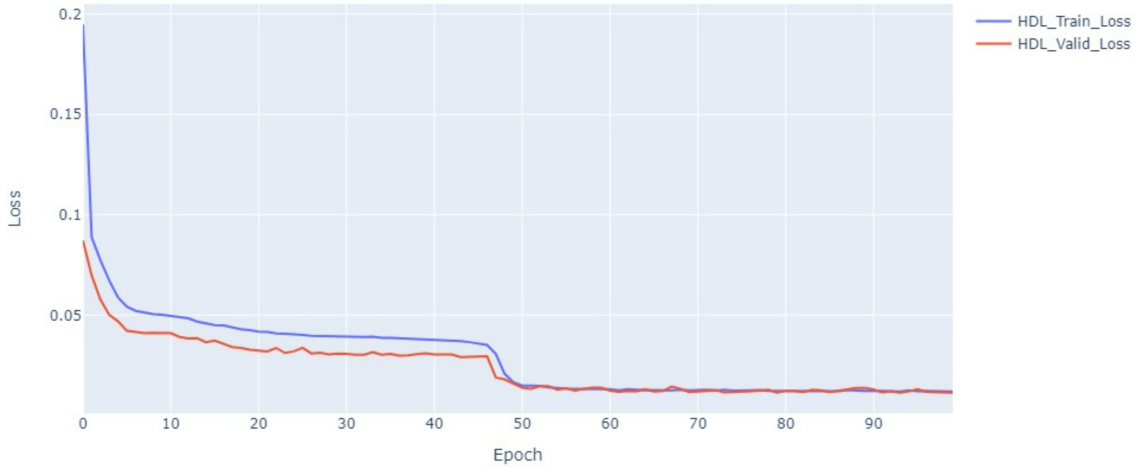


Figure 4.11: Training and Validation of the Advanced HDL Framework

4.5.1 Model Training for Microgrid Predictive Maintenance

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, microgrid 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.

Figure 4.11 illustrates the training as well as the validation of the proposed HDL framework for microgrid predictive maintenance incorporating the differences within the predicted values from the model and the real values. After passing several epochs, a remarkable reduction in losses can be seen from the figure. The trained advanced HDL architecture is implemented after that for the model compilation to identify the anomalies from the ac power signals of microgrid inverters, and generate

different alerts for maintenance based on their operations.

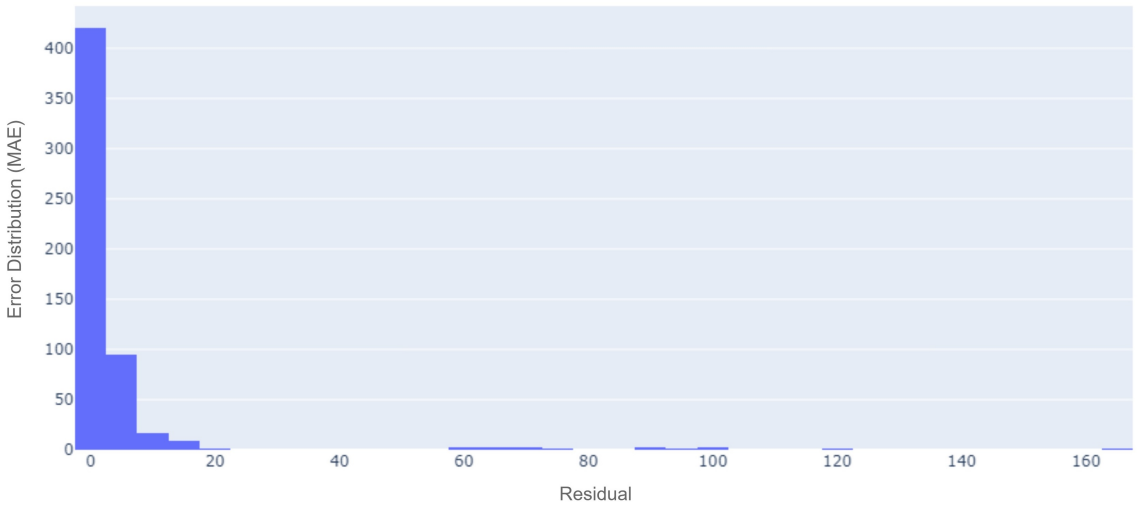


Figure 4.12: Gradient-based Optimization of MAE Distribution Function.

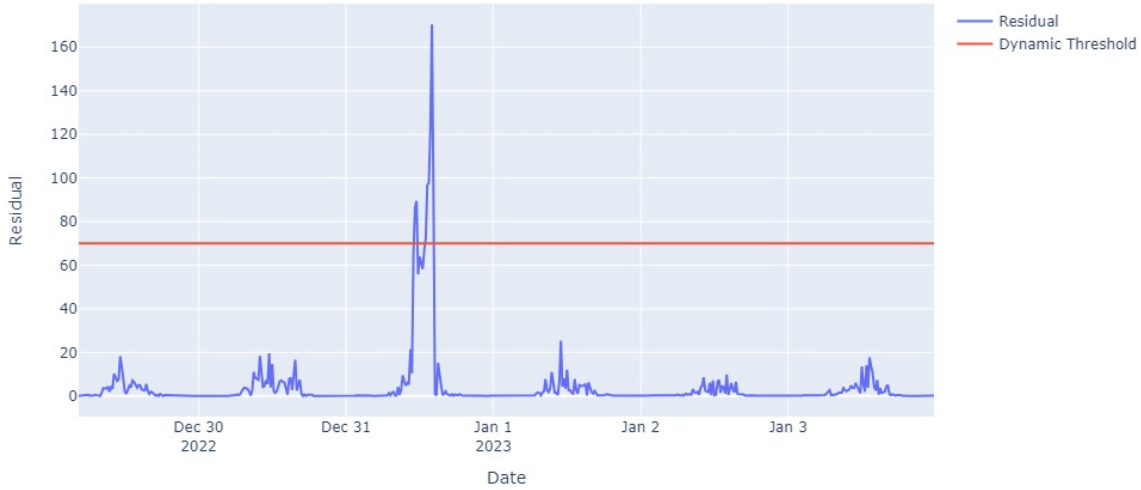


Figure 4.13: Residual-based Dynamic Threshold for Fault Detection.

4.5.2 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 microgrid inverter power signal from the advanced HDL framework as can be seen from Figure 4.12. Figure 4.13 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 microgrid inverter outputs. These peaks correspond to faulty or under-performing operations, consistent with the pattern observed in Figure 4.12, 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.

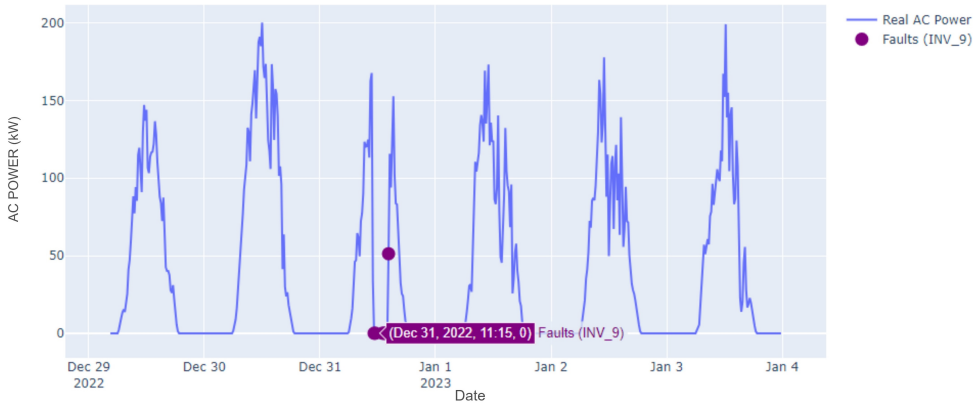


Figure 4.14: Detected Fault (INV-9) at 11.15 am.

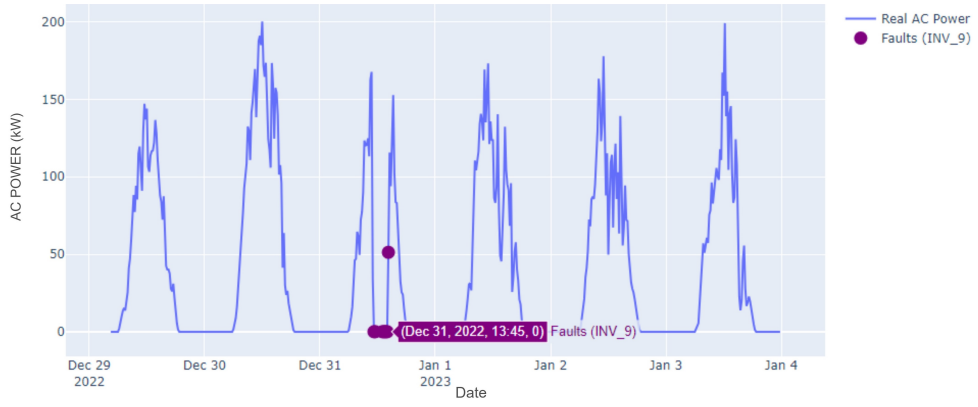


Figure 4.15: Detected Fault (INV-9) at 1.45 pm.

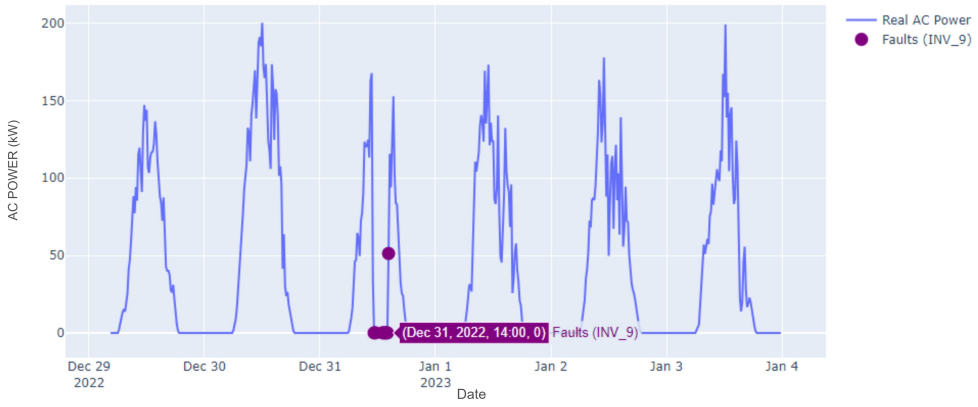


Figure 4.16: Detected Fault (INV-9) at 2.00 pm.

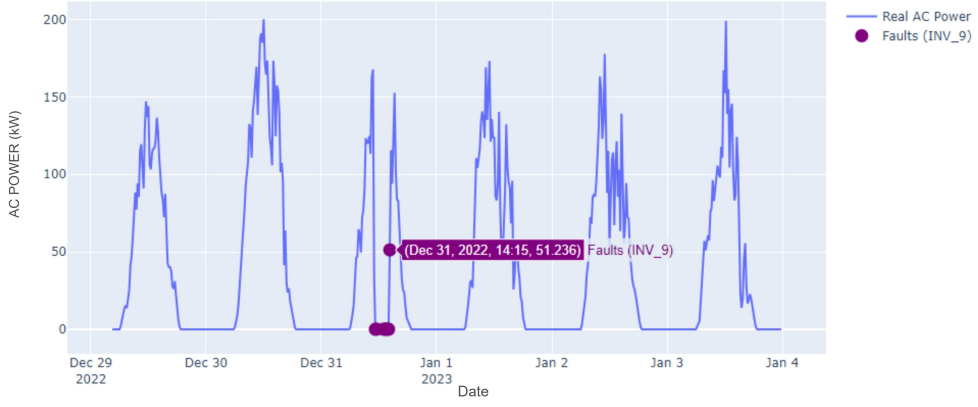


Figure 4.17: Detected Fault (INV-9) at 2.15 pm.

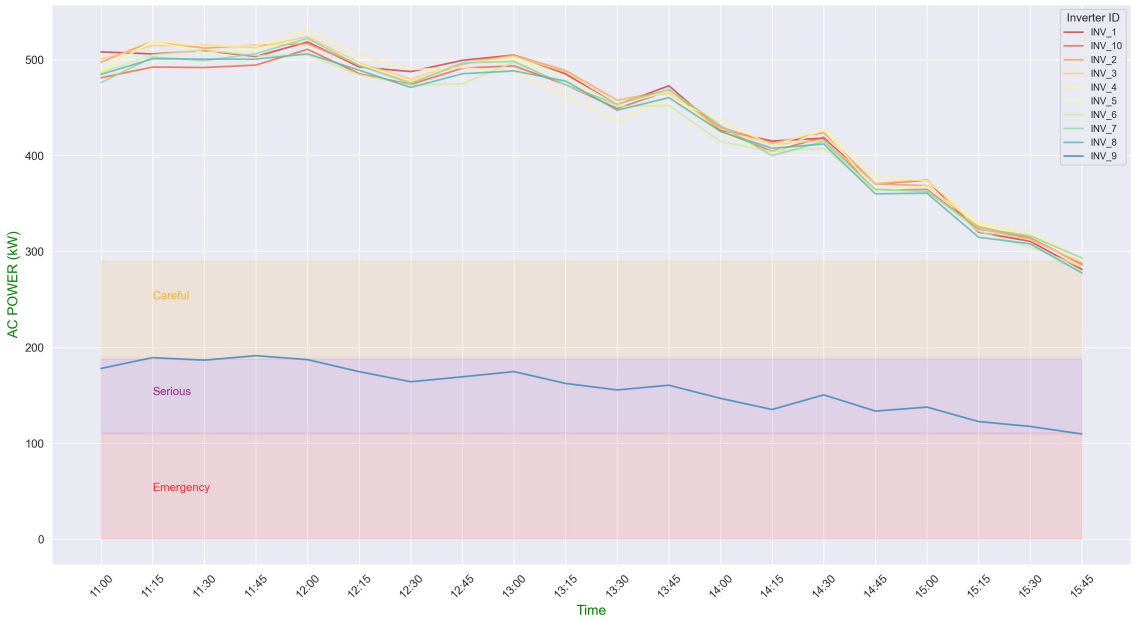


Figure 4.18: Priority Based Predictive Maintenance Alert Regions.

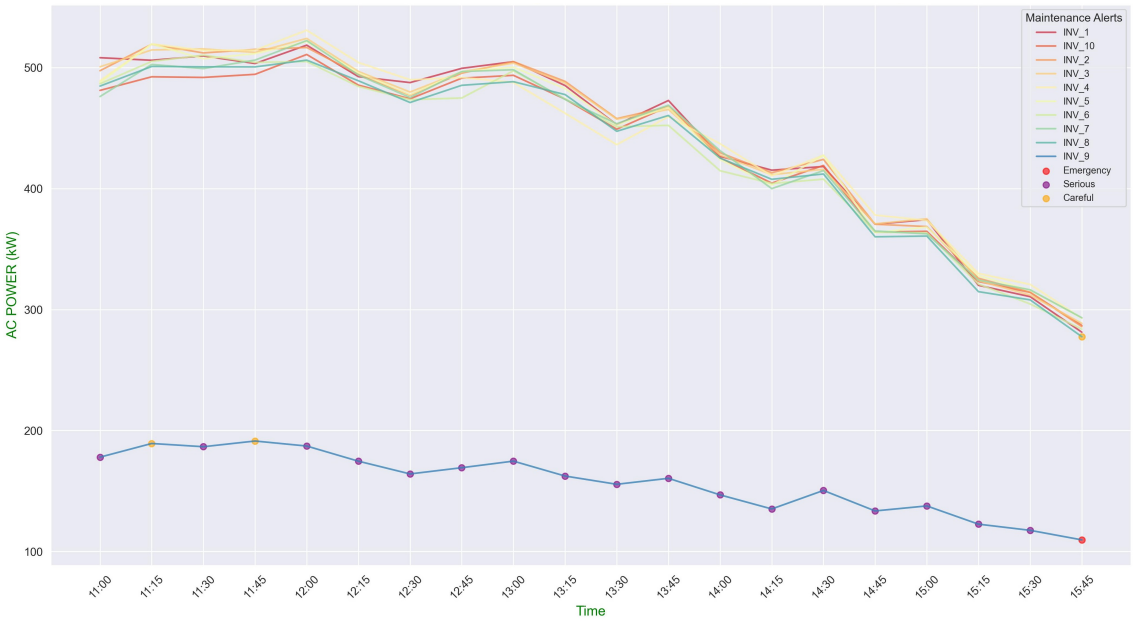


Figure 4.19: Triggered Alerts for Microgrid Predictive Maintenance Operations.

The detected faults of the microgrid inverter from the advanced HDL framework had been illustrated in Fig. 4.14 to Fig. 4.17. The encountered inverter 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 microgrid dataset. It can be seen that the faults encountered on 31st December 2022 from the time-frame 11.15 am to 1.45 pm, then 2.00 pm to 2.15 pm during the maximum sunlight hours by the inverter 9.

Figure 4.18 clearly illustrates how alert regions were generated by the advanced HDL algorithm, prioritizing maintenance operations during peak sunlight hours (11 AM to 4 PM) while effectively preventing false alarms under low irradiance and temperature conditions. Here, light orange, purple, and red regions indicate careful, serious, and emergency events respectively for predictive maintenance during the inverter operations. After that, through integrating non-linear patterns from the inverter operations and temporal dependencies along with the dynamic threshold, the proposed framework triggers different predictive maintenance alerts when the relevant regions get breached throughout inverter operations.

Figure 4.19 depicts the maintenance alerts for all inverter operations during the maximum sunlight hours based on breaching the regions. Here, the orange, purple, and red dots indicate the careful, serious, and emergency alerts for predictive maintenance 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 on each time steps according to the priority based on the generation performance.

For the evaluation process, the R^2 score as well as MAE matrices are implemented in this work to assess the performances of the proposed advanced HDL framework for microgrid predictive maintenance. The evaluation matrices are calculated through the equations as follows:

$$R^2 = 1 - \frac{\sum_{i=1}^{N}(X_i - Y_i)^2}{\sum_{i=1}^{N}(X_i - \bar{X})^2} \tag{4.26}$$

$$MAE = \frac{1}{N}\sum_{i=1}^{N}|X_i - Y_i| \tag{4.27}$$

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.

4.5.3 Discussion

The developed advanced HDL architecture has shown outstanding performance in the context of detecting microgrid inverter faults and generating the maintenance alerts for predictive maintenance. 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 4.1

enlists the proposed advanced HDL model's performance with respect to the traditional RNN, 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 predictive maintenance scenarios of microgrid inverter operations.

Table 4.1: 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

The traditional DL-based methods provided a good performance for microgrid predictive maintenance scenarios but still have few limitations especially for RNN, during processing the diverse microgrid 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 microgrid 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 predictive maintenance applications.

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

4.6 Conclusions

The advanced HDL-based framework developed in this work for microgrid predictive maintenance 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 predictive maintenance alerts from the multi-sensor microgrid 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 microgrid 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 predictive

maintenance applications in complex microgrid 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 predictive maintenance techniques for microgrid 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 microgrid 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 microgrid 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 microgrids for algorithm training and inference. Addressing these limitations, scalability issues, implementing in real-time, and integration of multiple data sources from diverse microgrid operational scenarios will be explored for future studies.

Chapter 5

Smart Predictive Maintenance for Microgrid DER: A Data-Centric Framework

5.1 Introduction

The necessity of developing sophisticated frameworks is getting indispensable with the rising complexity of microgrid systems for advanced and resilient maintenance ensuring reliable system operations. To enhance the operational efficiency and reliability of different energy sources in complex microgrids, advanced predictive maintenance frameworks are becoming essential for mitigating downtime and improving system resilience. The integration of intelligent machine learning in microgrids enables advanced performance analysis, early detection of malfunctions, triggering performance alerts by continuous monitoring if any sudden fall in power generations allowing advanced maintenance and reliable operation, upgrading predictive maintenance competence and sustainable resolution. To enhance the operational efficiency and system reliability of microgrids, advanced analysis of system performance and prompting maintenance alerts if any system malfunction or sudden drop in power generations from different energy sources are getting essential for enhancing the predictive maintenance capabilities. An intelligent hybrid ML-based predictive maintenance framework has been introduced in this work uniquely tailored on a real world complex microgrid scenario through advanced analysis of power signals, classifying the operational states within priority based maintenance events, analyzing the power degradation pattern and remaining future capacity from different energy sources. The developed framework has been implemented on a public dataset of complex microgrid network and achieved significant accuracy in terms of predicting maintenance needs within different energy sources. This study is expected to establish a benchmark in advanced predictive maintenance of microgrids for future research and assist the stakeholders in enhancing the operational reliability, energy resilience, and long-term sustainability.

5.2 Background and Contribution

The emerging global demand for energy, in combination with the need for sustainable development, has underlined the significant role of microgrids in the context of revolutionizing the global energy sector. The global demand for energy is expected to rise 50% by 2050 and to mitigate this demand, the integration of RES is required to be extended by 12% per year. In this context, microgrids are reshaping the conventional centralized grid paradigm by offering a transformative solution for integrating RES to achieve localized energy independence. The outstanding capabilities of microgrids, such as operating in conjunction with the main grid or autonomously, enable flexibility and resilience in energy distribution that can improve the reliability and accessibility of energy specifically in remote and under-served areas [188].

The coupling of diverse RES into microgrids fosters a global sustainable and clean energy landscape through promoting grid resiliency, decreasing environmental degradation, and improving energy efficiency. All these viable features of microgrids resonate closely with the Sustainable Development Goals (SDGs) [213] of the United Nations, specifically Goal 7 that supports the affordable, sustainable and clean modern energy ecosystem, Goal 9 that fosters the building of a resilient system that promotes sustainability for industries and Goal 13 that underscores climate action. Despite enormous potentials, it still remains a challenge to ensure the efficiency and reliability within microgrid network, particularly because of the complex, dynamic interactions within diverse components of microgrids. Fig. 5.1 illustrates the architecture of a complex industrial microgrid network composed of photovoltaic systems (PVS), fuel cells (FC), and gas-powered generator (GPG) as the DERs, ESS and some loads.

The complexity is rising with the rapid integration of diverse DER into the microgrid network. Predictive maintenance can perform an outstanding role to address these challenges, which enables the continuous advanced monitoring of diverse DER of microgrids through key performance matrices, for example by analyzing active power signals of the microgrid DER, classifying their operational states and analyzing power degradation pattern for the upcoming years. This can ensure proactive maintenance ahead of any unexpected failure, to stop any sudden disruption of energy into the network.

Energy management [214] and economic aspects [7] of microgrids are focused mainly in most of the current studies. Besides, a few studies have been conducted on fault detection. Research conducted in [197] focused the identification of feeder faults for dc microgrids by integrating multi-class AdaBoost algorithm with morphological analysis based classification method. Besides, multi-layer perceptron neural network model has been implemented in [207] for classifying dc arc faults in microgrid network where the method achieved 93.3% testing accuracy. Advanced deep learning based algorithms and their comparative performance analysis have been conducted in [215] for the identification of inverter faults in dc microgrids. A protection technique has been proposed in [176] by using features like current magnitudes, voltage sags and active power flow direction for low-voltage ac microgrids. Implementing on MATLAB/Simulink platform, the model showed better performance for balanced conditions in detecting low-impedance faults. Besides, dynamic threshold integrated advanced hybrid deep learning based algorithm has been developed in [216] for detecting the microgrid inverter faults and generating

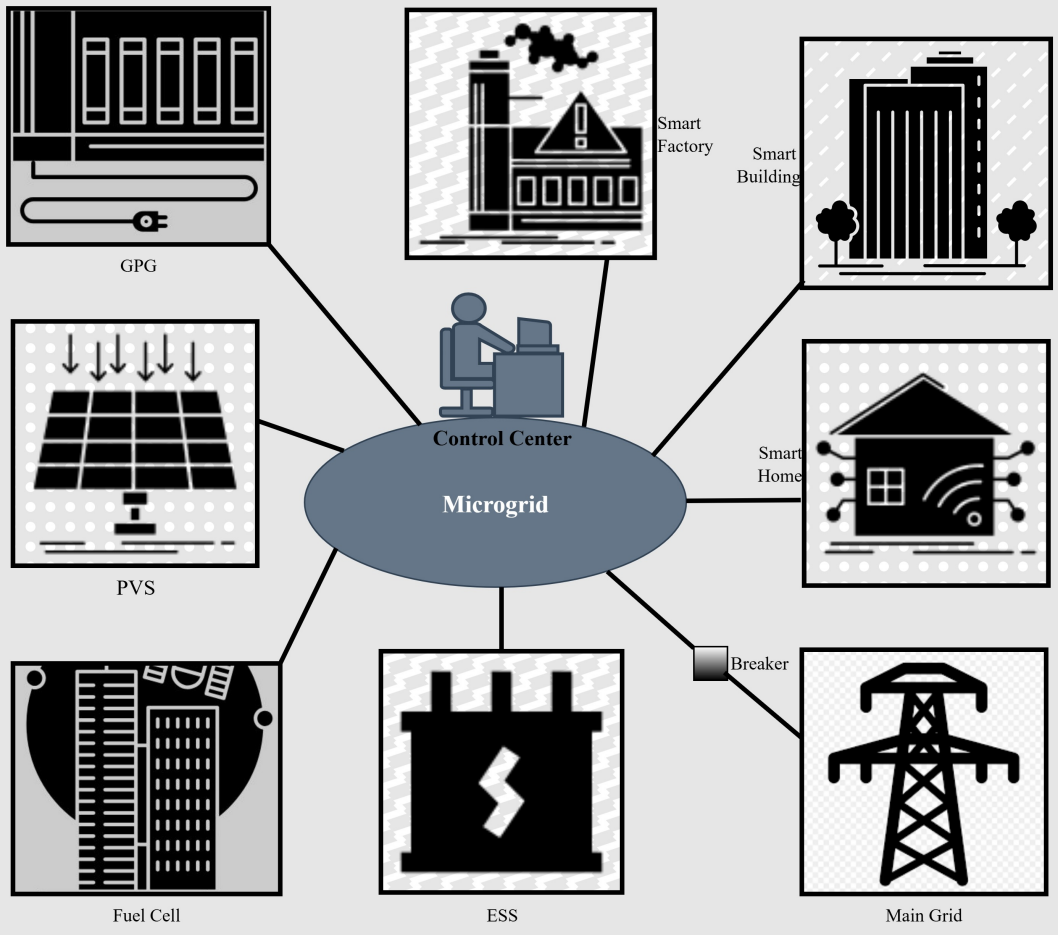


Figure 5.1: **Microgrid System with diverse DER.**

performance alerts. The algorithm had been implemented on a complex microgrid database in Python-3.10 with different exogenous factors and achieved 99.2% accuracy.

Another research [208] based on harmonic distortion measurements investigated the protection problems of LV microgrid focusing on point of common coupling, line faults, and distributed generation. The simulations were performed using the microgrid test systems on PSCAD/EMTDC platform. In addition, further investigation was carried on microgrid protection in [178] which was implemented on islanded microgrid scenario in PSCAD/EMTDC by integrating short-circuit faults. Based on the relay ground current and inductor voltage, another research was conducted utilizing similar platform in [177] to detect high and low resistance dc faults on LV microgrid system. An ML-based study has been conducted in [78] that investigated microgrid protection issues by integrating decision tree and wavelet transform methods to identify and classify faults. The developed algorithm was implemented on a data set consisting of 3860 samples, and the decision tree-based method was reported capable of identifying faults with an overall accuracy of 97%. Another ML-based technique integrating with wavelet transform has been investigated for microgrid fault detection in [209]. An overall accuracy of 97.76% was found for classification using testing cases.

Moreover, research has been conducted on different scheduling issues for microgrid DER in [31]. Several studies have been performed on different DER like PVS, FC, and GPG separately on various

aspects. For example, extensive studies [217], [218], [219], [220] have been conducted on the fault detection of PVS using different factors such as temperature, irradiance, voltage deviation, images. Similarly, a wide range of research has been performed for analysing the degradation patterns of FC from the electrochemical signals [221], [222], [223], [224], and GPG which is utilized as a backup power source has been studied in [225], [226], [227], [228] to identify generator irregularities and robust state estimation to enhance resilience.

Most existing studies only focus on the separate components of microgrids. There is a research gap in the context of developing advanced predictive maintenance framework considering the dynamic interaction of power flow within these diverse DER, classification of the operational states, and their capacity degradation over time in a complex microgrid scenario. In addition, traditional techniques, for example, rule-based and static threshold integrated deterministic methods are not capable of adapting to the dynamic and complex nonlinear characteristics of microgrids under diverse DER and operating states. Consequently, these traditional techniques have lower scalability, higher maintenance costs, and less efficiency and reliability in terms of diverse DER integration. By adopting cutting-edge ML algorithms in operation and maintenance applications of microgrids can amplify system reliability and sustainability. Advanced ML frameworks facilitate [185] accurate forecasting and diagnostic of malfunctions that can enable intelligent decision making for enhanced predictive maintenance frameworks to ensure operational reliability and prolonged DER performance within microgrid network.

Achieving reliability and sustainability in microgrid operations demands the development of advanced scalable ML-based predictive maintenance frameworks which can enhance operational efficiency while reducing the downtime and maintenance costs. Notwithstanding the widespread application of ML-based techniques for the predictive analytics and maintenance in different sectors like healthcare [229], [230], agriculture [231], transportation [232], construction [200], telecommunications [233], aerospace [234], mining [235], water treatment plants [236] and manufacturing [237], their advanced implementation for the continuous monitoring-based predictive maintenance framework of complex microgrid systems with diverse DER remains unexplored. From the present literature, there is a research gap in addressing the advanced predictive maintenance of microgrids through classifying dynamic operational states and analysing the capacity degradation by continuously monitoring active power signals from diverse microgrid DERs simultaneously. This gap underscores the demand for an advanced framework that can analyse the dynamic intricacies among diverse subsystems with actionable scheduling alerts and power capacity degradation modeling to improve the predictive maintenance capabilities in a complex microgrid scenario.

Existing studies focus on basic time-series forecasting or anomaly detection for microgrid components separately, lacking the classification of dynamic operational states of DERs, real-time actionable scheduling alerts and capacity degradation modeling of each DER simultaneously. The novelty of this work lies in addressing these knowledge gaps and implementing on a practical setup of a complex, industrial microgrid system. The major research contributions and technical novelties of this chapter are five-fold by the following key points:

- **Integrated Dynamic Classification and Degradation Forecast:** Proposed framework

uniquely integrates the real-time classification of dynamic operational states of complex DERs with long-term capacity degradation-aware forecasting from the power signals of PVS, FC, and GPG within the microgrid network which can enable short-term performance alerting with monthly scheduling and long-term capacity planning simultaneously. The developed novel power-aware adaptive kernel-based classifier is capable of classifying the subtle intricacies of dynamic and interactive DER power signals and generating maintenance alerts.

- **Intelligent Hybrid Capacity Degradation Algorithm:** This study introduces an intelligent hybrid degradation model, capable of simulating real-world physical degradation patterns by stochastic modeling of the DER active power signals through Wiener process and developing an advanced GRU architecture simultaneously for capturing the nonlinear temporal dependencies from the degradation process. This advanced hybrid model enables practical long-term forecasts of microgrid DER power capacity degradation process.

- **Multi-Level Maintenance States with Actionable Scheduling:** Based on the dynamic active power signals of each DER, a four-level classification of the operational states: normal, careful, serious, and emergency have been defined in the proposed framework, instead of just binary health status. This nuanced stratification can allow more granular insights in more informed decision making for proactive maintenance. Moreover, this intelligent framework introduces actionable schedule planning based on the multi-level maintenance alerts on a monthly window from the real power signals of each DER which bridges the gap between practical schedule planning and operational forecasting-only based methods.

- **Enhancing Operational Interpretability:** Proposed smart predictive maintenance approach integrates data-driven intelligent threshold engineering across the PVS, FC, and GPG power signals with sophisticated visualization framework. The classification thresholds have been engineered empirically in the algorithm based on the real signal distribution and domain constraints of each DER. Capacity degradation forecasts, maintenance alerts and scheduling have been visualized in monthly summary heatmaps with time-aligned, severity-colored alert plots to enhance practical reliability and operational interpretability.

- **Extensive Validation with Industrial microgrid Public Dataset:** An extensive validation has been performed for the developed predictive maintenance framework on a publicly available "Mesa del Sol" microgrid [238] incorporating PVS, FC and GPG as DERs. This work can be an excellent starting point to explore and develop advanced microgrid predictive maintenance frameworks for academia and industries.

This chapter explores the multifaceted contributions of developing advanced predictive maintenance frameworks for microgrid industries to addressing the energy crisis of the modern world. This study offers close alignment with the UN's SDGs by promoting affordable modern energy and sustainable infrastructure for upgrading the efficiency and resilience of the power industries. In addition, it underlines the importance of developing intelligent predictive maintenance frameworks coupled with advanced hybrid ML algorithms to improve the operational efficiency, reliability, and resilience of

microgrids to build more sustainable energy landscape which can have notable implications for policy makers, academia and industries.

Section 5.2 describes the background and contributions of this chapter. Section 5.3 formulates the problem statement of this study. Methodology of the proposed work has been described in Section Section 5.4. Section 5.5 presents the results and discussion of the proposed predictive maintenance framework. Finally, this work has been concluded in Section 5.6 with remarks.

5.3 Problem Formulation

Microgrids play a significant role in the paradigm shift of the modern energy landscape by integrating diverse DER such as FC, GPG, and PVS. These systems illustrate their outstanding ability to contribute to local energy autonomy as well as improve sustainability and energy resilience through microgrid networks. Nevertheless, maintaining the ultimate reliability of these systems amidst complex and dynamic operational conditions in microgrids demands advanced and robust predictive maintenance frameworks. This research work aims to enhance microgrid performance and reliability by using historical data from a public dataset of a complex microgrid setup, to classify the complex DER operational states in their dynamic interactions and analyze the DER capacity degradation over time to address the maintenance needs preemptively.

5.3.1 Power Models of Microgrid DER

Assuming that the power outputs of the Microgrid DERs (in kW) at time t, for PVS, fuel cell, and GPG have been denoted by $P_{\text{PVS}}(t), P_{\text{FC}}(t)$, and $P_{\text{GPG}}(t)$, respectively. These time-dependent active power signals are mainly subjected to different operational and physical characteristics of the system.

Let the efficiency of PVS be η_{PVS}, surface area (m^2) of the PVS panels be S_{PVS}, Solar irradiance (W/m^2) be $I(t)$ at time t, and the corresponding system losses like shading or wiring losses are denoted by $P_{\text{PVS loss}}$. The power generated from the PVS can be represented by the following equation:

$$P_{\text{PVS}}(t) = \eta_{\text{PVS}} \cdot I(t) \cdot S_{\text{PVS}} - P_{\text{PVS loss}} \tag{5.1}$$

Let the FC efficiency be η_{FC}, the hydrogen reactive enthalpy (J/mol) be ΔH_{FC}, hydrogen flow rate (mol/s) be $\dot{n}_{\text{H}_2}(t)$, and the corresponding system losses like electrical and thermal losses are represented by $P_{\text{FC loss}}$. The power generated from the FC can be represented by the following equation:

$$P_{\text{FC}}(t) = \eta_{\text{FC}} \cdot \Delta H_{\text{FC}} \cdot \dot{n}_{\text{H}_2}(t) - P_{\text{FC loss}} \tag{5.2}$$

Let the GPG efficiency be η_{GPG} which ($0 \leq \eta_{\text{GPG}} \leq 1$) indicates the chemical to electrical energy conversion rate, CV_{gas} be the calorific volume (J/kg) of natural gas that denotes the released quantity of energy during combustion of per unit gaseous mass, $\dot{M}_{\text{gas}}(t)$ be the gaseous mass flow rate (kg/s)

at time t, then the produced power can be denoted by the following equation:

$$P_{\mathrm{GPG}}(t) = \eta_{\mathrm{GPG}} \cdot \dot{M}_{\mathrm{gas}}(t) \cdot \mathrm{CV}_{\mathrm{gas}} \tag{5.3}$$

If the gaseous mass flow rate is represented in the context of gaseous density (ρ_{gas}) and volumetric ($\dot{V}_{\mathrm{gas}}(t)$) flow rate, then:

$$\dot{M}_{\mathrm{gas}}(t) = \dot{V}_{\mathrm{gas}}(t) \cdot \rho_{\mathrm{gas}} \tag{5.4}$$

Considering the corresponding total losses such as electrical, thermal losses, and mechanical losses of generator for friction, the actual power generated from the GPG can be represented by the following equation:

$$P_{\mathrm{GPG}}(t) = \eta_{\mathrm{GPG}} \cdot \dot{V}_{\mathrm{gas}}(t) \cdot \rho_{\mathrm{gas}} \cdot \mathrm{CV}_{\mathrm{gas}} - P_{\mathrm{GPG\ loss}} \tag{5.5}$$

5.3.2 Feature Engineering

For enhancing the accuracy of the classification and capacity degradation algorithms, feature engineering is a crucial tool which can tailor the overall predictive maintenance framework by extracting the most significant patterns from the raw signals of the complex microgrid DER. Different time-domain measures have been implemented in this work for this purpose. For statistical attributes such as mean, standard deviation and variance, the following equations have been implemented respectively with a sliding window (w) on the power signals for analyzing the power deviations:

$$\begin{cases} \mu_{P_{\mathrm{PVS}}(t)} = \frac{1}{w_{PVS}} \sum_{i=1}^{w_{PVS}} P_{\mathrm{PVS}}(t-i) \\ \mu_{P_{\mathrm{FC}}(t)} = \frac{1}{w_{FC}} \sum_{i=1}^{w_{FC}} P_{\mathrm{FC}}(t-i) \\ \mu_{P_{\mathrm{GPG}}(t)} = \frac{1}{w_{GPG}} \sum_{i=1}^{w_{GPG}} P_{\mathrm{GPG}}(t-i) \end{cases} \tag{5.6}$$

$$\begin{cases} \sigma_{P_{\mathrm{PVS}}(t)} = \sqrt{\frac{1}{w_{PVS}} \sum_{i=1}^{w_{PVS}} (P_{\mathrm{PVS}}(t-i) - \mu_{P_{\mathrm{PVS}}(t)})^2} \\ \sigma_{P_{\mathrm{FC}}(t)} = \sqrt{\frac{1}{w_{FC}} \sum_{i=1}^{w_{FC}} (P_{\mathrm{FC}}(t-i) - \mu_{P_{\mathrm{FC}}(t)})^2} \\ \sigma_{P_{\mathrm{GPG}}(t)} = \sqrt{\frac{1}{w_{GPG}} \sum_{i=1}^{w_{GPG}} (P_{\mathrm{GPG}}(t-i) - \mu_{P_{\mathrm{GPG}}(t)})^2} \end{cases} \tag{5.7}$$

$$\begin{cases} \mathrm{Var}(P_{\mathrm{PVS}}(t)) = \sigma^2_{P_{\mathrm{PVS}}(t)} \\ \mathrm{Var}(P_{\mathrm{FC}}(t)) = \sigma^2_{P_{\mathrm{FC}}(t)} \\ \mathrm{Var}(P_{\mathrm{GPG}}(t)) = \sigma^2_{P_{\mathrm{GPG}}(t)} \end{cases} \tag{5.8}$$

For understanding the trend of the power signals, the rate of change per time step t, and cumulative power have been investigated by the following equations respectively:

$$\begin{cases} \Delta P_{\text{PVS}} = P_{\text{PVS}}(t) - P_{\text{PVS}}(t-1) \\ \Delta P_{\text{FC}} = P_{\text{FC}}(t) - P_{\text{FC}}(t-1) \\ \Delta P_{\text{GPG}} = P_{\text{GPG}}(t) - P_{\text{GPG}}(t-1) \end{cases} \tag{5.9}$$

$$\begin{cases} \text{C}(P_{\text{PVS}}(t)) = \sum_{i=1}^{t} P_{\text{PVS}}(i) \\ \text{C}(P_{\text{FC}}(t)) = \sum_{i=1}^{t} P_{\text{FC}}(i) \\ \text{C}(P_{\text{GPG}}(t)) = \sum_{i=1}^{t} P_{\text{GPG}}(i) \end{cases} \tag{5.10}$$

The power dynamics has been investigated on the basis of the trends of the signals for detecting the periodic fluctuations and transient behaviors. The power deviations have been investigated then following the equation:

$$\begin{cases} \delta_{P(\text{PVS})} = \frac{P_{\text{PVS}}(t) - P_{\text{nominal, PVS}}}{P_{\text{nominal, PVS}}} \\ \delta_{P(\text{FC})} = \frac{P_{\text{FC}}(t) - P_{\text{nominal, FC}}}{P_{\text{nominal, FC}}} \\ \delta_{P(\text{GPG})} = \frac{P_{\text{GPG}}(t) - P_{\text{nominal, GPG}}}{P_{\text{nominal, GPG}}} \end{cases} \tag{5.11}$$

5.3.3 Classification of Operational States

The powers from the PVS, FC, and GPG systems $P_{\text{PVS}}(t), P_{\text{FC}}(t), P_{\text{GPG}}(t)$ are analysed to classify the operational states $\mathcal{O}_{\mathcal{S}}(t)$ of the DER based on the advanced engineered features $\mathbf{Y}$:

$$\mathcal{O}_{\mathcal{S}}(t) = f(\mathbf{Y}(t), \alpha) \tag{5.12}$$

Here, at time step t, the feature vector $\mathbf{Y}(t)$ is represented by the following equation:

$$\mathbf{Y}(t) = \begin{cases} [\mu_{P_{\text{PVS}}(t)}, \sigma_{P_{\text{PVS}}(t)}, \text{Var}(P_{\text{PVS}}(t)), \delta_{P_{\text{PVS}}(t)}, \text{C}(P_{\text{PVS}}(t))] \\ [\mu_{P_{\text{FC}}(t)}, \sigma_{P_{\text{FC}}(t)}, \text{Var}(P_{\text{FC}}(t)), \delta_{P_{\text{FC}}(t)}, \text{C}(P_{\text{FC}}(t))] \\ [\mu_{P_{\text{GPG}}(t)}, \sigma_{P_{\text{GPG}}(t)}, \text{Var}(P_{\text{GPG}}(t)), \delta_{P_{\text{GPG}}(t)}, \text{C}(P_{\text{GPG}}(t))] \end{cases} \tag{5.13}$$

5.3.4 DER Capacity Degradation Analysis

A novel hybrid algorithm by integrating stochastic Wiener degradation process with advanced GRU architecture has been implemented in this work. After extracting the temporal patterns from the stochastic degradation process of the DER power signals, the degradation process has been modeled by the hybrid algorithm where $\hat{P}^{w}_{\text{PVS}}(t+1), \hat{P}^{w}_{\text{FC}}(t+1)$, and $\hat{P}^{w}_{\text{GPG}}(t+1)$ are the capacity degradation of PVS, FC, and GPG respectively for the upcoming 5 years. The yearly power degradation (kW) of each DER is calculated and then annual capacity loss is computed according to the following equation:

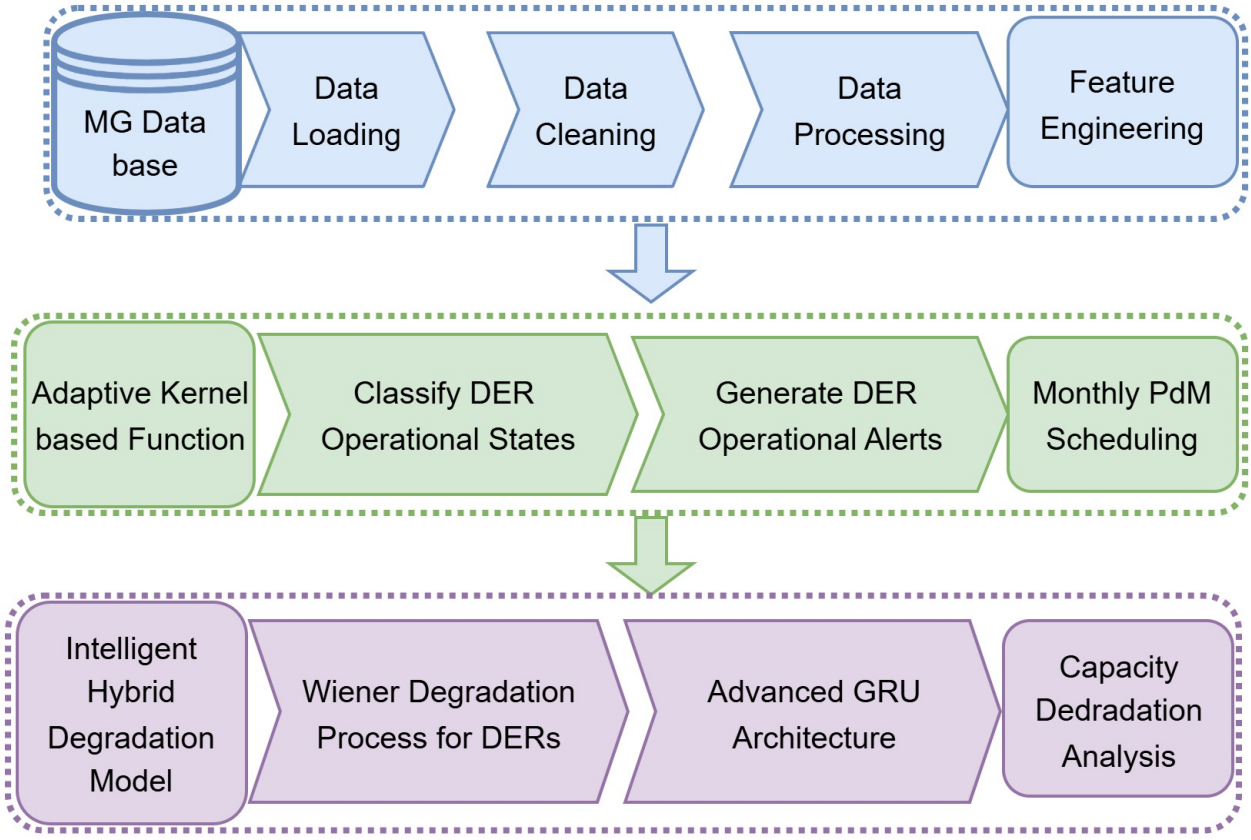


Figure 5.2: Proposed Smart Intelligent Predictive Maintenance Framework.

$$\mathcal{P}_y^{DER}(\%) = \left(\frac{\hat{\mathcal{P}}_{y-1} - \hat{\mathcal{P}}_y}{\hat{\mathcal{P}}_{y-1}} \right) \times 100 \tag{5.14}$$

5.4 Methodology

This study introduces an intelligent predictive maintenance framework which facilitates advanced predictive insights for complex microgrid operations with a robust classification model implemented on a dynamic, real-world microgrid scenario for classifying the DER operational states. Besides, the work also focuses on developing an advanced forecasting algorithm for analyzing the future power degradation pattern and capacity loss of the microgrid DER in advance for proactive maintenance to improve the operational efficacy and reliability of the system. An overview of the utilized public dataset for this research work, advanced data analysis technique integrating different analytics for data preparation and identification of most significant features, and the proposed advanced predictive maintenance framework have been presented in this section for the proactive maintenance of a dynamic, real-world microgrid scenario. Figure 5.2 shows the step by step processes of the proposed advanced microgrid predictive maintenance framework.

5.4.1 Data set

In this study, a public dataset [238] has been implemented that incorporates a dynamic real-world microgrid scenario. The microgrid consists of PVS ($50kW$), FC ($80kW$), and GPG ($240kW$) as the DER. Different data on power, voltage, temperature and frequency had been collected from May 2022 for 15 months until July 2023. In this data set, dynamic operational scenarios that reflect diverse real-world challenges have been incorporated.

The active power values of the DER—specifically PVS, FC, and GPG were found negative at certain time intervals during pre-processing. In order to ensure consistency and relevance for microgrid predictive maintenance analysis, these negative values had been clipped to zero, considering the DER were not able to produce active powers into the microgrid network. This approach helps to identify if the developed framework is capable of classifying those true zero-generation events accurately to check if that aligns with the real-world operational perspective that zero power output from a generation source constitutes an emergency state issuing an immediate maintenance alert, thereby upgrading the algorithm's sensitivity to potential failures and system down-times.

Python 3.10 programming language was implemented for this study. Different libraries and frameworks such as TensorFlow, scikit-learn, Matplotlib, Keras, Pandas and NumPy were utilized which enabled different parts of the framework such as data cleaning, visualization and processing, statistical analysis, model designing and implementation for the microgrid predictive maintenance framework.

5.4.2 Advanced Data Analysis

The performance of the implemented algorithms can be impacted significantly by the extreme outliers through affecting the statistical analytics of the algorithm notably. For handling the extreme outliers of the microgrid dataset, an interquartile range technique [239] (IQRT) has been deployed in this study. This IQRT is capable of designing more robust base for the advanced data analytics.

The implemented IQRT in this work can be expressed as the range between two quartiles i.e. the first P_1 and the third P_3 quartiles of the microgrid data distribution as follows:

$$\text{IQRT} = P_3 - P_1 \tag{5.15}$$

Here, P_1 and P_3 indicate the 25th and the 75th percentiles of the microgrid data, respectively. Considering the utilized dataset $\mathbf{Y}$ having i features and j observations. Here, $\mathbf{Y}_{mn}$ indicates the m-th observation from the n-th feature. The quartiles have been calculated for every feature f_n as follows:

$$P_1(f_n) = \text{Quantile}(f_n, 0.25) \tag{5.16}$$

$$P_3(f_n) = \text{Quantile}(f_n, 0.75) \tag{5.17}$$

Here, $\text{Quantile}(f_n, p)$ denotes the point below which a fraction p of the microgrid data in feature f_n

lies. The IQRT of each feature f_n is enumerated by:

$$\mathrm{IQRT}(f_n) = P_3(f_n) - P_1(f_n) \tag{5.18}$$

For each feature f_n, the lower and upper bounds have been calculated for mitigating the extreme outliers from the microgrid data by the following equation:

$$B_l(f_n) = P_1(f_n) - 1.5 \times \mathrm{IQRT}(f_n) \tag{5.19}$$

$$B_u(f_n) = P_3(f_n) + 1.5 \times \mathrm{IQRT}(f_n) \tag{5.20}$$

From every observation $\mathbf{Y}_{mn}$, in case of any value lying outside these bounds, it gets replaced by the median value $M(f_n)$ of the corresponding feature as follows:

$$\mathbf{Y}_{mn} = \begin{cases} M(f_n), & \text{if } \mathbf{Y}_{mn} < B_l(f_n) \text{ or } \mathbf{Y}_{mn} > B_u(f_n) \\ \mathbf{Y}_{mn}, & \text{else} \end{cases} \tag{5.21}$$

The implemented IQRT has proven to be a powerful tool for the advanced high-dimensional data analysis in this work. The integrity of the complex microgrid data distribution has been preserved by handling the extreme outliers of the data set that could degrade the model performance by distorting the statistical measures.

The microgrid data set contains 18 features that consist of numerous information regarding different attributes. Consequently, it is crucial to identify the most relevant and important features to improve the PdM performance within the system and to reduce the training complexity. In this study a nonparametric-based advanced measure has been implemented to classify the correlation of highly nonlinear attributes of the microgrid dataset.

The correlation coefficient $\rho_{K,L}$ between two attributes K and L has been enumerated through the following monotonic function where m indicates the observation number and for each i-th observation, the difference in the ranks between K and L has been denoted by d_i :

$$\rho_{K,L} = 1 - \frac{6 \sum_{i=1}^{m} d_i^2}{m(m^2 - 1)} \tag{5.22}$$

The correlation matrix $\mathbf{M}$ of the dataset $\mathbf{Y}$ having n features can be enumerated as an $n \times n$ matrix by the following equation:

$$\mathbf{M} = \begin{pmatrix} 1 & \rho_{12} & \cdots & \rho_{1n} \\ \rho_{21} & 1 & \cdots & \rho_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ \rho_{n1} & \rho_{n2} & \cdots & 1 \end{pmatrix} \tag{5.23}$$

After that feature pair analysis has been conducted for determining the key features for this predictive

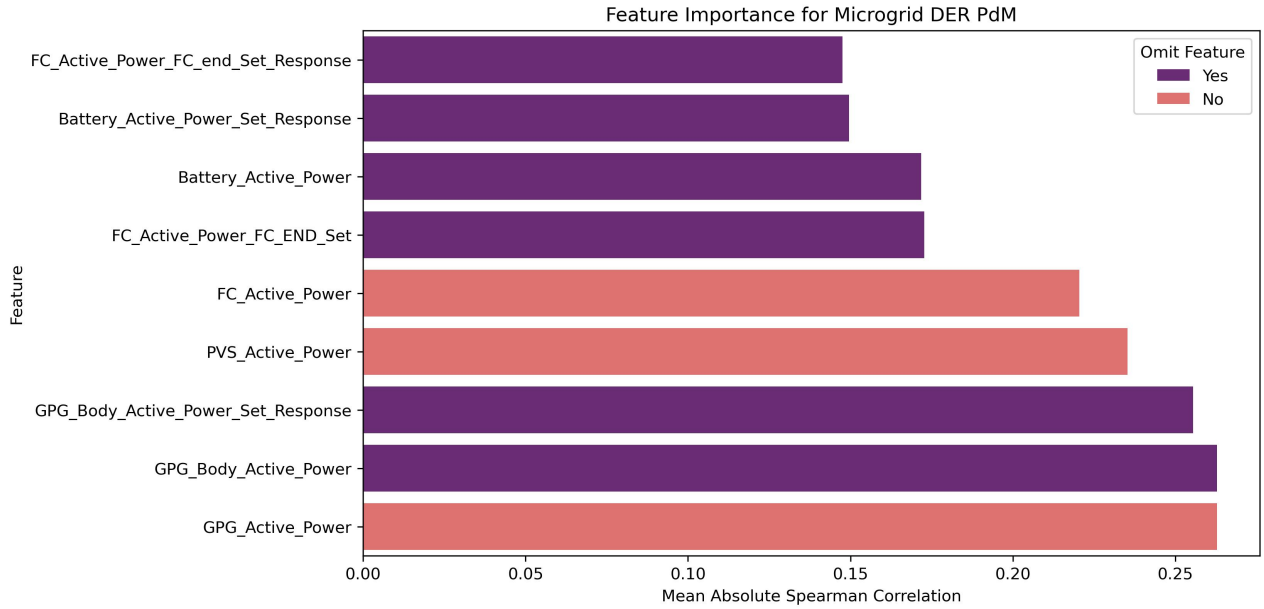


Figure 5.3: Feature Selection using Mean Absolute Spearman Correlation.

maintenance framework. The features having $|\rho|$ value greater than ϵ were considered to be redundant where ϵ is the algorithm threshold. For this analysis, the set of all features from the microgrid dataset has been defined as: $\mathcal{F} = \{f_1, f_2, \ldots, f_n\}$. Here, the set $\mathcal{R}$ consisting redundant features was calculated using the following equation:

$$\mathcal{R} = \{(f_m, f_n) \,|\, |\rho_{mn} > \epsilon\} \tag{5.24}$$

Based on the absolute differences enumerated from the Spearman correlation method, the redundant features are omitted and the key features for this study have been selected as can be seen from the Figure 5.3. The set of key features is $\mathcal{A}$. The importance for each feature f_j from the microgrid dataset has been defined by the following equation:

$$I(f_m) = \frac{1}{|\mathcal{A}|} \sum_{f_n \in \mathcal{A}} |\rho_{mn} - \bar{\rho}| \tag{5.25}$$

Here, the mean of the correlation coefficient of key features is represented by $\bar{\rho}$ such that:

$$\bar{\rho} = \frac{1}{|\mathcal{A}|^2} \sum_{f_m \in \mathcal{A}} \sum_{f_n \in \mathcal{A}} \rho_{mn} \tag{5.26}$$

5.4.3 Classification States

The data from the PVS, FC, and GPG systems are implemented here for modeling the classification states. After the advanced feature engineering step, the feature vector $\mathbf{X}(t)$ at time step t is implemented to classify the operational states $\mathcal{O}_{\mathcal{S}}(t)$ of the microgrid DER. Here, $\mathcal{O}_{\mathcal{S}}(t) \in \{\text{Normal}, \text{Careful}, \text{Serious}, \text{Emergency}\}$. The operational states have been determined by the following equation where $\mathcal{P}_{\text{DER}}(t)$ indicates the power, $T_{\text{th}}^{\text{N}}, T_{\text{th}}^{\text{C}}$, and T_{th}^{S} are the dynamic state thresholds of the

specific DER respectively.

$$\mathcal{O}_{\mathcal{S}}(t) = \begin{cases} \text{Normal State}, & \text{if } \mathcal{P}_{\text{DER}}(t) \geq T_{\text{th}}^{\text{N}} \\ \text{Careful State}, & \text{if } T_{\text{th}}^{\text{N}} > \mathcal{P}_{\text{DER}}(t) \geq T_{\text{th}}^{\text{C}} \\ \text{Serious State}, & \text{if } T_{\text{th}}^{\text{C}} > \mathcal{P}_{\text{DER}}(t) \geq T_{\text{th}}^{\text{S}} \\ \text{Emergency State}, & \text{if } \mathcal{P}_{\text{DER}}(t) < T_{\text{th}}^{\text{S}} \end{cases} \tag{5.27}$$

An adaptive power-aware decision function capable of dynamically tuning the decision boundaries in terms of power variations is designed for the classification model. In lieu of a static kernel, this power-aware adaptive kernel function can adjust dynamically with power fluctuations which has been implemented according to the Equation 5.30. This adaptive classification model determines the operational states of microgrid DER based on advanced feature-engineered power vectors.

$$\mathcal{K}(\mathbf{Y}_m, \mathbf{Y}_n) = \exp\left(-\zeta \frac{\|\mathbf{Y}_m - \mathbf{Y}_n\|^2}{\sigma_{P_{\text{DER}}}^2 + \gamma}\right) \tag{5.28}$$

Here, ζ denotes the adaptability parameter of the kernel function, stability is ensured by $\sigma_{P_{\text{DER}}}^2$ under power fluctuations, and division errors are prevented by γ in the case of near-zero variability. This adaptive decision boundary adjusts dynamically according to the following power-aware function:

$$L_m\big(\mathbf{w} \cdot f(\mathbf{Y}_m^*) + b_s\big) \geq 1 - \theta_m \tag{5.29}$$

Here, L_m indicates the classification label for every m-th sample of the DER power signal. The orientation of the decision boundary is represented by the weight vector ($\mathbf{w}$). The nonlinear transformation operation is performed by $f(\mathbf{Y}_m^*)$ for the robust classification accuracy, where the feature vector has been mapped ($\mathbf{Y}_m^*$) into a higher-dimensional space. The decision score for classifying every m-th sample is enumerated through the dot product $\mathbf{w} \cdot f(\mathbf{Y}_m^*)$. For improving the classification accuracy, the decision boundary is optimized by the bias operator (b_s). In this proposed adaptive classification algorithm, instead of fixed margin of 1 used in conventional classification method, an adaptive margin ($1 - \theta_m$) has been implemented where the power deviation-based decision challenges have been addressed by the following equation:

$$\theta_m = \tau e^{-\kappa|\delta_P|} \tag{5.30}$$

Here, flexibility operator for the decision boundary and sensitivity operator for the power deviations are τ and κ respectively. The relative deviation is calculated through $|\delta_P|$ with respect to the nominal power of each DER. Algorithm 5.1 shows the step by step procedure of the proposed adaptive power-aware Kernel-based approach.

5.4.4 DER Power Degradation Analysis

For analyzing the microgrid DER power degradation over time and the capacity losses in the upcoming years, a hybrid approach incorporating Wiener degradation model with advanced GRU architecture has been presented in this study. The Wiener process in this hybrid approach implements stochastic degradation pattern for capturing the active power losses from the microgrid DER. The degradation trends have been enumerated through tailoring the variability and drift components in the algorithm.

The advanced GRU layer of this hybrid model is implemented to capture the complex temporal patterns from the power signals and forecast the gradual degradation rate in the upcoming years to predict the proactive maintenance needs in advance. Algorithm 5.2 explains the proposed intelligent hybrid degradation process step by step.

Stochastic Degradation Pattern

This process aims in modeling the DER active power degradation pattern from the complex MG database. Stochastic Wiener model has been implemented here to discern the degradation rate from the active power signals of each DER according to the following equation:

$$\mathcal{P}^{w}_{\mathrm{DER}}(t) = \mathcal{P}_{\mathrm{DER}}(0) + \beta t^{q} + \gamma W_{\mathrm{DER}}(t) \tag{5.31}$$

Here, $\mathcal{P}^{w}_{\mathrm{DER}}(t)$ indicates the degradation rate of the power signals for each DER at time step t, initial power capacity of each DER is represented by $\mathcal{P}_{\mathrm{DER}}(0)$, the drift and variability coefficients for the stochastic degradation model are β and γ which indicate the DER aging rate and degradation volatility, respectively. $W_{\mathrm{DER}}(t)$ denote the Brownian motion in the standard Wiener degradation process for the DER. The model is non-linear when $q \neq 1$. Different DER has varying aging depending on the working conditions, built, and locations. The drift coefficient β has been randomized for characterizing the variability in gradual DER performance degradation. The stochastic distribution for coefficient β has been represented by the following equation where the randomness of the DER degradation pattern is measured through the variance (σ_{β}) and mean values (μ_{β}) of the normal distribution:

$$\beta \sim \mathcal{N}(\mu_{\beta}, \sigma^{2}_{\beta}) \tag{5.32}$$

Algorithm 5.1: Adaptive Kernel-based Classification: DER Operational States.

Input: $\mathbf{Y} = \{y_t \mid t = 1, 2, \ldots, (T-1), T\}$ - input sequence of DER power signals, where $y_t \in \{P_{\text{PVS}}(t), P_{\text{FC}}(t), P_{\text{GPG}}(t)\}$

parameter: $\tau, \kappa \rightarrow$ kernel hyper-parameters, $w \rightarrow$ sliding window size, $\mathcal{O}_{\mathcal{S}}(t) \in \{\text{Normal}, \text{Careful}, \text{Serious}, \text{Emergency}\} \rightarrow$ DER operational states, $T_{\text{th}}^{\text{N}}, T_{\text{th}}^{\text{C}}$, and T_{th}^{S} indicate the dynamic state thresholds

Output: Classification label L_i of operational states $\mathcal{O}_{\mathcal{S}}(t)$ for each time step t.

`/* Step 1: Feature Extraction */`

foreach $y_t \in \{P_{PVS}(t), P_{FC}(t), P_{GPG}(t)\}$ **do**

  for $t = w + 1$ *to* T **do**

    Compute all the equations from (6) to (11)

    Form feature vector:

$$\mathbf{Y}(t) = \begin{cases} [\mu_{P_{\text{PVS}}(t)}, \sigma_{P_{\text{PVS}}(t)}, \text{Var}(P_{\text{PVS}}(t)), \delta_{P_{\text{PVS}}(t)}, \text{C}(P_{\text{PVS}}(t))] \\ [\mu_{P_{\text{FC}}(t)}, \sigma_{P_{\text{FC}}(t)}, \text{Var}(P_{\text{FC}}(t)), \delta_{P_{\text{FC}}(t)}, \text{C}(P_{\text{FC}}(t))] \\ [\mu_{P_{\text{GPG}}(t)}, \sigma_{P_{\text{GPG}}(t)}, \text{Var}(P_{\text{GPG}}(t)), \delta_{P_{\text{GPG}}(t)}, \text{C}(P_{\text{GPG}}(t))] \end{cases}$$

  end

end

`/* Step 2: Operational states` $\mathcal{O}_{\mathcal{S}}(t)$ `Assignment */`

foreach $\{P_{PVS}(t), P_{FC}(t), P_{GPG}(t)\} \in \mathcal{P}_{DER}(t)$ **do**

$$\mathcal{O}_{\mathcal{S}}(t) = \begin{cases} \text{Normal State}, & \text{if } \mathcal{P}_{\text{DER}}(t) \geq T_{\text{th}}^{\text{N}} \\ \text{Careful State}, & \text{if } T_{\text{th}}^{\text{N}} > \mathcal{P}_{\text{DER}}(t) \geq T_{\text{th}}^{\text{C}} \\ \text{Serious State}, & \text{if } T_{\text{th}}^{\text{C}} > \mathcal{P}_{\text{DER}}(t) \geq T_{\text{th}}^{\text{S}} \\ \text{Emergency State}, & \text{if } \mathcal{P}_{\text{DER}}(t) < T_{\text{th}}^{\text{S}} \end{cases}$$

end

`/* Step 3: Adaptive Kernel Function */`

foreach *pair* (Y_m, Y_n) **do**

  Compute Euclidean distance: $\|Y_m - Y_n\| = \sqrt{\sum_{k=1}^{n}(Y_{m,k} - Y_{n,k})^2}$

  Implement adaptive kernel similarity function:

  $\mathcal{K}(\mathbf{Y}_m, \mathbf{Y}_n) = \exp\left(-\zeta \frac{\|\mathbf{Y}_m - \mathbf{Y}_n\|^2}{\sigma_{P_{\text{DER}}}^2 + \gamma}\right)$

end

`/* Step 4: Classification with Dynamic Decision Boundary */`

foreach Y_m^* **do**

  Compute adaptive kernel margin: $\theta_m = \tau \cdot e^{-\kappa|\delta_P|}$

  Compute decision boundary function: $L_m\big(\mathbf{w} \cdot f(\mathbf{Y}_m^*) + b_s\big) \geq 1 - \theta_m$

  if $L_m = +1$ **then**

    `// Classified normal state as decision boundary satisfied`

  else

    `// Classified other states according to` $\mathcal{O}_{\mathcal{S}}(t)$

  end

end

return *Classification labels* (L_m) *for all time steps* $(t = 1, 2, \ldots, T)$

Algorithm 5.2: Intelligent Hybrid Algorithm to Analyze DER Degradation.

Input: $\mathbf{Y} = \{y_t \mid t = 1, 2, \ldots, (T-1), T\}$ - input sequence of DER power signals, where $y_t \in \{\mathcal{P}_{\text{DER}}(t)\}$

parameter: $\beta, \gamma, q \rightarrow$ drift, variability, and model coefficients, $w \rightarrow$ sliding window size, $\mathcal{P}_{\text{DER}}(0) \rightarrow$ initial power capacity of each DER

Output: Yearly DER power and capacity degradation: $\mathcal{P}^{\hat{w}}_{\text{DER}}(t+1)$, $\Delta\mathcal{P}^{\%}_{y}$

`/* Step 1: Apply Stochastic Degradation Process */`

foreach $y_t \in \{P_{PVS}(t), P_{FC}(t), P_{GPG}(t)\}$ **do**
  for $t = 1$ *to* T **do**
    Measure Randomness: $\beta \sim \mathcal{N}(\mu_\beta, \sigma^2_\beta)$
    Compute degradation of each DER by implementing Wiener process:

$$\mathcal{P}^{w}_{\text{DER}}(t) = \mathcal{P}_{\text{DER}}(0) + \beta t^q + \gamma W_{\text{DER}}(t)$$

  end
end

`/* Step 2: Model DER Degradation Sequences */`

foreach $\mathcal{P}_{DER}(t)$ **do**
  Quantize $\mathcal{P}^{w}_{\text{DER}}(t)$ into sequences of length w
  For each $y_t \in \{\mathcal{P}^{w}_{\text{DER}}(t)\}$:
  Govern Update Gate: $u_t = \sigma_u(G_u \cdot [h_{t-1}, y_t] + v_u)$
  Govern Reset Gate: $r_t = \sigma_r(G_r \cdot [h_{t-1}, y_t] + v_r)$
  Compute Candidate State: $\tilde{h}_t = \tanh(G_h \cdot [r_t \cdot h_{t-1}, y_t] + v_h)$
  Enumerate Latest Hidden State: $h_t = (1 - u_t) \cdot h_{t-1} + u_t \cdot \tilde{h}_t$
  Output: $z_t = \sigma_o(G_o \cdot h_t + v_o)$
end

`/* Step 3: Compile Advanced Hybrid Degradation Process */`

for $e = 1$ *to* 50 **do**
  Predict next-step power degradation for each batch of sequences:

$$\mathcal{P}^{\hat{w}}_{\text{DER}}(t+1) = \sigma_o(G_o \cdot h_t + v_o)$$

  Minimize MSE loss: $\mathcal{L} = \frac{1}{N}\sum_{t=1}^{N}\left(\mathcal{P}^{\hat{w}}_{\text{DER}}(t+1) - \mathcal{P}^{w}_{\text{DER}}(t+1)\right)^2$
end

`/* Step 4: Forecast DER Power Degradation and Capacity Loss */`

for $t = T + 1$ *to* $T + 5 * 365$ **do**
  Generate power degradation forecasts for each DER
  Enumerate yearly capacity loss (kW): $\Delta\mathcal{P}_y = \hat{\mathcal{P}}_{y-1} - \hat{\mathcal{P}}_y$
  Compute annual capacity degradation rate (%) for each DER:

$$\Delta\mathcal{P}^{\%}_{y} = \left(\frac{\Delta\mathcal{P}_y}{\hat{\mathcal{P}}_{y-1}}\right) \times 100$$

end
return $\mathcal{P}^{\hat{w}}_{DER}(t+1)$, *and* $\Delta\mathcal{P}^{\%}_{y}$ *per year for each DER*

Forecast DER Degradation with Advanced GRU Architecture

An advanced GRU architecture has been tailored into this hybrid approach for modeling the temporal variations from the DER power signals followed by the stochastic Wiener process to better capture the degraded temporal dependencies over time. Figure 5.4 depicts the mechanisms of the advanced GRU architecture for analyzing and modeling the DER degradation pattern. In order to govern the advanced layer operations, this architecture implements a number of parameters and equations that have been presented as follows:

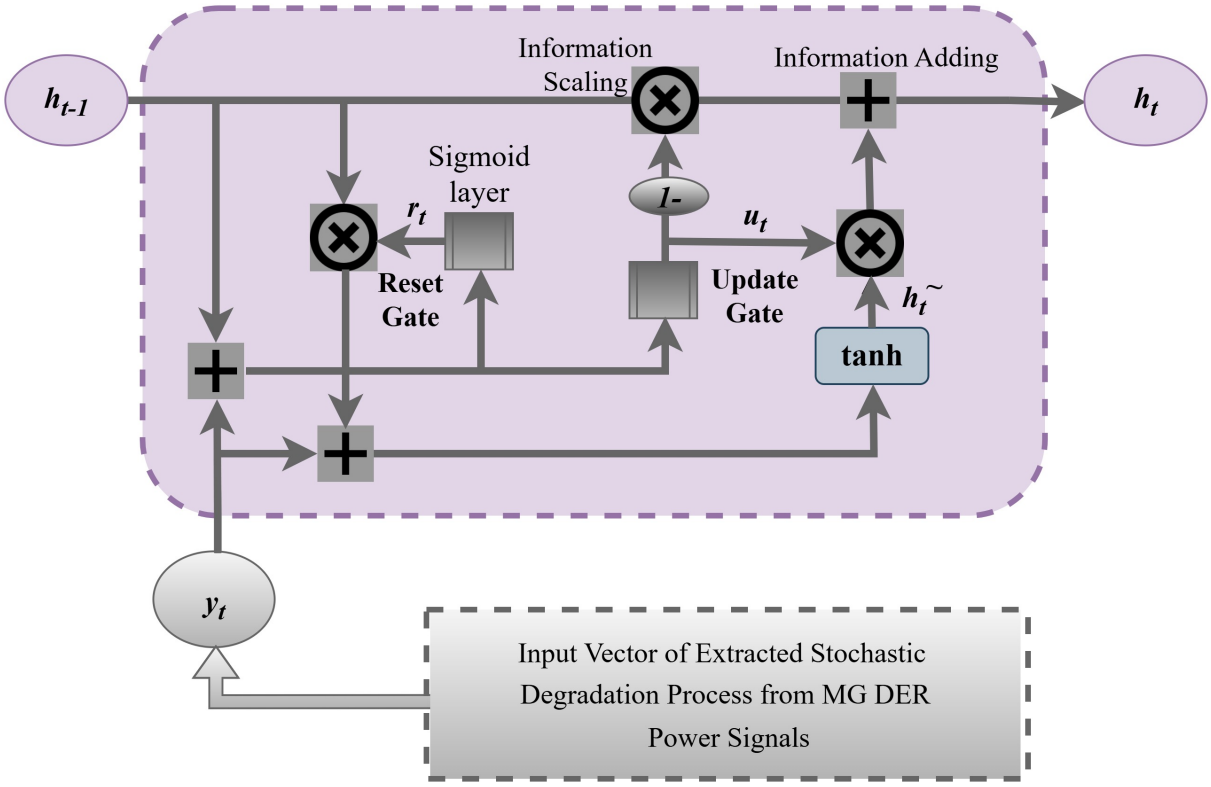


Figure 5.4: Advanced GRU layer for modeling microgrid DER power degradation pattern.

$$u_t = \sigma_u(G_u \cdot [h_{t-1}, y_t] + v_u) \tag{5.33}$$

$$r_t = \sigma_r(G_r \cdot [h_{t-1}, y_t] + v_r) \tag{5.34}$$

$$\tilde{h}_t = \tanh(G_h \cdot [r_t \cdot h_{t-1}, y_t] + v_h) \tag{5.35}$$

$$h_t = (1 - u_t) \cdot h_{t-1} + u_t \cdot \tilde{h}_t \tag{5.36}$$

$$z_t = \sigma_o(G_o \cdot h_t + v_o) \tag{5.37}$$

Here, for each time stamp t, y_t and z_t represent the input and output feature vectors for the advanced GRU layer. The update and reset gate operations, candidate and latest hidden states operations have been indicated by u_t, r_t, and $\tilde{h}_t$, h_t, respectively; σ indicates the implemented sigmoid activation function at the corresponding gates and output; The previous hidden state yielded from previous time stamp $(t-1)$ has been represented by h_{t-1}; the concatenation between the vectors h_{t-1} and y_t has been

expressed through $[h_{t-1}, y_t]$; v_u, v_r, v_h, v_o represent the corresponding bias vectors and G_u, G_r, G_h, G_o indicate the implemented weight matrices at the update gate, reset gate, candidate hidden state and the output, respectively for the advanced GRU operation of the MG DER data.

5.5 Results and Discussion

The evaluation and performance of the power-aware adaptive kernel function for classifying the DER operational states, the training and validation of the intelligent hybrid degradation algorithm for analyzing the gradual degradation process from DER power signals and remaining capacity are presented in this section.

5.5.1 Classification of DER Operational States

To evaluate the effectiveness of the proposed power-aware adaptive kernel-based algorithm in terms of classifying the DER operational states, four standard metrics have been utilized for the evaluation which are: accuracy, precision, recall, and F1-score. These evaluation metrics have been enumerated in the context of confusion matrix that marks the counts between actual classes and predicted classes. For the implemented multi-class classification among normal state, careful state, serious state, and emergency state, these metrics have been enumerated per class and averaged into macro or weighted average afterwards. Here, the positive instances which have been predicted correctly by the algorithm are counted as true positives (TP), the negative instances which have been predicted correctly by the algorithm are counted as true negatives (TN). Conversely, the positive and negative instances that have been predicted incorrectly by the algorithm are counted as false positives (FP) and false negatives (FN), respectively. The proportion of total correct predictions is denoted by accuracy. The overall correctness is represented by it which has been computed for the proposed classifier by the following equation:

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \tag{5.38}$$

How many of the positive labels were predicted exactly by the classifier can be measured by precision. The algorithm's ability of not identifying a negative label as positive is reflected by precision. Besides, how many of the actual positive instances were captured exactly by the classifier can be quantified by recall or true positive rate. This is an essential metric in predictive maintenance applications as missing an emergency maintenance can lead to significant penalty or system downtime. Another important metric specifically in case of quantifying any imbalanced classification performance is F1-score which can be computed by balancing both recall and precision by the following equations:

$$\text{Precision} = \frac{TP}{TP + FP} \tag{5.39}$$

$$\text{Recall} = \frac{TP}{TP + FN} \tag{5.40}$$

$$\text{F1-score} = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \tag{5.41}$$

Figure 5.5 depicts the classified operational states over time with maintenance alerts for the microgrid DER operations where Fig. 5.5(a), (b), and (c) illustrate the classified operational states for PVS, FC, and GPG over time respectively. The purple, orange, and red circles indicate the careful, serious, and emergency operational states respectively of the microgrid DER for proactive decision making as can be seen from the figure.

For enumerating the maintenance schedules of each DER based on the classified operational states, a scheduling function has been implemented according to the following equation where s is the monthly frequency for the alert states for each DER, the set for all time-steps in a particular month a is represented by M_t, and $\mathbb{I}[\cdot]$ represents the indicator function.

$$\mathcal{F}^{(s)}_{\text{DER}}(a) = \sum_{i \in M_t} \mathbb{I}\left[L_m(\mathcal{P}_{\text{DER}}(t)_m(i)) = s\right] \tag{5.42}$$

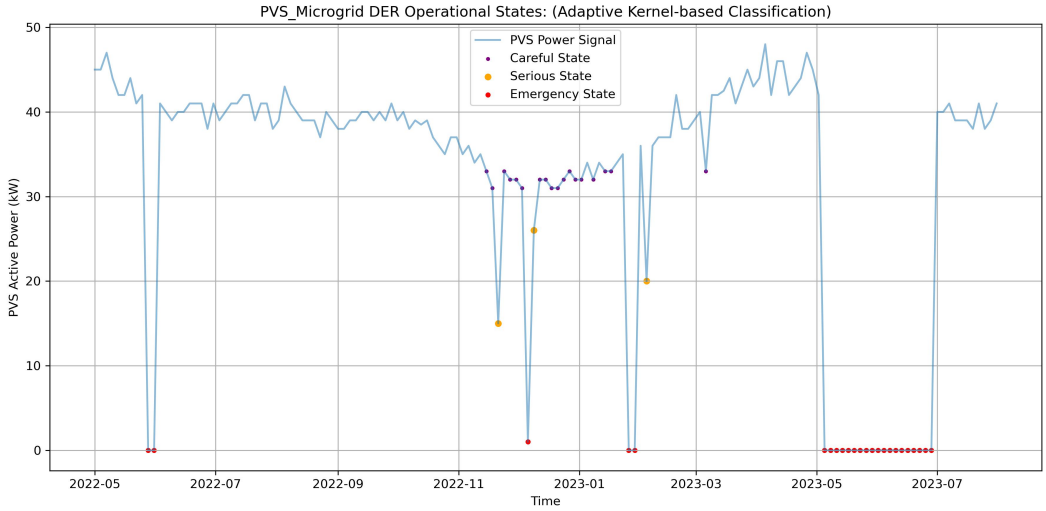
Figure 5.6 depicts the monthly DER maintenance scheduling based on the classified alert counts where Fig. 5.6(a), (b), and (c) illustrate the monthly predictive maintenance scheduling with alert events for PVS, FC, and GPG respectively. The purple, orange, and red colored bars indicate the careful, serious, and emergency events based on the classified operational states respectively. The purple stacked bar indicates early performance degradation signs, orange stacked bar identifies significant drop, and the red stacked bar indicates critical failure.

5.5.2 DER Power Degradation Analysis

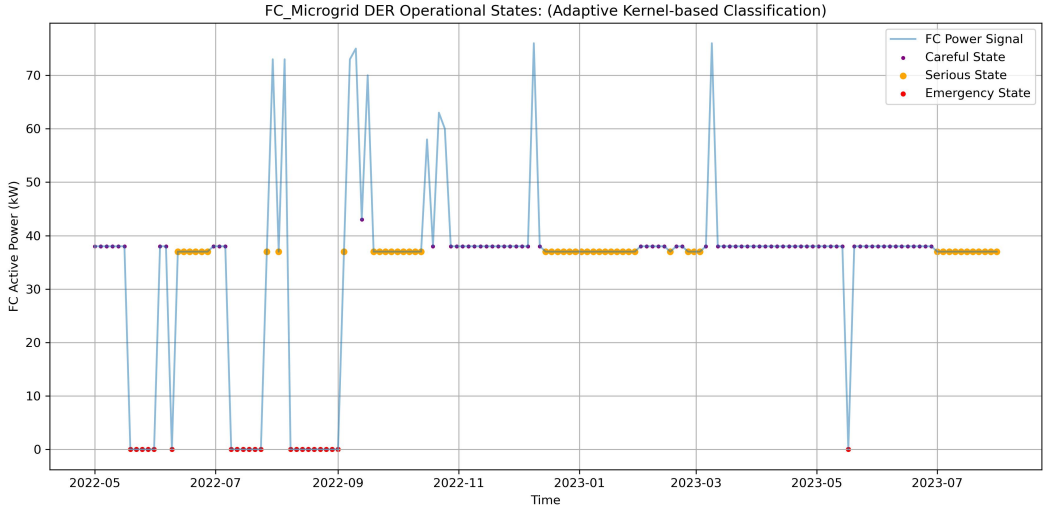
For analyzing the DER power degradation and predicting required maintenance over time by the yearly capacity losses, a novel hybrid approach by coupling Wiener stochastic degradation process with advanced GRU architecture has been implemented. Figure 5.7 illustrates the training and validation step of the proposed advanced hybrid degradation architecture where a noteworthy minimization of training and validation losses (close to 0) are noticeable for all DER after 50 epochs. The developed advanced model is implemented then to forecast the DER power degradation process over next 5 years following the equations:

$$\mathcal{P}^{\hat{w}}_{\text{DER}}(t+1) = \sigma_o(G_o \cdot h_t + v_o) \tag{5.43}$$

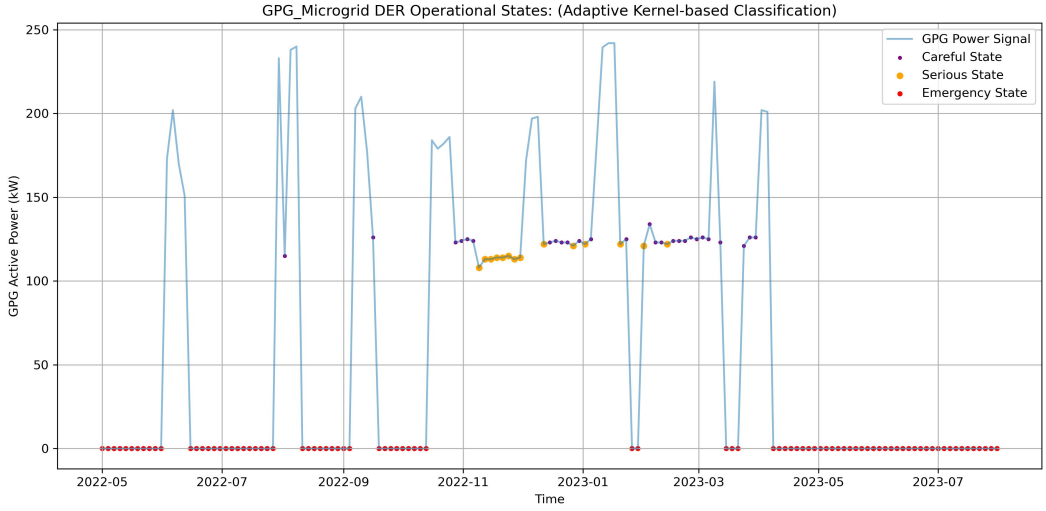
$$\mathcal{L} = \frac{1}{N} \sum_{t=1}^{N} \left(\mathcal{P}^{\hat{w}}_{\text{DER}}(t+1) - \mathcal{P}^{w}_{\text{DER}}(t+1)\right)^2 \tag{5.44}$$



(a)

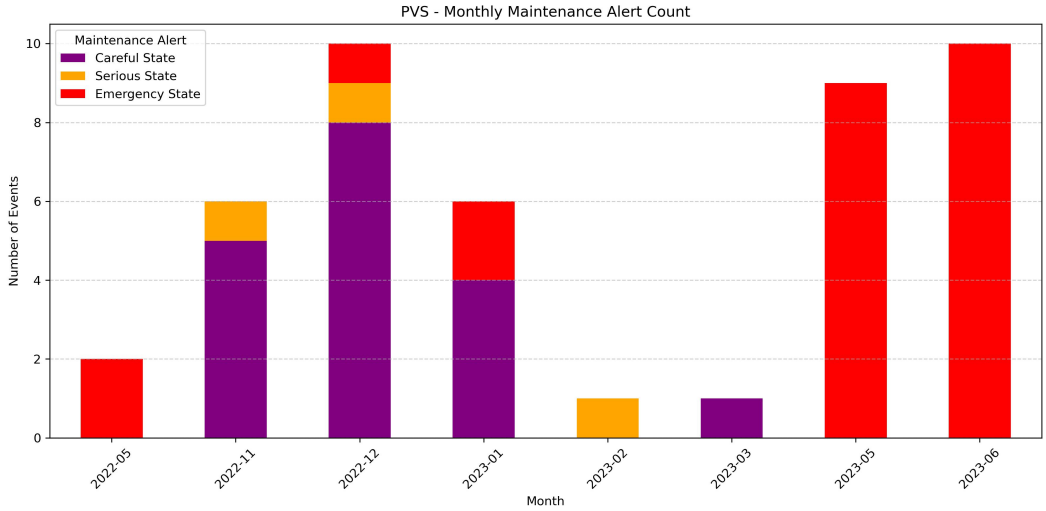


(b)

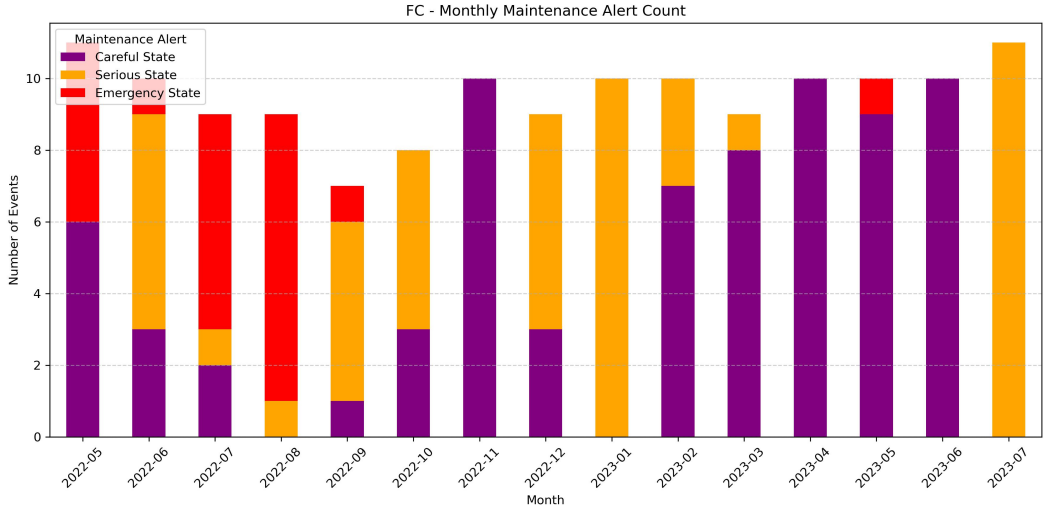


(c)

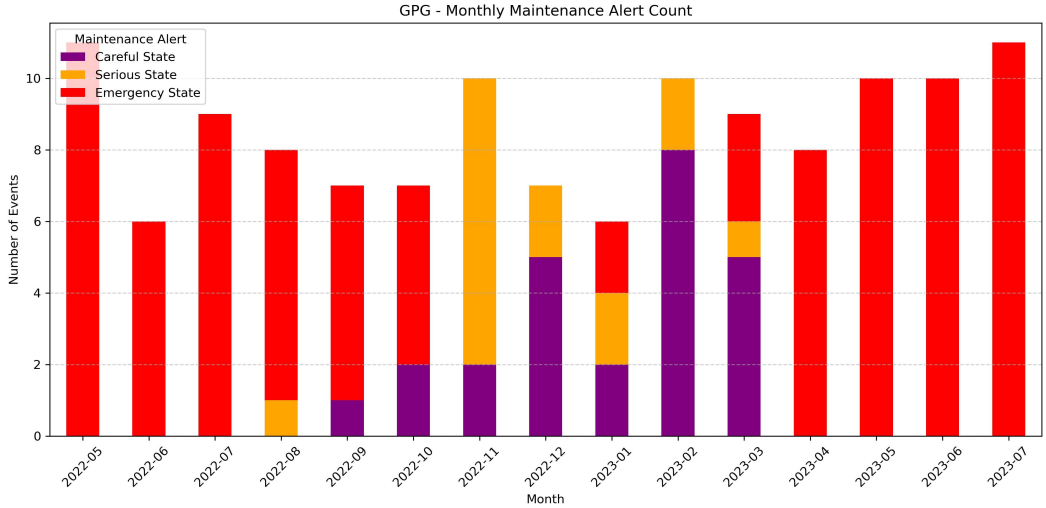
Figure 5.5: Classified Operational States with Maintenance Alerts: (**a**) PVS. (**b**) FC. (**c**) GPG.



(a)



(b)



(c)

Figure 5.6: Monthly DER Maintenance Scheduling by Alert Counts: (**a**) PVS. (**b**) FC. (**c**) GPG.

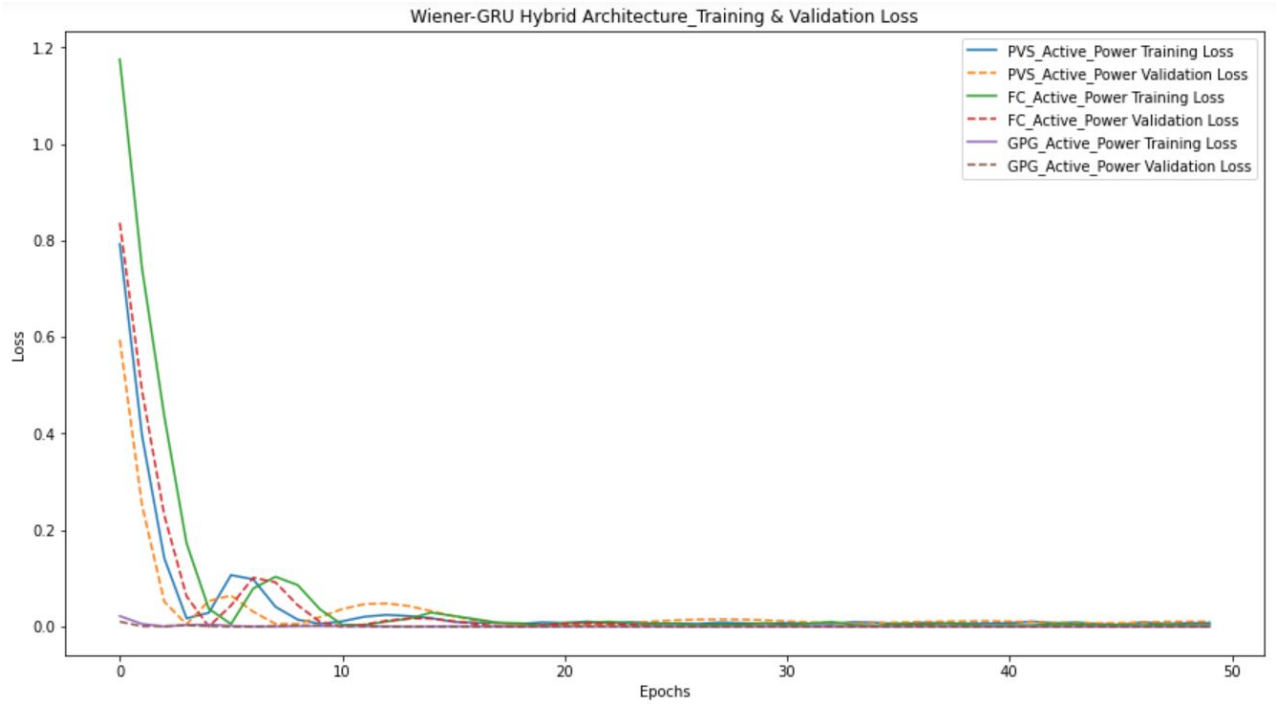


Figure 5.7: Training and Validation of the advanced Hybrid Degradation Algorithm.

Figure 5.8 depicts the power degradation process of the microgrid DER for the upcoming 5 years where Fig. 5.8(a), (b), and (c) illustrate the gradual yearly power capacity degradation of PVS, FC, and GPG respectively. For enabling efficient predictive maintenance planning in advance, the annual power losses (kW) during operations and the percentage of capacity degradation for each of the DER have been calculated using the following equations:

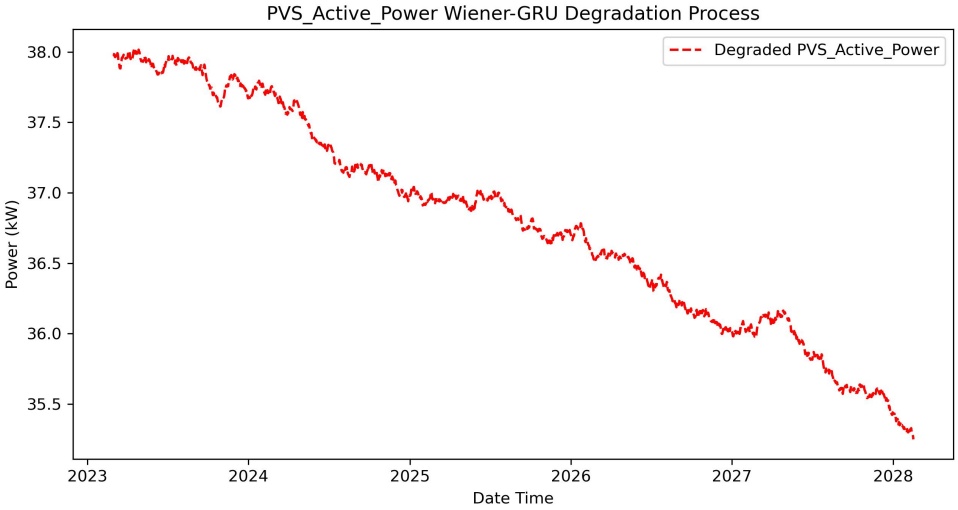
$$\Delta\mathcal{P}_y = \hat{\mathcal{P}}_{y-1} - \hat{\mathcal{P}}_y \tag{5.45}$$

$$\mathcal{P}_y^{\%} = \left(\frac{\Delta\mathcal{P}_y}{\hat{\mathcal{P}}_{y-1}}\right) \times 100 \tag{5.46}$$

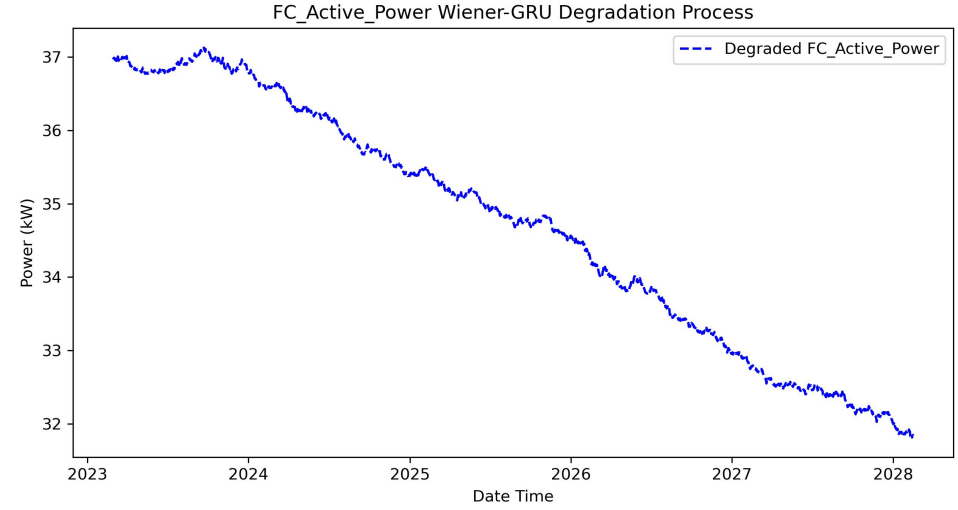
5.5.3 Discussion

Table 5.1 illustrates the performance of the proposed predictive maintenance approach for microgrid using the DER power signals. The scores of 0.99, 0.99, and 0.99 for accuracy; 1.00, 0.97, and 0.99 for precision; 0.96, 1.00, and 0.99 for recall; 0.98, 0.99, and 0.99 for F1-score for PVS, FC, and GPG respectively indicate the excellent performance of the proposed method for enabling proactive maintenance for complex industrial microgrid system with diverse DERs.

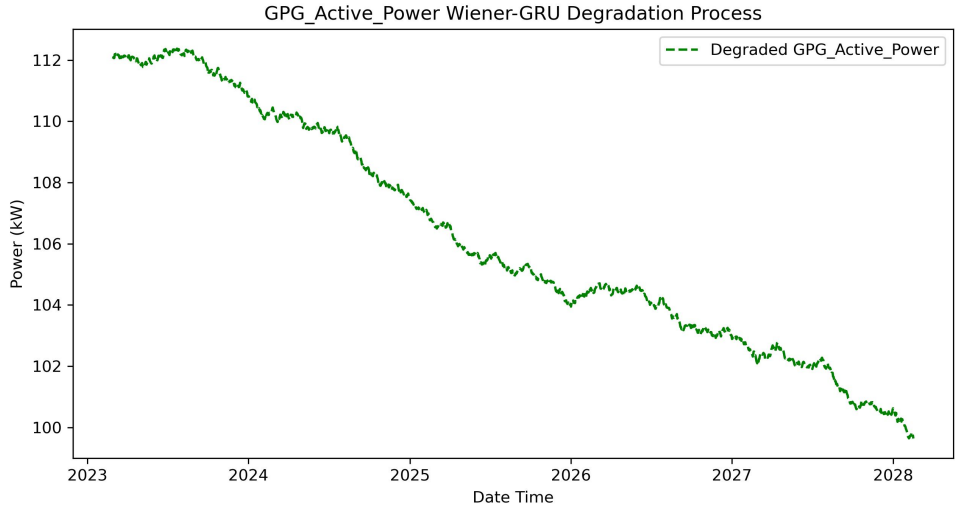
Figure 5.9 illustrates the percentage of annual power capacity degradation of microgrid DER for the upcoming 5 years where Fig. 5.9(a), (b), and (c) depict the gradual decremental yearly remaining capacity rate (%) for PVS, FC, and GPG respectively. A decremental remaining capacity of 98.48% to 97.42% to 95.98% to 94.58% and finally to 93.20% for PVS, 98.01% to 94.69% to 91.62% to 87.98%



(a)

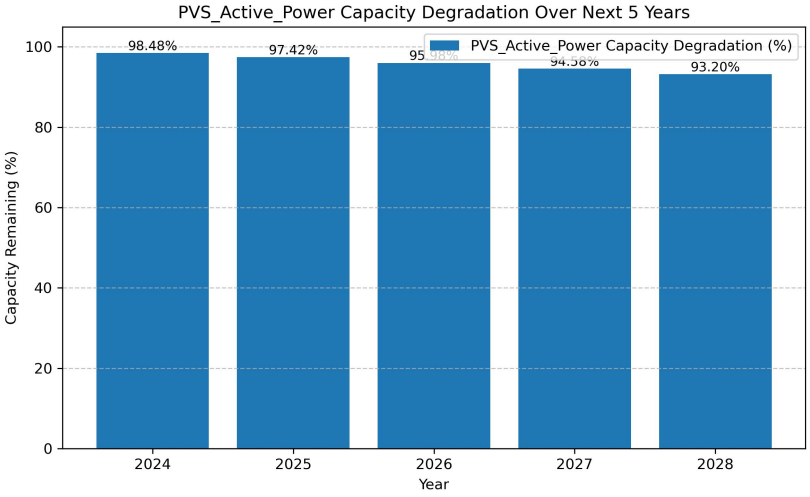


(b)

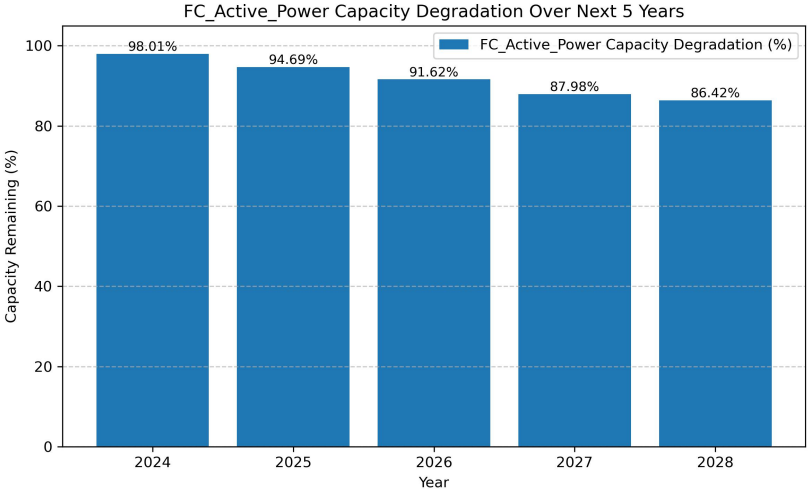


(c)

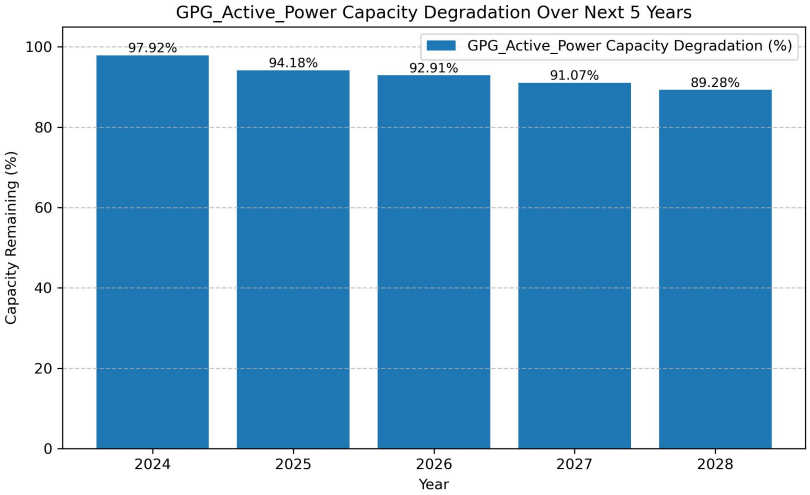
Figure 5.8: Degradation Process of Microgrid DER: (**a**) PVS. (**b**) FC. (**c**) GPG.



(a)



(b)



(c)

Figure 5.9: Annual Capacity Degradation (%) of Microgrid DER: (**a**) PVS. (**b**) FC. (**c**) GPG.

Table 5.1: Performance Evaluation of the Proposed PdM Framework for Diverse DERs.

DER	Accuracy	Precision	Recall	F1-Score
PVS	0.99	1.00	0.96	0.98
FC	0.99	0.97	1.00	0.99
GPG	0.99	0.99	0.99	0.99

and finally to 86.42% for FC, and 97.92% to 94.18% to 92.91% to 91.07% and finally to 89.28% for GPG, respectively can be observed from the developed intelligent hybrid degradation approach.

The performance of the developed predictive maintenance technique has been compared with respect to traditional popular ML methods like SVC and RF. Figure 5.10 depicts the relative performance comparison of the proposed model with SVC and RF in terms of accuracy, precision, recall, and F1-score where the ash, blue, and purple colored bars represent the performances of the SVC, RF, and proposed model respectively. The overall scores of 92.8%, 95.7%, and 99.3% for accuracy; 87.5%, 92.7%, and 98.8% for precision; 87.5%, 94.5%, and 97.3% for recall; 87.5%, 93.4%, and 98.1% for F1-score of the SVC, RF, and proposed technique respectively indicate the excellent performance of the proposed method for enabling proactive maintenance for complex industrial microgrid system with diverse DERs.

The developed predictive maintenance framework demonstrated excellent performances in terms of

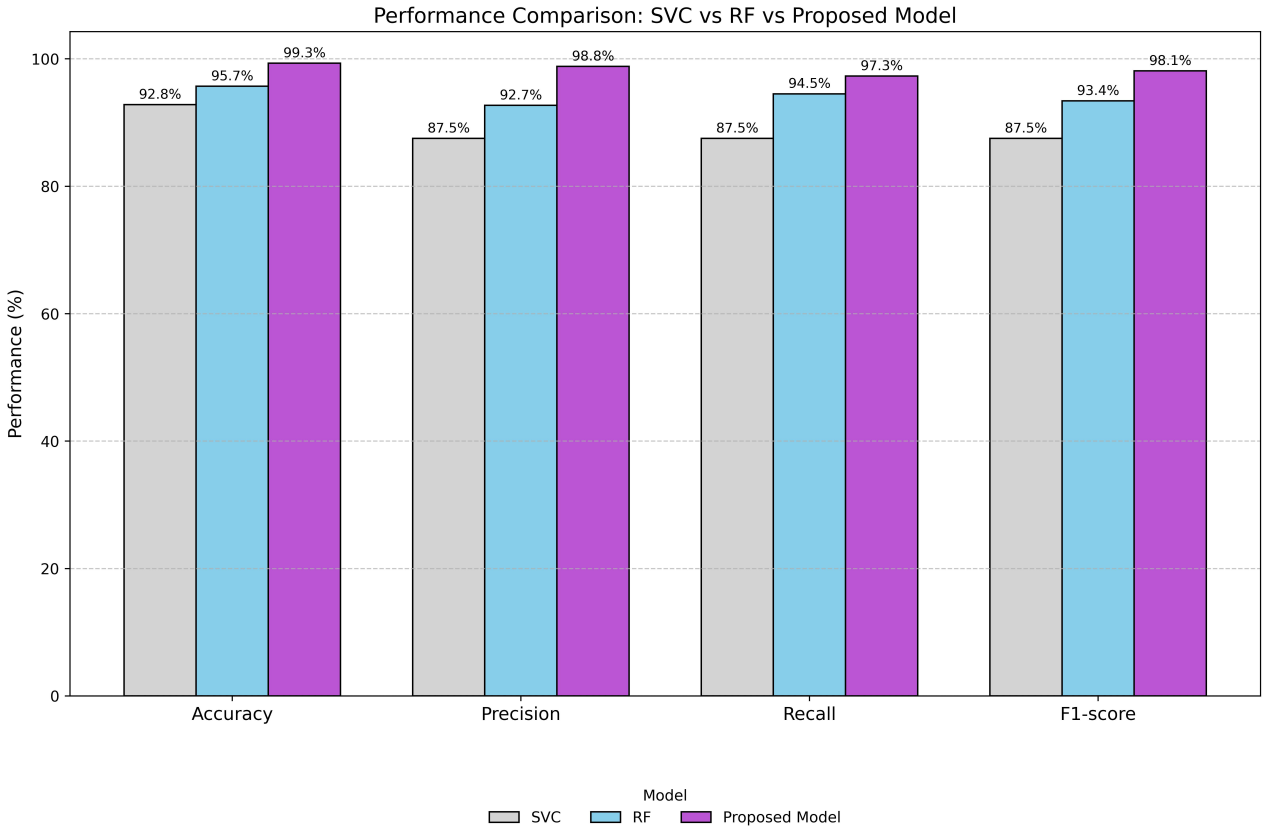


Figure 5.10: Relative Performance Comparison of the Proposed Model for Diverse DERs.

both classifying the complex DER operational states and analyzing the DER gradual degradation pattern and remaining capacity. However, there could be some challenges if implemented to more complex, diverse, and larger industrial microgrid setups. Handling the uncertainty and variability in the power signals from diverse, complex DER is one of the major challenges. Besides, tackling the scalability concern in the context of larger microgrid network and balancing the sensitivity and robustness are crucial for minimizing the false positives and negatives which are very significant in predictive maintenance applications.

5.6 Concluding Remarks

A novel hybrid ML-based framework has been developed in this study for addressing the critical research problems of accurately classifying DER operational states with maintenance alerts and assessing the annual capacity degradation for enhanced predictive maintenance capabilities of complex microgrid scenario by coupling a power-aware adaptive kernel function with a hybrid Wiener-GRU degradation algorithm. The overall accuracy of 99% demonstrates the excellent performance of the proposed framework which can allow early identification of performance degradation, enabling proactive scheduling for the maintenance actions which can ensure enhanced reliability, reduced maintenance costs, and improved operational efficiency in complex microgrid networks. This can pave the way for a resilient, sustainable and greener energy landscape. Despite the merits, there can be few challenges while deploying this framework practically in more complex and larger microgrid setups. One of the key challenges includes the handling of uncertainty and variability in the power generations from diverse DER, which can impact the algorithm accuracy. Moreover, balancing the sensitivity and robustness while maintenance alert classification is also significant to reduce the false positives and negatives. The scalability in terms of larger and more complex microgrid setups having heterogeneous energy sources with diverse, dynamic operational conditions needs further investigation. Moreover, real-time deployment with IoT networks, addressing scalability and generalization concerns regarding large microgrids, implementing more advanced classification and forecasting hybrid ML algorithms can be investigated in future research. By leveraging the outstanding potential of advanced ML approaches through bridging the theoretical advancements with practical implementations can help achieve a resilient, sustainable and greener energy landscape in an era defined by both technological innovation and environmental responsibility.

Chapter 6

Conclusions and Recommendation for Future Works

6.1 Conclusions

Advanced deep learning architectures and their correlative performances on identifying the faulty operations of microgrid, intelligent hybrid DL algorithms and their excellent performances combined with residual based dynamic threshold framework for microgrid predictive maintenance and a smart predictive maintenance framework combining a novel power-aware adaptive kernel function for classifying the microgrid DER operational states, generating maintenance alerts based on priority and a novel hybrid degradation algorithm for analyzing the degradation process from DER power signals and calculating the remaining capacity for the upcoming years have been presented in this thesis.

Chapter 3 presents advanced DL frameworks for microgrid predictive maintenance by performing a comprehensive correlative analysis of RNN, LSTM, and GRU for PV based dc microgrids. Results demonstrate strong predictive capabilities of all, with the proposed advanced LSTM method outperforming RNN, GRU, and the traditional techniques. The applicability of these DL methods is promising, but still has challenges in terms of generalization through diverse microgrid scenarios for an enhanced malfunction diagnosis to improve overall microgrid energy efficiency by minimizing downtime. Besides, some limitations of this research consist of computational complexity, data dependency as DL architectures highly depend on historical high-quality data and in the case of missing values or inconsistencies in the data set the prediction accuracies can be affected, and some factor variability as in this analysis some other factors such as SPV module aging, microgrid topology variations, cloud cover variations were not considered, which can affect the performance of microgrid inverters over time. Developing more advanced hybrid architectures considering these limitations, with more enhanced interpretability and error reduction capabilities with IoT setups can be an excellent avenue for real-time implications of diverse large-scale microgrid scenarios. This work can contribute to the emerging technology for predictive maintenance of microgrids and provide significant insights into the modeling and performance of RNN architectures for improving fault detection in microgrid systems.

Chapter 4 introduces an intelligent data-driven hybrid fault detection framework for microgrid predictive maintenance utilizing an advanced HDL architecture, combined with advanced data analysis and a residual-based dynamic threshold technique. An adaptive gradient technique is employed to optimize the loss function of the proposed hybrid algorithm for microgrid predictive maintenance. The results show significant accuracy in fault identification for predicting the maintenance needs within MGs. This research offers valuable insights for designing and enhancing hybrid algorithms for fault detection in microgrid systems, contributing to advancements in predictive maintenance technology and promoting a resilient and cost-effective operation of MGs. 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 microgrid 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 microgrids for algorithm training and inference. These findings can have noteworthy implications to enhance the efficiency and resilience in microgrid systems, thereby evolving the renewable energy technologies in power sector and contributing to the sustainable and greener energy landscape.

Chapter 5 proposes a smart predictive maintenance framework for addressing the critical research problems of accurately classifying DER operational states with maintenance alerts and assessing the annual capacity degradation for enhanced predictive maintenance capabilities of complex industrial microgrid scenario by coupling a novel power-aware adaptive kernel function with a hybrid Wiener-GRU degradation algorithm. The overall accuracy of 99% demonstrates the excellent performance of the proposed framework which can allow early identification of performance degradation, enabling proactive scheduling for the maintenance actions which can ensure enhanced reliability, reduced maintenance costs, and improved operational efficiency in complex microgrid networks. Despite the merits, there can be few challenges while deploying this framework practically in more complex and larger microgrid setups. One of the key challenges includes the handling of uncertainty and variability in the power generations from diverse DER, which can impact the algorithm accuracy. Moreover, balancing the sensitivity and robustness while maintenance alert classification is also significant to reduce the false positives and negatives which are crucial in predictive maintenance applications.

In summary:

- This thesis provides a comprehensive review of the state-of-the-art machine learning techniques that could be used for microgrid predictive maintenance and highlights the gaps and challenges that need to be addressed.
- This study introduces advanced RNN-based frameworks and their correlative performance analysis in the context of microgrid inverter fault detection.
- An adaptive threshold-integrated anomaly detection procedure has been implemented with the developed advanced DL architectures. Based on the statistical properties of the prediction errors of the deployed DL architectures, the threshold level gets adjusted by the proposed technique.

Consequently, the sensitivity to anomalies of those models gets enhanced, which enables an efficient detection of deviations from the microgrid inverter power signals.

- A correlative study among these advanced RNN-based DL architectures has been presented. For capturing the temporal dependencies as well as patterns in the inverter data-points, each of the advanced DL architecture has been leveraged, providing a comprehensive evaluation of the performances of the implemented and conventional approaches in terms of identifying anomalies from microgrid inverter data.

- 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 microgrid operations. The developed data analysis technique establishes a strong foundation for model training, which can enhance the accuracy and interpretability of the predictive maintenance framework for microgrid inverters, ultimately improving predictive maintenance capabilities within the microgrid network.

- Design and integration of an intelligent HDL architecture to capture the dynamic and complex patterns within the ac power signals of microgrid inverters with respect to exogenous factors. Additionally, the mean absolute error loss function of the proposed hybrid algorithm has been optimized to improve the adaptability of the model.

- Deployment of a residual-based dynamic threshold technique within the algorithm. Traditional approaches often struggle to adapt to the complexity and dynamics of microgrid inverters, which can lead to delayed responses and false alarms in the presence of critical, fluctuating data points. Proposed technique enhances predictive maintenance 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 the microgrid operations.

- Development of a predictive maintenance framework uniquely integrating the real-time classification of dynamic operational states of DERs with long-term capacity degradation-aware forecasting from the power signals of PVS, FC, and GPG within the microgrid network which can enable short-term performance alerting with monthly scheduling and long-term capacity planning simultaneously.

- This study introduces an intelligent hybrid degradation model, capable of simulating real-world physical degradation patterns by stochastic modeling of the DER active power signals through Wiener process and developing an advanced GRU architecture simultaneously for capturing the nonlinear temporal dependencies from the degradation process. This advanced hybrid model can enable practical long-term forecasts of power capacity degradation process of microgrid DERs.

- Based on the dynamic active power signals of each DER, a four-level classification of the operational states: normal, careful, serious, and emergency have been defined in the proposed

framework, instead of just binary health status. This nuanced stratification can allow more granular insights in more informed decision making for proactive maintenance.

- An extensive validation has been performed for the developed predictive maintenance framework on a publicly available "Mesa del Sol" microgrid incorporating PVS, FC and GPG as DERs.

In future, studies can continue to explore and contribute to developing more advanced algorithms for microgrid predictive maintenance applications for academia and industries. This study is expected to establish a benchmark in advanced predictive maintenance of microgrids for future research and assist the stakeholders in enhancing the operational reliability, energy resilience, and long-term sustainability.

6.2 Recommendation for Future Works

The future of implementing advanced ML-based techniques on microgrid predictive maintenance is promising, as these technologies have the potential to significantly improve the efficiency and reliability of microgrids. Some key recommendations for implementing ML-based techniques in microgrid predictive maintenance have been made in this section as follows:

- **Accuracy improvement:** One of the future contributions through implementing ML based predictive maintenance in microgrids can be improving the accuracy. Traditional predictive maintenance methods [240], [241] rely on rule-based algorithms and heuristics, which can be prone to errors and may not be able to adapt to changing conditions. ML algorithms can analyze large amounts of data and learn from it, allowing for more accurate predictions of equipment failure. This can be done by using supervised and unsupervised learning algorithms that can be trained on historical data to predict the probability of equipment failure. Some of the popular algorithms that can be used include Random Forest [242], LSTM [243], Gradient Boosting [244] and Neural Networks [245].

- **Diagnosing faults in real-time:** Another way of contributing to the ML based predictive maintenance application for microgrids could be through detecting and diagnosing faults in real-time. By analyzing sensor data in real-time, ML algorithms can detect patterns that indicate a potential fault, allowing for proactive maintenance and reducing the likelihood of power outages.

  One way to detect and diagnose faults in real-time is by using anomaly detection algorithms [246]. These algorithms can detect deviation from normal operation and identify potential faults. Some of the popular algorithms that can be used include K-means [247], Gaussian Mixture Model [248], and One-class SVM [249]. K-means algorithm can be used to cluster the sensor data based on the similarity of data points, which can be used to identify abnormal data points that may indicate a potential fault. Gaussian Mixture Model can be used to model the distribution of sensor data, and detect data points that deviate from the normal distribution, which may possess the likelihood of a probable failure. One-class SVM can be used to separate normal data points from abnormal data points, which may possess a potential fault.

Another way to detect and diagnose faults in real-time is by using deep learning algorithms. These algorithms can be trained on large amounts of sensor data to identify patterns that indicate the likelihood of a probable failure. Some popular deep learning algorithms that can be used include Convolutional Neural Networks [44] and Recurrent Neural Networks [250]. CNNs can be used to analyze sensor data from images and identify patterns that indicate a potential fault. RNNs can be used to analyze sensor data from time series and identify patterns that indicate the likelihood of a probable failure.

- **Optimizing the scheduling of maintenance activities:** Another future research in this sector could be through implementing ML algorithms capable of optimizing the scheduling of maintenance activities. By analyzing historical data and sensor data, ML algorithms can predict when equipment is likely to fail, allowing for the scheduling of maintenance activities at the most optimal time. This can help to minimize the impact of maintenance on the operation of the microgrid and reduce the possibility of power outages. This can be done by using optimization algorithms that can schedule maintenance activities based on the predicted failure probability and the availability of resources. Some of the popular algorithms that can be used include Genetic Algorithm [251], Particle Swarm Optimization [252] and Cuckoo search algorithm [253], [254].

- **Predicting system-wide failure:** ML techniques can also be implemented for the prediction of system-wide failure in microgrid. By analyzing sensor data from multiple equipment and system level data, ML algorithms can predict potential failure scenarios that could lead to system-wide blackouts. This can be implemented by using algorithms that can analyze sensor data and predict the likelihood of system-wide failure. Some of the popular algorithms that can be used include Bayesian Network [255], Markov Chain [256], and Hidden Markov Model [257].

- **Integrating IoT devices:** Integrating Internet of Things (IoT) devices in microgrids is another important research scope where ML-based techniques can be applied in predictive maintenance. IoT devices, such as sensors and actuators, can provide a wide range of data on the operation of equipment in the microgrid. This data can be used to train ML models for predicting when equipment or any sub-system is prospecting to failure, allowing for proactive maintenance.

  One way to integrate IoT devices in microgrids can be through using edge computing. Edge computing [258], [259] involves processing data at the edge of the network, close to the source of the data. This allows for real-time analysis of sensor data and enables the use of ML algorithms for predictive maintenance. Edge computing can also reduce the amount of data that needs to be transmitted to a central location for processing, reducing the load on the network and increasing the speed of analysis.

  Another way of integrating IoT devices could be through implementing fog computing [260], [261]. Fog computing is similar to edge computing, but it involves processing data at multiple locations in the network, rather than just at the edge. This can be useful for microgrids where there is a large amount of sensor data that needs to be analyzed. Fog computing can also help to distribute the load of data processing across multiple locations, reducing the risk of system failure.

ML algorithms can be used to analyze the data from IoT devices to predict when equipment is likely to fail [253], [262]. For example, data from sensors on equipment such as solar panels, wind turbines, and generators can be used to train ML models to predict when equipment is likely to fail. This can be done by using supervised and unsupervised learning algorithms that can be trained on historical data to predict the probability of equipment failure.

Moreover, IoT devices can be used to monitor the performance of equipment in real-time [263] and detect potential issues before they become critical. For example, sensors can be used to monitor the temperature, vibration and other parameters of equipment, and ML algorithms can be used to analyze this data to predict when equipment is likely to get faulty.

- **Hybrid models for feature engineering:** Another potential future research scope in this sector could be through implementing ML based hybrid algorithms for the feature engineering which can help in achieving better performance through analyzing extensive validation as well as enhancing data quality. For improving the interpretability in the domain of feature engineering [264], developing of both knowledge-driven and data-driven hybrid models has emerged to be a promising research area.

  There are plenty of features in a raw dataset typically, all of which do not possess significant patterns and insights for the ML model building. For extracting these innate, crucial features as well enhancing the predictive maintenance capabilities of the developed algorithms, hybrid advanced techniques of feature engineering play a significant role. Based on the advanced feature engineered data, the operational states of different microgrid components such as inverters, DERs can be modeled into different level classification algorithms based on the performances. For example, if the output power from the DERs are as expected or less than the required level. Based on this, normal, careful, serious, or emergency states can be classified based on the real-time performances of the microgrid components.

  Instead of just binary health status as used in the fault detection-only based techniques for microgrid predictive maintenance, this nuanced stratification can allow more granular insights in more informed decision making for proactive maintenance in the context of microgrid maintenance which is a gap observed in the existing predictive maintenance frameworks for microgrids. Moreover, the processed signal or data of microgrid components through hybrid feature engineering techniques can be further implemented in modeling intelligent framework integrating enhanced actionable schedule planning based on the multi-level maintenance alerts on a weekly or monthly window for short-term maintenance scheduling. This can bridge the gap between practical schedule planning and operational forecasting-only based methods of the existing predictive maintenance frameworks for microgrids.

- **Data Implementation:** Microgrid related data could be collected from different sources. These data sources can be used in combination with each other to provide a more comprehensive view of the microgrid and improve the accuracy of failure predictions. Additionally, ML models can be trained using a combination of historical and real-time data, which can help to improve the accuracy of failure predictions and enable the early detection of potential issues.

More data from the available public datasets of complex, industrial microgrid setups can be implemented for advanced hybrid feature engineering for building for sophisticated and enhanced predictive maintenance frameworks for microgrid components. Besides, intelligent capacity degradation models can be built, capable of simulating real-world physical capacity degradation patterns of different microgrid components by stochastic modeling of the microgrid data through Wiener degradation process and developing advanced architectures using RNN, LSTM or GRU layers simultaneously for capturing the nonlinear temporal dependencies from the degradation process in the implemented data. This advanced hybrid model can enable the practical long-term forecasts of real-world capacity degradation of different microgrid components —a gap observed in most physics-based or ML-only based methods.

Moreover, existing studies focus on basic time-series forecasting or anomaly detection for microgrid components separately, lacking the classification of dynamic operational states of different microgrid components, real-time actionable scheduling alerts and capacity degradation modeling of each different microgrid components simultaneously. By implementing more data from the available public datasets of complex, industrial microgrid setups, more advanced predictive maintenance frameworks can be modeled for different microgrid components by integrating the real-time classification of dynamic operational states of complex microgrid components with long-term capacity degradation-aware forecasting from the data within the microgrid network which can enable short-term performance alerting with weekly or monthly scheduling and long-term capacity planning simultaneously which can enhance the predictive maintenance capabilities of the developed algorithms for different microgrid components.

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