International Journal of Environmental Sciences
ISSN: 2229-7359
Vol. 11 No. 22s, 2025
https://www.theaspd.com/ijes.php

Predictive Analytics For Fault Detection And Maintenance Optimization In Smart Microgrids: A Systematic Literature Review

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abstract
Future decentralized and renewable energy systems depend heavily on microgrids. However, fault detection and predictive maintenance are crucial due to their intricacy and dependence on variable sources. With an emphasis on fault detection, forecasting, and maintenance optimization, this review offers a targeted analysis of machine learning-based predictive analytics in microgrids. We suggest a methodical framework that combines neural networks, adaptive neuro-fuzzy inference systems (ANFIS), and condition-based monitoring. Along with a critical examination of these approaches' shortcomings and applicability, a comparative assessment of them is covered. In order to improve microgrid resilience, future research directions highlight the necessity of scalable, explainable AI models and real-time data integration.
Keywords: *Microgrid; Predictive Analytics; Fault Detection; Predictive Maintenance; Machine Learning; Artificial Neural Networks (ANN); Support Vector Machines (SVM); Adaptive Neuro-Fuzzy Inference System (ANFIS); Renewable Energy Forecasting; Condition-Based Monitoring; Energy Resilience; Smart Grid*

1. INTRODUCTION

The global energy transition is speeding up the use of microgrids (MGs), which are small, self-sufficient energy networks that can work with or without a grid. Microgrids combine different types of distributed energy resources (DERs), like solar photovoltaic (PV) systems, wind turbines (WTs), battery energy storage systems (BESS), and combined heat and power (CHP) units. This makes the power system more resilient, reliable, and flexible [1,2]. Their decentralized design makes it easier to use renewable energy, cuts down on transmission losses, and improves power quality. This is why they are such an important part of modern smart grids [3].
Microgrids, on the other hand, have their own problems with running because of the way renewable energy comes and goes, the way systems interact with each other in nonlinear ways, and the way multiple sources work together. Changes in solar irradiance, wind speed, and load demand can make the system unstable, which can affect both the quality of the power and the reliability of the system [4]. Also, equipment failures, like broken inverters or degraded BESS, can cause unplanned downtime and big financial losses [5]. Conventional maintenance strategies, including reactive maintenance (repairing after a failure) and preventive maintenance (scheduled servicing), are inadequate for these intricate, evolving systems due to their failure to foresee breakdowns and enhance resource efficiency [6].

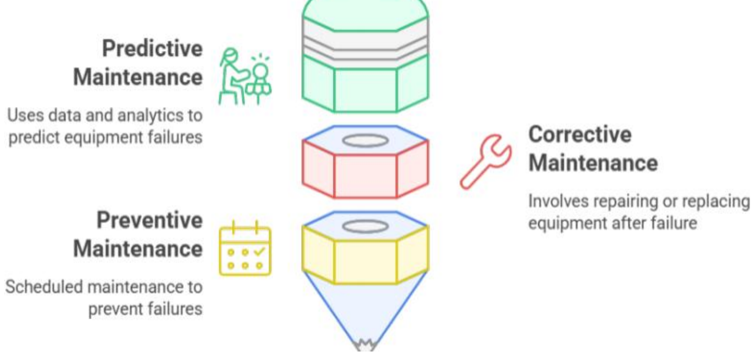

Figure 1: Types of Maintenance

Predictive Maintenance (PdM) is a proactive solution that uses predictive analytics and real-time condition monitoring. PdM can find early fault signatures, figure out how long components will last, and plan interventions just in time to stop catastrophic failures by using machine learning (ML) and data-driven models [4,7]. Also, AI-powered fault detection systems can find unusual operating conditions in milliseconds, which lets automated isolation and recovery actions happen [8].

Recent research has examined diverse machine learning methodologies for microgrid applications, encompassing Artificial Neural Networks (ANNs) [5,9], Support Vector Machines (SVMs) [7,10], and Adaptive Neuro-Fuzzy Inference Systems (ANFIS) [11,12]. These models have been effectively utilized in renewable energy forecasting, anomaly detection, and maintenance optimization, frequently surpassing conventional statistical techniques like AutoRegressive Integrated Moving Average (ARIMA) in managing nonlinear and non-stationary data [13,14]. Nevertheless, difficulties persist in attaining model generalization across various microgrid configurations, guaranteeing real-time adaptability, and enhancing interpretability for operational decision-making [15].

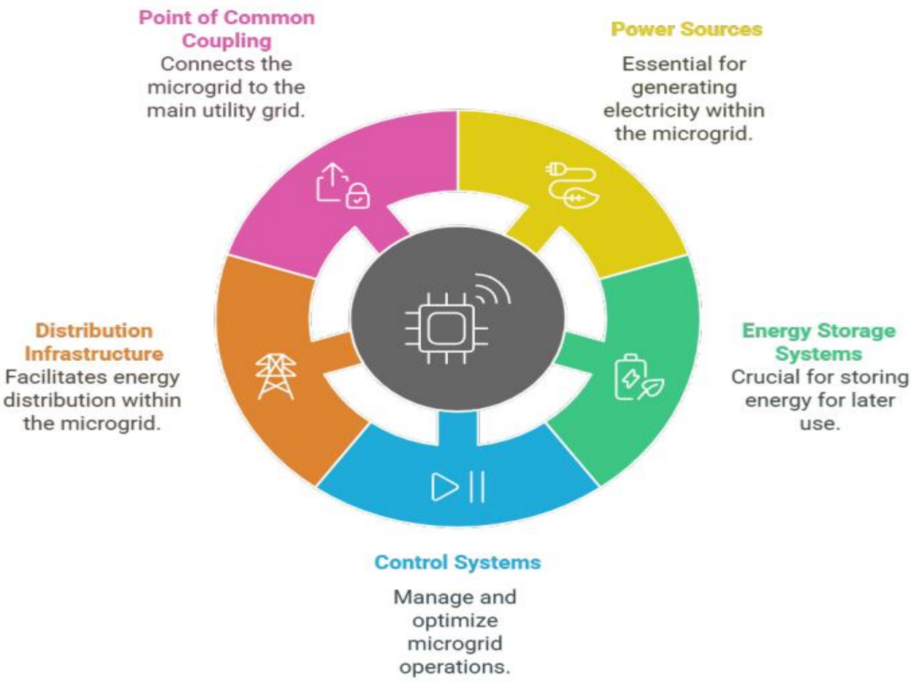

Figure 2: Microgrid Breakdown

Research Gap and Aim

Although there have been improvements in forecasting, fault detection, and predictive maintenance, there aren't any integrated frameworks that bring these features together into a single, scalable architecture for managing microgrids in real time. Most current research is either simulation-based or focused on specific domains (e.g., solar-only microgrids), which restricts their relevance to hybrid and large-scale systems [4,7,16].

This paper fills in these gaps by:

Examining and rigorously evaluating cutting-edge machine learning methodologies for predictive analytics in microgrids.

Looking at how well algorithms work in terms of accuracy, data needs, and scalability.

Putting forward a unified predictive analytics framework that brings together forecasting, fault detection, and PdM to make microgrids more reliable.

The rest of this paper is set up like this: Section 2 presents the literature review; Section 3 elucidates the function of fault management in predictive maintenance; Section 4 examines machine learning methodologies; Section 5 delineates forecasting techniques; Section 6 engages in a discourse; and Section 7 concludes with findings and prospective avenues.

2. LITERATURE REVIEW

The integration of predictive analytics into microgrid operation and maintenance has attracted significant research interest over the past decade. The literature can be broadly categorized into three key areas:

(1) machine learning models for fault detection and predictive maintenance,

International Journal of Environmental Sciences
ISSN: 2229-7359
Vol. 11 No. 22s, 2025
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(2) forecasting methods for load and renewable energy generation, and
(3) integrated systems combining these approaches for real-time microgrid management.

2.1 Machine Learning in Predictive Maintenance

Machine learning (ML) algorithms have proven highly effective in identifying degradation patterns, predicting failure, and optimizing maintenance schedules in microgrids. Arafat et al. [4] provided a comprehensive overview of ML applications in microgrid predictive maintenance, outlining potential frameworks and challenges. Reinforcement learning-based control strategies have been explored for hybrid renewable microgrids [5], showing promise in dynamically adjusting system behavior based on changing grid conditions.

Deep learning methods, such as Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) models, have been leveraged for real-time fault diagnosis and energy output prediction. Al Masoudi [7] demonstrated how hybrid ML models can enhance grid resilience through fast fault identification and correction. Similarly, Sujith et al. [8] introduced a fuzzy logic-assisted ML model for anomaly detection in renewable systems, contributing to enhanced system robustness.

However, the practical deployment of these models is often hindered by challenges such as high data dependency, computational cost, and lack of generalizability across different microgrid configurations.

2.2 Forecasting Techniques for Renewable Energy and Load

Forecasting plays a critical role in energy scheduling, load balancing, and failure prevention in microgrids. Time-series models such as ARIMA and Exponential Smoothing have traditionally been used, but their performance is limited in handling nonlinearities and weather-induced variability.

To address this, data-driven methods using ANNs, SVMs, and ANFIS have been adopted for solar irradiance and temperature forecasting [17,18,19]. Wang et al. [20] and Mellit et al. [21] demonstrated how multilayer perceptrons (MLPs) and hybrid neuro-fuzzy systems can significantly improve forecast accuracy, especially under stochastic environmental conditions.

Despite promising results, most of these models are trained on static or historical data. Real-time forecasting with adaptive learning remains an underexplored area, especially for distributed microgrid systems with varying load profiles and renewable mixes.

2.3 Integrated Predictive Analytics Frameworks

Some recent studies attempt to integrate forecasting, condition-based monitoring (CbM), and predictive maintenance into unified frameworks. De Benedetti et al. [22] presented a model that predicts performance degradation in solar PV systems using ANN-based analysis of nominal vs actual output. Similarly, Platon et al. [23] compared fuzzy logic models with hybrid decision systems to identify pre-failure symptoms in PV networks.

However, most of these systems are domain-specific (e.g., only for solar PV or isolated microgrids) and lack scalability. There is still a notable absence of modular, interoperable frameworks that combine real-time data analytics, hybrid ML models, and automated fault response mechanisms.

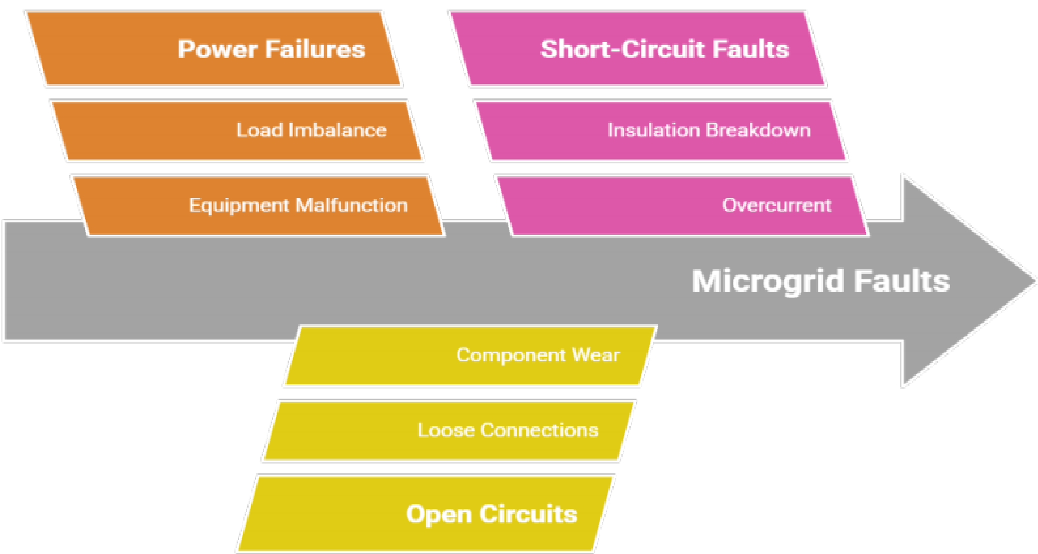

Figure 3. Types of Microgrid Fault

2.4 Summary and Research Gap

Table 1 summarizes some key studies, their focus areas, and limitations:

Study	Focus	Method	Limitations
Arafat et al. (2024) [4]	Predictive maintenance frameworks	ML (SVM, ANN)	Conceptual; lacks real-world case
Al Masoudi (2023) [7]	Real-time fault detection	Hybrid ML	No scalability testing
Wang et al. (2012) [20]	Solar irradiance forecasting	ANN	High data requirement
Mellit & Pavan (2010) [17]	24-h solar forecasting	MLP, ANFIS	Computationally expensive
De Benedetti et al. (2021) [22]	Anomaly detection in PV systems	ANN	Static data; limited to PV systems

This review shows that while there has been a lot of progress in using smart technologies in microgrids, there is still a need for a single, flexible, and scalable predictive analytics framework. Also, not many studies test their methods on real-world or benchmark datasets, which makes it hard to reproduce and compare results.

3. The Importance of Fault Management in Predictive Maintenance

In microgrids, where a lot of different types of distributed energy resources (DERs), storage systems, and power electronics work together, faults can make the system less reliable, damage equipment, and even cause widespread outages. Microgrids have tighter tolerance limits and dynamic load-generation balances than centralized grids. This makes fault detection and mitigation an important part of keeping the system resilient and providing service continuity.

3.1 The Importance of Fault Management in Microgrids

Fault management is the process of finding, locating, classifying, and fixing problems or system failures as soon as they happen. Most traditional fault management methods are either reactive or depend on regular preventive checks. But these methods don't work well for complicated microgrids because of the following problems:

Power generation from renewable sources like solar and wind can change a lot.

Infrastructure that is spread out and has more places where things could go wrong.

Intelligent protection schemes are needed for bidirectional power flow and islanding.

Latency in manual detection or decisions made by a central control.

To fix these problems, modern microgrids need to use intelligent fault management systems that use data and combine real-time monitoring with predictive maintenance.

3.2 Predictive Maintenance as a Strategy for the Future

Predictive Maintenance (PdM) uses sensor data, past records, and analytical models to find early signs of equipment wear and tear or system instability. PdM cuts down on unplanned downtimes, lowers repair costs, and makes more energy available by predicting problems before they happen.

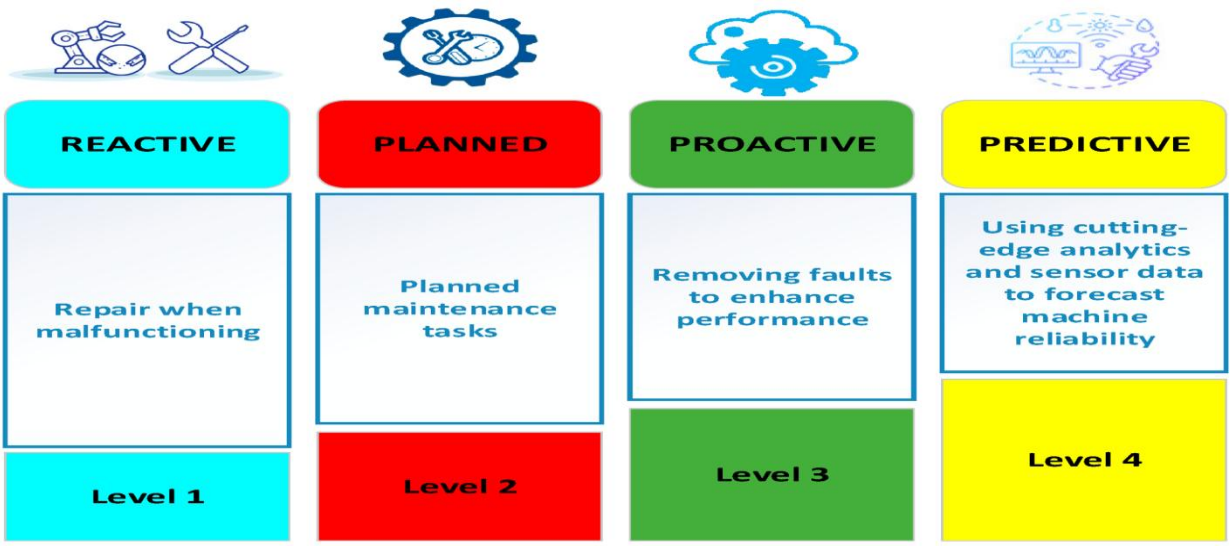

Figure : Diverse levels of system maintenance

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Some important parts of PdM in microgrids are:
Condition-based monitoring (CbM) checks the condition of equipment by looking at real-time health indicators like voltage, current, and temperature.
Using ML models, anomaly detection algorithms find things that are different from normal operating patterns.
Predicting failure modes: Uses learned behavior from past data to guess what kinds of failures will happen.
This method makes sure that maintenance is done at the right time, instead of too late or too early, which is especially important for microgrids that are isolated or critical to the mission.

3.3Different kinds of faults and their effects

Table 2: Microgrid operations are often affected by these types of faults:

Fault Type	Description	Impact on Microgrid
Power Failures	Caused by external events (e.g., lightning, debris, wildlife, grid instability)	Sudden outages, voltage sags, frequency fluctuations
Short-Circuit Faults	Low-impedance faults between phases or to ground	Equipment damage, overheating, protection tripping
Open-Circuit Faults	Occur due to broken conductors or failed switches	Load imbalance, voltage spikes, isolation of critical paths
Grounding Issues	Poor earthing or insulation failures	Safety hazards, erratic behavior, data corruption
Inverter/BESS Faults	Failures in power electronic converters or battery systems	Reduced energy conversion efficiency, backup failure

Recent studies (e.g., Rajaei et al. [24], Samanta et al. [25]) have demonstrated the efficacy of wavelet transforms, Markov models, and LSTM-based predictors for the prompt diagnosis of faults in smart grids. These methods let the system respond in real time by isolating broken parts and stopping failures from spreading.

3.4 Managing Faults and Being Independent of the Grid

An efficient fault management system also improves the self-healing and independence of microgrids.
For example:
In grid-connected mode, quick fault detection makes sure that safe disconnection or load shedding happens to keep faults from going back to the main grid.
To keep service going without interruption, fault isolation and reconfiguration are very important in islanded mode.
Microgrids can work on their own and safely, even when there are problems, by combining PdM with real-time fault analytics.

4. Machine Learning Methods for Predictive Analytics in Microgrids

Modern microgrids generate vast amounts of operational data through sensors, smart meters, and embedded monitoring systems. Machine Learning (ML) techniques offer powerful tools to extract meaningful patterns from this data to enable forecasting, fault detection, and predictive maintenance. Unlike traditional statistical models, ML algorithms can capture nonlinear, time-varying, and high-dimensional relationships—making them highly suitable for complex, real-time microgrid environments.
This section discusses widely used ML models in microgrid applications, with a focus on their architecture, benefits, limitations, and suitability for predictive analytics.

4.1 Artificial Neural Networks (ANN)

Artificial Neural Networks are inspired by the structure of biological neurons. In microgrid analytics, ANNs are especially effective at mapping complex nonlinear relationships between input variables (e.g., temperature, voltage, solar irradiance) and outputs (e.g., power output, fault classification).
A typical ANN consists of:

- Input layer: Receives real-time or historical data.
- Hidden layers: Apply weighted transformations using activation functions (e.g., ReLU, sigmoid).

- Output layer: Provides predictions such as future load demand or fault likelihood.

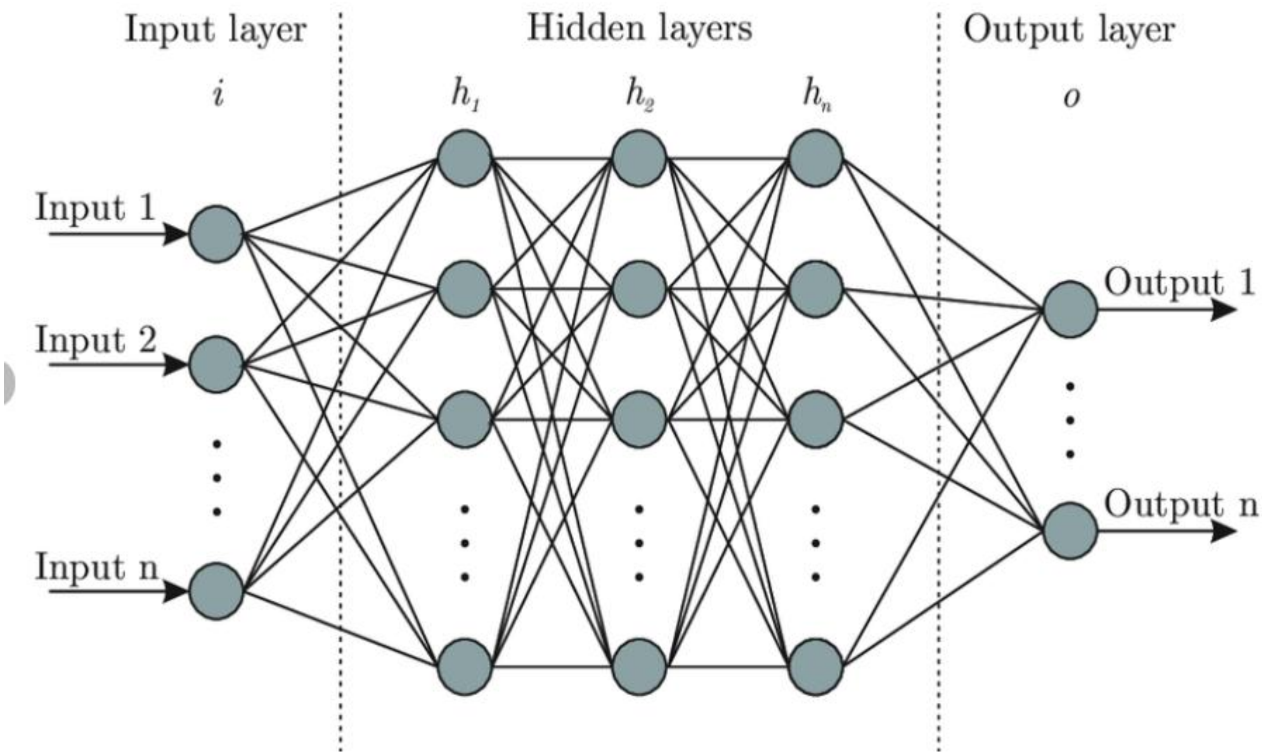

Figure: Artificial neural network architecture (ANN i-h 1-h 2-h n-o).
Image source: https://www.researchgate.net/profile/Facundo-Bre/publication/321259051/figure/ fig1/AS:614329250496529@1523478915726/Artificial-neural-network-architecture-ANN-i-h-1-h-2-h-n-o.png

Advantages:

- High accuracy in capturing nonlinear behaviors.
- Effective for short- and medium-term forecasting.
- Suitable for classification tasks (e.g., fault types).

Limitations:

- Requires large labeled datasets.
- Prone to overfitting if not properly tuned.
- Training is computationally intensive.

Use Case: Wang et al. [20] used ANN to forecast solar irradiance up to 72 hours, achieving high correlation even under dynamic weather conditions.

4.2 Support Vector Machines (SVM)

Support Vector Machines are supervised learning algorithms used for classification and regression. In microgrids, SVMs are widely applied for fault diagnosis and operational state classification.
SVM maps input data into a high-dimensional space using kernel functions (e.g., linear, radial basis function), then constructs a hyperplane that separates different classes or predicts continuous values.

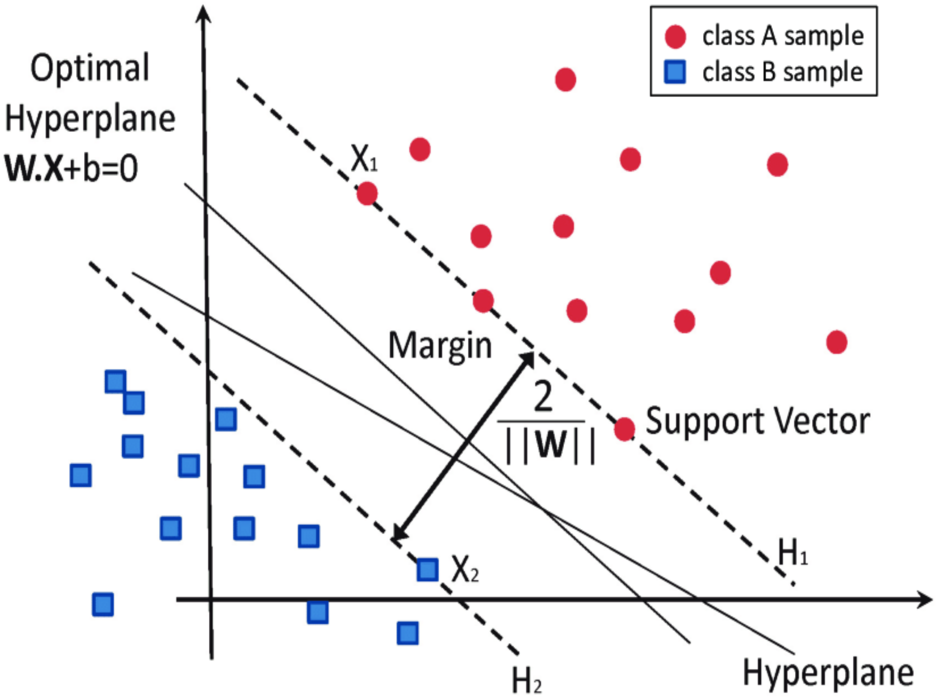

Figure: Classification of data by support vector machine (SVM).
Image source: https://www.researchgate.net/publication/304611323/figure/fig8/AS:668377215406089@1536364954428/Classification-of-data-by-support-vector-machine-SVM.png

Advantages:

- Works well with small datasets.
- High generalization capability.
- Effective for binary classification (e.g., normal vs faulty).

Limitations:

- Performance drops on noisy data.
- Requires careful kernel and parameter selection.
- Less interpretable than decision-tree-based models.

Use Case: Ramli et al. [26] showed SVM outperformed ANN in solar radiation forecasting in dry climates with lower training time and comparable accuracy.

4.3 Adaptive Neuro-Fuzzy Inference System (ANFIS)

ANFIS combines the learning power of ANNs with the interpretability of fuzzy logic systems. It is particularly useful for applications where the system dynamics are partially known or hard to model analytically.
An ANFIS architecture consists of five layers:

- Fuzzification Layer: Converts input values into fuzzy sets.
- Rule Layer: Applies fuzzy logic rules (if–then format).
- Normalization Layer: Balances the firing strengths of rules.
- Defuzzification Layer: Converts fuzzy outcomes into crisp outputs.
- Output Layer: Aggregates all outputs into a final prediction.

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https://www.theaspd.com/ijes.php

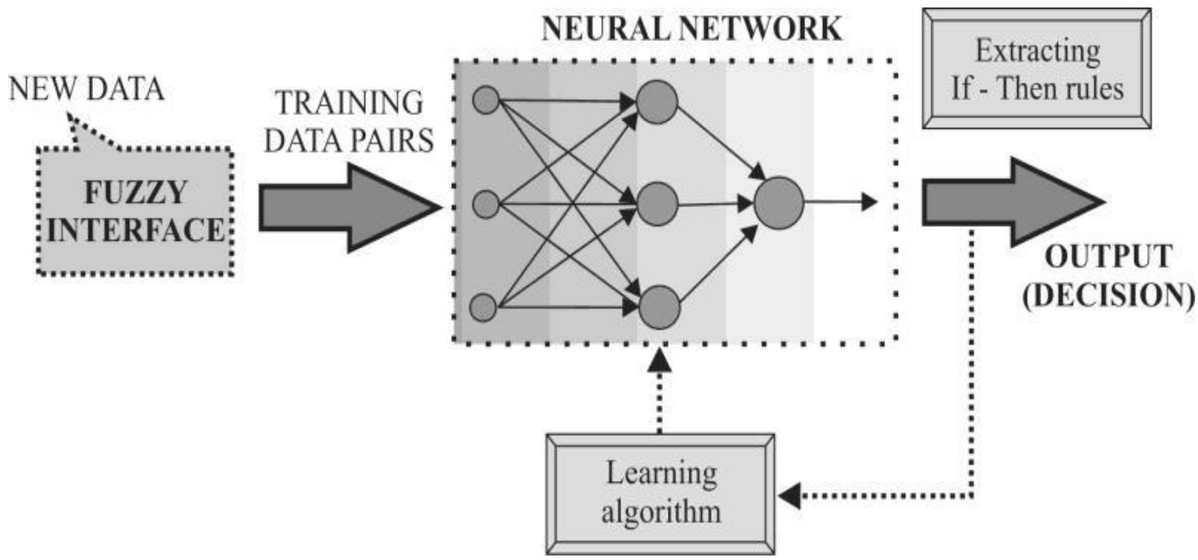

Figure : The basic structure of Adaptive Neuro-Fuzzy Inference Systems
Image source: https://www.researchgate.net/profile/Sinisa-Sremac/publication/328290563/figure/fig1/AS:696380993593344@1543041575008/The-basic-structure-of-Adaptive-Neuro-Fuzzy-Inference-Systems.ppm

Advantages:

- Better interpretability than black-box ML models.
- High accuracy in small- to medium-size systems.
- Handles uncertainty well.

Limitations:

- Not scalable to high-dimensional datasets.
- Rule explosion with more inputs or fuzzy sets.
- Training requires hybrid learning approaches (e.g., gradient descent + least squares).

Use Case: Mellit et al. [11] demonstrated ANFIS-based models outperform ANN in predicting solar radiation using only ambient temperature and sunshine duration.

4.4 Long Short-Term Memory (LSTM) Networks

LSTM is a special type of **Recurrent Neural Network (RNN)** designed to capture **long-term dependencies** in sequential data. Unlike vanilla RNNs (which tend to "forget" information as the sequence grows), LSTMs use *memory cells* with gates that decide what to remember, update, or discard.

- **Input Gate:** decides which new information to store.
- **Forget Gate:** discards irrelevant past information.
- **Output Gate:** decides what part of memory to pass forward.

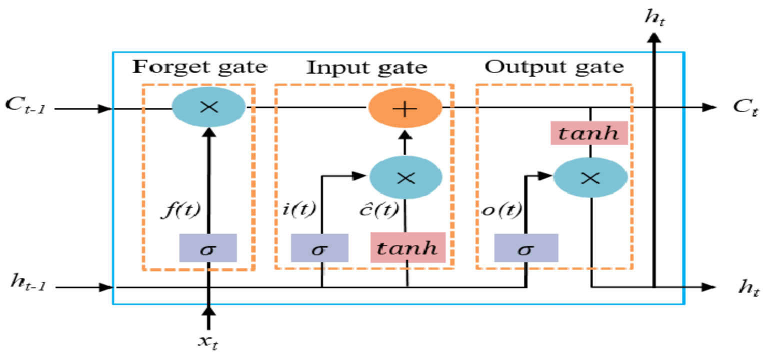

Figure: A Long short-term memory (LSTM) unit architecture.
Image source: https://www.researchgate.net/profile/Ahmed-Elkaseer/publication/356018554/figure/fig1/AS:1088159563677697@1636448865987/A-Long-short-term-memory-LSTM-unit-architecture.png

This architecture makes LSTMs particularly good for handling **time-series data with nonlinear patterns, noise, and seasonality**.

Advantages

- **Captures Temporal Dependencies:** Can learn long-term trends and seasonal variations, e.g., solar irradiance patterns across days/months.
- **Handles Nonlinear Data:** More accurate than ARIMA/linear models when data is stochastic.
- **Multi-step Forecasting:** Useful for both short-term (minutes) and medium-term (hours/days) predictions.
- **Versatile:** Works with multivariate inputs — weather, load, voltage, etc.

Limitations

- **Computational Cost:** Training is slow and requires GPUs for large datasets.
- **Data Hungry:** Needs large, high-quality labeled datasets to generalize well.
- **Risk of Overfitting:** If not regularized, can memorize instead of generalizing.
- **Complexity:** Hyperparameter tuning (layers, units, learning rate) can be tricky.
- **Interpretability:** A "black box" compared to ANFIS or decision trees.

Use Cases in Microgrids

1. **Solar Irradiance Forecasting**

Example: Husein & Chung (2019) used LSTM for **day-ahead solar irradiance prediction** in microgrids, outperforming traditional RNN and ARIMA models.

2. **Load Forecasting**

Example: Utilities use LSTM to predict **hourly/daily load demand** in hybrid microgrids, enabling smarter scheduling of storage and diesel backup.

3. **Fault Prediction**

Example: Recent works combine **LSTM + wavelet transforms** to detect anomalies in voltage/current signals before equipment failure.

4. **Battery Degradation Modeling**

Predicting remaining useful life (RUL) of BESS using multivariate LSTM trained on temperature, voltage, and cycle history.

4.4 Comparison of Methods

Table 3: Comparison of Methods

Method	Best Use	Strengths	Limitations
ANN	Load & energy forecasting	Nonlinear mapping, self-learning	Requires large datasets, risk of overfit
SVM	Fault classification	Small data, high accuracy	Sensitive to kernel choice, less scalable
ANFIS	Uncertain systems, low data env.	Interpretable, high precision in small sets	Limited scalability, rule explosion
LSTM	Multivariate forecasting	Captures temporal dependencies	High computation

4.5New Trends and Chances

Some recent improvements in ML for microgrids are:
Using LSTM and CNN for multivariate forecasting with Deep Learning (DL).
Ensemble models that use SVM, ANN, and decision trees together.
Transfer Learning lets you change pre-trained models to work with new microgrids.
Explainable AI (XAI) for following the rules and being open about how things work.

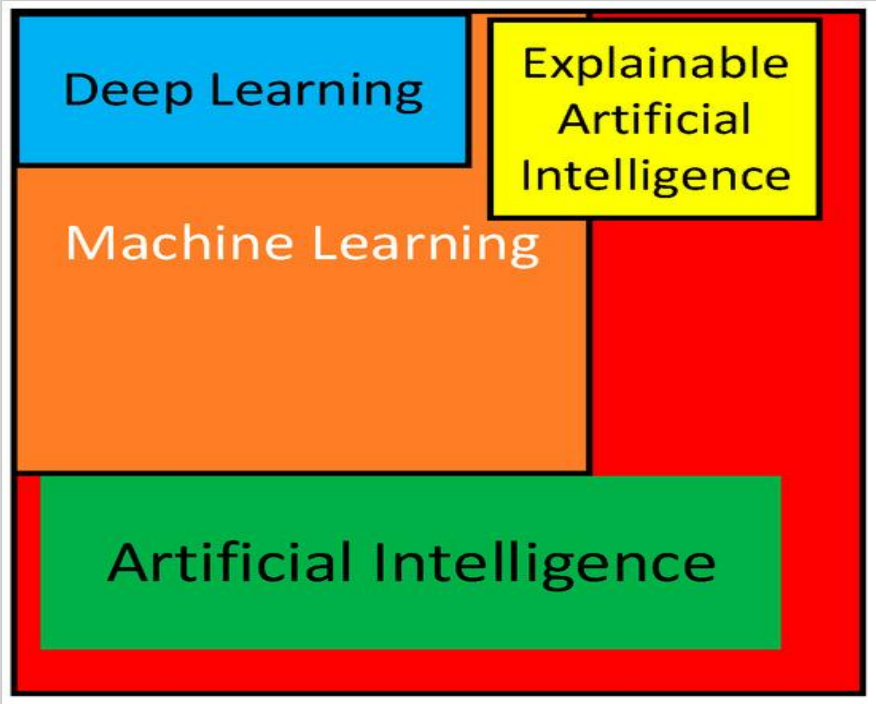

Figure 2. The connection between AI, ML, DL, and XAI.

Image src: https://www.mdpi.com/applsci/applsci-14-00898/article_deploy/html/images/applsci-14-00898-g002-550.jpg

There is also growing interest in deploying ML models at the edge, using embedded systems and IoT-based architectures for real-time inference and low-latency decision-making.

5. Forecasting Method in microgrid operations

Forecasting is an important part of running a smart microgrid. Making accurate short-term and long-term predictions about things like renewable generation, load demand, and ambient temperature makes it possible to plan maintenance, control in real time, and avoid problems. Because renewable sources like solar and wind are random, traditional forecasting methods often don't work well with nonlinear dependencies and variability. Modern forecasting depends a lot on data-driven models that combine past measurements, weather data, and system parameters. This part breaks down important forecasting methods into two groups: traditional statistical models and more advanced machine learning-based methods. It also talks about how these methods can be used in microgrid settings.

5.1 Existing ways to Predict Time Series

Traditional forecasting methods depend on finding patterns and trends in historical time series data, which is based on the idea that the data is stationary or follows a consistent cycle.

5.1.1 ARIMA (AutoRegressive Integrated Moving Average)

People often use ARIMA to make predictions about linear time series. It makes data stationary by using autoregression, moving averages, and differencing. It works well for predicting demand when things are stable.

Pros: Easy to understand, works well with linear data.

Cons: Doesn't work well with nonlinear, unstable, or multivariate data.

5.1.2 TMA and Exponential Smoothing (ES)

Exponential Smoothing (ES) and Triangular Moving Average (TMA) are two methods that give more weight to recent values by weighing past observations exponentially.

Used for: predicting load and making noisy renewable generation data easier to read.

Limitations: Not good at dealing with changes in weather and seasonality.

5.2 Forecasting Methods Based on Machine Learning

Machine learning (ML) methods have become more popular because microgrid variables are nonlinear and change over time. These models learn from multivariate data and adjust to new situations better than traditional methods.

5.2.1 Artificial Neural Networks (ANN)

People often use ANNs to predict things like solar irradiance, PV power output, and temperature. The network learns from past data and can figure out how different inputs (like humidity, wind speed, and solar angle) are related to each other in a complicated way.

For instance, Mellit and Pavan [09] used ANN to predict solar irradiance for 24 hours using weather data from the area.

Limitations: Needs a lot of training data and fine-tuning of parameters.

5.2.2 Support Vector Regression (SVR)

SVR is a type of SVM that is used to predict continuous values like solar radiation or ambient temperature. It works well with small datasets and is not affected by outliers.

Use Case: Ramli et al. [26] demonstrated that SVR attains comparable accuracy to ANN in arid regions with reduced data and abbreviated training durations.

5.2.3 Deep Learning Models (LSTM, CNN)

Recurrent Neural Networks (RNNs), particularly Long Short-Term Memory (LSTM) networks, are adept at learning temporal dependencies and managing sequential data, such as solar irradiance or load demand.

Pros:

- Can show how things depend on each other over time.
- Good for predicting several steps ahead.

Cons: Needs a lot of computing power and big datasets.

5.2.4 Mixed Models (e.g., ANFIS + ARIMA, ANN + GA)

Researchers have come up with hybrid techniques that combine statistical and intelligent models to get around the problems with single-model forecasting.

- ANFIS-ARIMA: This combines ARIMA's ability to find trends with ANFIS's ability to learn in a nonlinear way.
- ANN-GA: Uses genetic algorithms to make ANN weights better so that they work better.

5.3 Temperature and Solar Radiation in the Environment Making predictions

The temperature of the air and the amount of sunlight are two important factors in predicting how well a microgrid's PV and battery will work.

They base their predictions on:

- Weather data: temperature of the air, speed of the wind, amount of cloud cover, and angles of the sun.
- Temporal Resolution: For MPPT (Maximum Power Point Tracking) and grid interaction to work well, predictions need to be made every hour or less.

Models like ANFIS have been very helpful in places where there isn't a lot of data. Mellit et al. [49] showed that just using temperature and sunshine duration can make accurate predictions in places where there aren't many sensors or people.

5.4 Performance Comparison of Forecasting Techniques

Table 4: Performance Comparison of Forecasting Techniques

Method	Forecast Type	Strengths	Weaknesses
ARIMA	Univariate	Interpretable, good for stable trends	Linear only, weak with noisy/volatile data
ANN	Multivariate	Handles nonlinearities, adaptable	Needs large training sets, prone to overfit
SVR	Univariate	Robust with small data, good generalization	Sensitive to parameter tuning
LSTM	Multivariate	Good for sequence data, temporal accuracy	Training complexity, computational cost
ANFIS	Hybrid	Interpretable, works with limited data	Rule explosion with multiple inputs

6. DISCUSSION

The use of predictive analytics, machine learning, and real-time monitoring in microgrids is a big change in how we manage distributed energy systems. As mentioned in earlier sections, these smart methods are better at finding faults, predicting system problems, and planning maintenance than older methods. But the successful use of these technologies in real-life microgrids depends on a number of technical and operational factors.

6.1 The Coming Together of Forecasting, Fault Detection, and Maintenance

One of the most important things to learn from recent research is that we need unified frameworks that bring together forecasting, anomaly detection, and predictive maintenance. Current research frequently examines these domains in isolation; however, they are, in reality, interdependent:

- Correctly predicting solar irradiance or load conditions makes it possible to find unusual changes early on.
- These deviations can set off fault detection systems, which find possible problems before they get worse.
- Fault trends, in turn, help make predictive maintenance schedules, which let operators take action before problems happen.

This convergence makes it easier to make decisions based on data, which leads to less downtime, better use of assets, and lower costs of doing business.

6.2 Problems with Implementation in the Real World

Even though there have been some promising steps forward, there are still a lot of problems that make it hard to use ML-based predictive systems on a large scale in microgrids:

- The quality and availability of data

Many microgrids, especially those in rural or developing areas, don't have access to a lot of different, high-frequency, and labeled data. If sensor data is missing or noisy, it can make models less accurate and reliable.

- Understanding the Model

Deep neural networks (DNNs) and other black-box models are very accurate, but they aren't very clear, which is important in systems that are important for safety. Explainable AI (XAI) methods are becoming more popular to fix this problem.

- Generalization and Scalability

A model trained on one microgrid topology may not apply to another because of differences in the mix of distributed energy resources (DER), the climate, or how the microgrid is used. Transfer learning and meta-learning may assist in bridging this gap.

- Safety and Security Online

More digitalization makes things less secure. False positives caused by malicious attacks or sensor spoofing must not be a problem for fault detection systems.

6.3 What Microgrid Operators Need to Know

For utilities, operators, and energy planners who are interested in microgrids, the practical value of predictive analytics is in:

- Early warning systems that find problems that are starting to happen in PV arrays, inverters, or battery storage.
- Dynamic scheduling of maintenance based on the current health of the equipment instead of set times.
- Smart load forecasting helps optimize resources by cutting down on curtailment and overprovisioning.
- Better protection against blackouts by quickly finding and fixing problems.

De Benedetti et al. [22], for instance, used ANN-based models to find solar problems weeks before they caused major damage, which saved money and time.

6.4 Possibilities for Future Research

To maximize the potential of predictive analytics in microgrids, subsequent efforts must concentrate on:

1. Edge and Federated Learning

Deploying lightweight ML models on local microgrid controllers will make you less reliant on cloud infrastructure.

Federated learning lets you train on more than one microgrid without sharing private information.

2. Systems that adapt in real time

Most of the time, current models are trained offline. To be operationally resilient, you need adaptive learning techniques that keep getting better in real time as new data comes in.

3. Datasets and benchmarks that are the same for everyone

There aren't any common datasets in the field for comparing performance. Open-source microgrid data platforms will help researchers do research that can be repeated and compare models.

4. Hybrid Intelligence Systems
Combining domain knowledge (like physics-based models) with data-driven methods (like machine learning) could lead to solutions that are more robust and easier to understand.
5. **Explainable AI (XAI)**:
Make models interpretable for operators is the goal of explainable artificial intelligence (XAI).

7. CONCLUSION

For microgrids to have a future, they need to be able to manage resources on their own, predict outages, and deal with operational problems. They can last longer, be more reliable, and work better with machine learning, predictive analytics, and problem detection. We look at old ways of predicting how much energy will be used and made, finding mistakes, and making maintenance plans better. Microgrids use methods like Adaptive Neuro-Fuzzy Inference Systems (ANFIS), Support Vector Machines (SVMs), and Artificial Neural Networks (ANNs) to model complex, nonlinear dynamics. Microgrids can move from a reactive to a proactive approach by using real-time monitoring, maintenance based on conditions, and AI-driven analytics. But there are problems with widespread adoption, such as data availability, model interpretability, scalability, and cybersecurity. Data scientists, energy engineers, and control system designers must work together to solve these problems. To make microgrids more reliable, a conceptual framework that combines data sources, machine learning algorithms, fault detection, and predictive maintenance is created. Predictive analytics for microgrid fault detection and maintenance is a quickly growing but disorganized area. The goal of the research agenda is to make standardized datasets, hybrid machine learning models that can be understood, and test frameworks that can be used in real-world microgrid testbeds. Advancements in this domain will augment microgrid intelligence, safety, and resilience by hastening the transition from reactive to proactive maintenance.

Future studies

Future studies ought to investigate:
- Using edge computing and federated learning to make real-time adaptive models.
- Datasets for benchmarking and standard metrics for evaluating model performance.
- Hybrid models that use both physical (physics-based) and data-driven methods to make them more robust and easier to understand.

Predictive analytics that take resilience into account, especially when there are threats from cyber-physical systems or extreme weather.

NOMENCLATURE

Acronyms
AI – Artificial Intelligence
ANN – Artificial Neural Network
ANFIS – Adaptive Neuro-Fuzzy Inference System
ARIMA – AutoRegressive Integrated Moving Average
BESS – Battery Energy Storage System
CBM – Condition-Based Maintenance
DER – Distributed Energy Resource
EMS – Energy Management System
LSTM – Long Short-Term Memory
ML – Machine Learning
MLP – Multilayer Perceptron
MG – Microgrid
PdM – Predictive Maintenance
PV – Photovoltaic
RUL – Remaining Useful Life
SVM – Support Vector Machine
WT – Wind Turbine

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International Journal of Environmental Sciences
ISSN: 2229-7359
Vol. 11 No. 22s, 2025
https://www.theaspd.com/ijes.php

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