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Research Paper

Enhancing Microgrid Resilience with LSTM and Fuzzy Logic for Predictive Maintenance

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Abstract— *Microgrids have become integral to modern energy systems, providing decentralized and resilient energy solutions. However, ensuring the reliability of microgrid assets poses significant challenges, particularly given aging infrastructure and unpredictable environmental conditions. While existing methods—such as predictive maintenance, real-time monitoring, and fault detection utilizing Support Vector Machines, Random Forests, and Principal Component Analysis—enhance reliability, they often fall short due to insufficient multidimensional data analysis and limited support for realistic decision-making. This underscores the need for advanced approaches in microgrid management. In this paper, we propose an innovative machine learning-based methodology that integrates Long Short-Term Memory networks with fuzzy logic for predictive maintenance of microgrid assets. The proposed approach effectively addresses the inherent fluctuations and dynamic behavior of microgrids, enhancing system resilience and reducing downtime. By leveraging LSTM's ability to capture temporal patterns alongside fuzzy logic's capacity for handling uncertainties, the method proactively identifies and mitigates potential equipment failures. Traditional maintenance strategies predominantly rely on reactive mechanisms, resulting in higher costs and increased system vulnerabilities. Simulation results indicate that the proposed algorithm achieves a 10% to 40% improvement in fault detection across varying failure levels, demonstrating significant advantages over conventional techniques.*

Keywords—Microgrids, predictive maintenance, machine learning, LSTM networks, fuzzy logic.

1. Introduction

In the era of modern energy systems, microgrids have emerged as pivotal solutions, exemplifying resilience and sustainability within the dynamic landscape of power generation and distribution. Unlike traditional centralized grids, which are characterized by their susceptibility to single points of failure and widespread outages, microgrids provide a decentralized alternative, empowering communities and industries to independently manage their energy needs [1]. These systems integrate a diverse array of distributed energy resources (DERs), including solar panels, wind turbines, combined heat and power systems, and energy storage units, embodying the principles of flexibility, reliability, and autonomy. However, despite their numerous advantages, microgrids face challenges stemming from aging infrastructure, environmental variability, and the pressures of rising energy demand [2]. Ensuring the efficient operation and maintenance of microgrid assets is critical to guaranteeing an uninterrupted power supply, particularly in applications such as military bases, hospitals, and rural communities where reliability is non-negotiable. Traditional maintenance practices, which depend on reactive approaches and predetermined schedules, often fail to adequately address the dynamic and evolving nature of microgrid operations. Consequently, there is an urgent need to implement innovative strategies that proactively identify potential faults, optimize maintenance activities, and enhance system resilience [3]. The power industry is notoriously capital-intensive, with substantial costs and prolonged manufacturing and installation timelines associated with key assets, including electrical power generators, transformers, transmission lines (TLs), and distribution networks (DNs). Furthermore, these power system components are expected to operate continuously for extended periods, often spanning several decades, emphasizing the necessity for sophisticated maintenance and management techniques [4].

Even brief power outages have become intolerable, with potential severe repercussions on both individual lives and societal affairs. Consequently, there is an urgent and considerable demand for approaches aimed at monitoring, maintaining, and prolonging the operational lifespan of power system equipment. Power infrastructure asset management encompasses a blend of disciplines such as engineering, management, and economics, with the primary objective of maximizing the value of service relative to the associated costs. This management process encompasses the entire lifecycle of assets, including design, construction, commissioning, operation, maintenance, repair, modification, replacement, and decommissioning/disposal [3]. During the operational and maintenance phases, condition monitoring (CM) systems play a crucial role in identifying potential defects before they cause service interruptions. However, managing physical assets in the power system presents unique challenges, as many components are outdoor facilities (e.g., transformers, TLs, DNs) located in unguarded environments, thus exposing them to harsh weather conditions and external threats. Additionally, some failure

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mechanisms of these assets are not yet fully understood, leading to a lack of reliable predictive models [5].

Despite significant advancements in utilizing distributed energy resources, IoT, and machine learning to enhance grid resilience, insufficient focus on temporal data analysis and flexible decision-making remains a research gap. Current studies primarily emphasize real-time data processing, with limited exploration of leveraging long-term temporal dependencies for predictive decision-making. Additionally, the lack of flexible decision-making mechanisms that can autonomously adapt to changing conditions and grid anomalies highlights the need for further research. Traditional predictive maintenance methods often struggle with handling the complexities and uncertainties of real-world data, leading to limitations in decision-making flexibility [5]. These methods frequently rely on static models and assumptions, which may not account for the dynamic nature of sensor data and operational conditions. As a result, they can miss nuanced patterns and fail to adapt to evolving scenarios, affecting the accuracy and reliability of maintenance predictions. Thus, this paper presents a novel approach to predictive maintenance in microgrids by integrating fuzzy logic with deep learning. Key contributions include:

- *Advanced data analysis with LSTM:* The paper introduces a novel approach to predictive maintenance by first analyzing sensor data using a LSTM network. This network excels at capturing temporal dependencies and patterns in sequential data, providing a detailed classification of operational states.
- *Enhanced decision-making through fuzzy logic:* Following the LSTM analysis, the output is processed by a fuzzy logic system. This integration allows for handling uncertainties and imprecisions in the data, enabling more nuanced and flexible decision-making that reflects the complex nature of real-world scenarios.

1.1. Literature review

This collection of papers provides a comprehensive review of recent advancements and methodologies in applying machine learning (ML) and artificial intelligence (AI) to enhance various aspects of modern energy systems. The scope is divided into several key categories, each highlighting different areas of innovation and improvement within energy networks. The first category focuses on enhancing reliability and control of energy systems using ML techniques. Papers in this section review research that bridges reliability management with machine learning approaches. Notably, one paper examines the integration of ML in power system protection and asset management, addressing growing complexities related to renewable energy integration and climate change [1]. Another paper discusses the utilization of AI in modern power grids to improve reliability, efficiency, and sustainability, emphasizing the use of hybrid machine learning models for fault prediction and detection, which can lead to quicker fault resolution and support cleaner energy systems [2]. The next category covers predictive maintenance and fault detection, exploring advanced approaches aimed at improving system reliability. Key papers in this section discuss advancements in predictive maintenance for power converters, focusing on various approaches such as model-based, data-driven, and physics-informed machine learning (PIML) methods [3]. Additionally, the integration of distributed energy resources (DERs) into microgrid systems is analyzed, particularly concerning their resilience against cyber threats and the role of ML in enhancing operational reliability [4]. Research also presents innovative methods for detecting intrusions and anomalies in inverter-centric cyber-physical microgrids, employing advanced machine learning techniques to bolster security [5]. In the realm of resilience and security, several papers introduce methodologies to enhance maintenance coordination in renewable-powered grids [5] and assess the resilience of energy systems in the face of extreme weather events [6]. Furthermore, innovative approaches in grid technology are detailed in papers discussing the use of linear antenna arrays for multiple-input multiple-output (MIMO) applications and methods for detecting cyberattacks on microgrids using machine learning techniques [7].

The role of artificial intelligence in renewable energy is also a major focus, with papers discussing AI-based methods for estimating maintenance needs for distribution transformers and the broader application of AI in predictive maintenance and energy optimization for renewable sources such as solar and wind [8]. Additionally, research on quantifying the resilience of multi-energy systems (MES) in response to disruptions caused by extreme weather is presented, emphasizing the use of ML techniques to improve planning and reliability [9]. Papers on energy management systems (EMS) for microgrids showcase frameworks that integrate decentralized energy sources, IoT, and cloud computing to optimize energy usage and enhance grid resilience [10]. One study proposes an EMS that utilizes an incentive-based demand response program and battery storage to optimize operational costs and emissions, validated through simulations [11]. Another paper introduces a resilient operation model for microgrids that incorporates electric vehicles (EVs) as energy storage systems to maintain service continuity during outages, employing stochastic programming to address uncertainties in market pricing and resource scheduling [12]. Moreover, day-ahead programming strategies for microgrids using a two-stage stochastic programming approach are examined, focusing on managing uncertainties in electricity market prices and load demand while minimizing operational costs and environmental emissions [13]. This collection of papers underscores the transformative potential of ML and AI in advancing energy systems, paving the way for more reliable, efficient, and secure power networks in the future [14]. The final papers also introduce advanced fault classification techniques through intelligent classifiers and further explore the integration of AI into modern power grids to enhance fault detection and grid sustainability [15] and resilience [16]. In the category of predictive maintenance and fault detection, several papers focus on advancements in predictive maintenance for power converters and other critical components in energy systems. These include approaches such as model-based methods, data-driven strategies, and physics-informed machine learning (PIML) techniques to enhance operational reliability [17]. The research emphasizes the role of machine learning in predictive maintenance, particularly in solar farms and smart grids, demonstrating the potential for reduced downtime and improved fault prediction [18].

Furthermore, the integration of distributed energy resources (DERs) into microgrid systems is explored in depth, highlighting the need for resilient architectures capable of operating autonomously during outages. This integration includes the use of Internet of Things (IoT) technology for real-time monitoring and control, which enhances load management and maintenance practices [19]. A specific study presents innovative methods for detecting intrusions and anomalies in inverter-centric cyber-physical microgrids, employing advanced machine learning techniques such as Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks to achieve high accuracy in identifying security breaches [20]. Papers addressing the resilience of energy systems under extreme weather conditions are also prominent, with one study employing ensemble methods to forecast outages in smart grids. The results show remarkable accuracy rates, thereby supporting effective energy management and enhancing overall production efficiency [21]. Another paper reviews methods for quantifying the resilience of multi-energy systems (MES) in the context of interconnected contingencies, focusing on machine learning-based techniques to improve planning and reliability [22]. The research on energy management systems (EMS) reveals frameworks that optimize the operation of microgrids, integrating distributed generations and implementing demand response programs. One approach utilizes a multi-objective group search optimization (MOGSO) algorithm to manage cost and emissions effectively [23]. Another study introduces a resilient operation model that incorporates electric vehicles (EVs) as energy storage systems, optimizing resource scheduling through stochastic programming to address uncertainties in market conditions and renewable energy generation [24]. In the context of day-ahead programming, a paper explores a two-stage stochastic programming approach for microgrids, focusing on managing uncertainties in electricity market prices and load demand while aiming to minimize operational costs and environmental emissions. The effectiveness of the proposed methods is demonstrated through simulations based on real data [25]. Overall, these papers collectively highlight the transformative potential of machine learning and artificial intelligence in enhancing the reliability, efficiency, and security of modern energy systems, paving the way for sustainable and resilient power networks of the future [26]. The integration of AI and ML technologies into energy systems is portrayed as a vital step towards improving decision-making processes and addressing challenges associated with renewable energy integration, cyber threats, and environmental sustainability [27]. Additionally, studies present intelligent classification schemes for fault detection and examine hybrid models designed for effective fault prediction, thereby contributing to the ongoing evolution of energy management strategies [28, 29].

This collection highlights ongoing challenges in energy systems where neural networks can bring significant improvements, particularly in enhancing fault detection, predictive maintenance, and resilience against dynamic and unexpected disruptions. Neural networks, especially deep architectures like CNNs and LSTMs, offer advanced pattern recognition that supports reliability and cybersecurity in modern energy networks.

1.2. Organization paper

The rest of the paper is as follows. Section 2 reviews advancements in using ML and AI to enhance energy systems, with a focus on predictive maintenance for microgrids. Section 3 details the use of sensors, IoT devices, and ML techniques for monitoring and predicting the condition of microgrid components. It introduces a combined approach of fuzzy logic and LSTM networks to handle data uncertainties and improve prediction accuracy. Finally, Section 4 concludes the paper.

2. Methodology

Predictive maintenance in microgrids leverages sensors, IoT devices, and advanced analytics, including machine learning (ML), to monitor the health of critical components such as batteries, inverters, and transformers. This approach involves collecting real-time and historical data to build predictive models capable of forecasting potential failures. By analyzing this data, maintenance can be scheduled proactively, reducing unexpected downtimes and enhancing system performance. Modeling asset lifetime within a microgrid is a complex task that combines statistical analysis with ML techniques to estimate the remaining useful life (RUL) of components. For instance, batteries are monitored for charge cycles and temperature variations to predict their degradation patterns. Similarly, inverters and transformers are assessed based on factors like voltage stability and insulation quality [5]. Advanced analytics and IoT integration play crucial roles in this process. IoT devices provide continuous monitoring and data collection, which ML algorithms use to refine predictive models and detect early signs of potential issues. This proactive approach not only optimizes asset performance but also minimizes maintenance costs and extends the lifespan of critical components. By implementing predictive maintenance strategies, microgrids can achieve greater operational efficiency and reliability, ensuring that components are maintained before failures occur and performance remains optimal [7].

This process begins with the collection of historical and real-time data from sensors that monitor parameters like temperature, voltage, current, and mechanical vibrations. Fig. 1 illustrates a microgrid integrating renewable energy sources—wind turbines, solar panels, and energy storage systems—with the main grid and various loads, including residential units. The energy from renewables is converted via AC/DC and DC/DC converters for efficient distribution. Sensors monitor the performance of all components, transmitting data through gateways to logical controllers, which manage operations and predict maintenance needs. This setup ensures seamless energy flow, stability, and reliability, with real-time monitoring and predictive maintenance optimizing performance and extending the lifespan of the assets.

Time series data exhibit significant variations, and the temporal relationships between them must be carefully considered to improve results. This involves not only capturing the individual data points but also understanding the underlying patterns and trends that evolve over time. By analyzing these temporal dynamics, we can gain deeper insights into how different factors influence the system's performance across various timeframes. Properly accounting for these relationships allows for more accurate forecasting, anomaly detection, and overall performance assessment, ultimately leading to more informed decision-making and optimized outcomes in complex systems.

2.1. Integrating fuzzy logic with deep learning

Integrating LSTM networks with fuzzy logic for predictive maintenance in microgrids provides a comprehensive approach to capturing the dynamic interactions within time series data and the complexities of real-world scenarios. In this method, time series data, such as current, voltage, and vibration readings, are first analyzed using LSTM networks to model temporal patterns and relationships. The results are then processed through a fuzzy logic network, which captures the uncertainties and interactions within the data. By converting sensor readings into fuzzy values and applying fuzzy rules, this approach determines risk levels that reflect real-time operational dynamics. These defuzzified risk scores are used for advanced predictive maintenance, improving prediction accuracy, enabling proactive scheduling, and minimizing unexpected failures, thereby extending the lifespan of microgrid components.

The proposed model, as illustrated in Fig. 2, employs a sophisticated two-step process designed to analyze sensor data and derive actionable decisions effectively.

A) Data collection and LSTM analysis

In the initial step, the model gathers real-time data from a network of sensors strategically deployed throughout the system. This sensor data, characterized by its sequential nature, is then fed into a Long Short-Term Memory (LSTM) network. The LSTM network is specifically chosen for its proficiency in handling sequential data due to its unique architecture, which includes memory cells that capture and retain temporal dependencies.

The LSTM's strength lies in its capability to remember and utilize long-term dependencies within the data. This makes it exceptionally well-suited for interpreting sensor readings that change over time, allowing it to discern intricate patterns and trends. By effectively mapping sensor data into distinct output classes—each representing different states or conditions of the system—the LSTM network provides a foundation for understanding the system's behavior over time. The first phase of the model captures sequential data from the system's sensors, represented as $X = \{x_1, x_2, \ldots, x_t\}$, where each x_i corresponds to a sensor reading at time i. This time-series data is processed by a Long Short-Term Memory (LSTM) network, which effectively captures long-term dependencies due to its selective memory capabilities.

The LSTM network processes sequential input data to capture temporal dependencies. The operations are defined as follows [30]:

1. Forget gate: This gate removes irrelevant information from the previous time step:

$$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f) \tag{1}$$

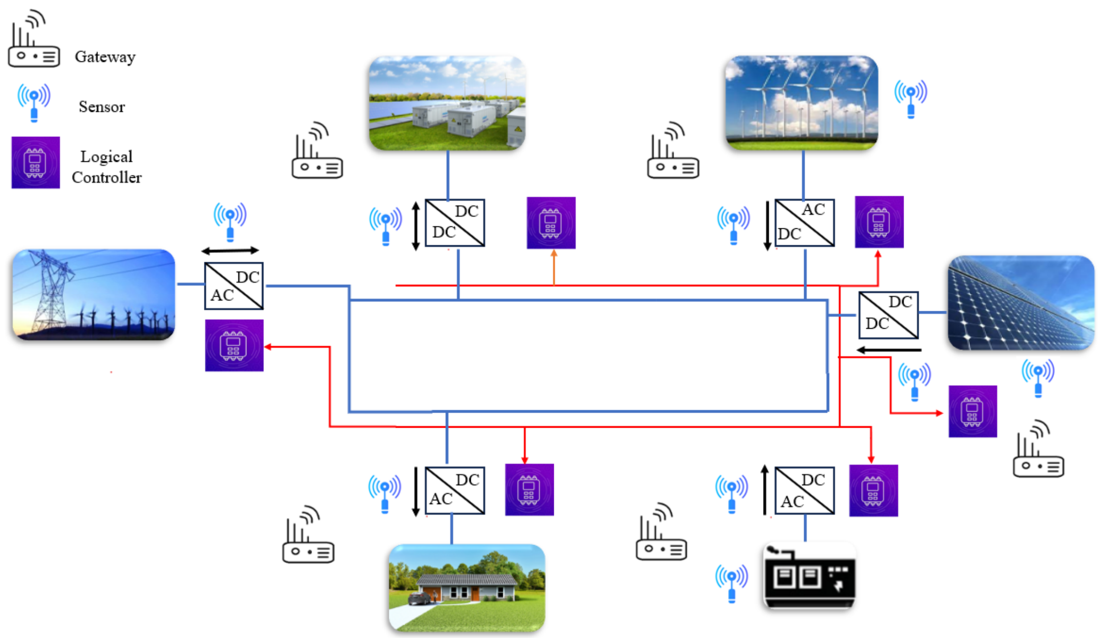


Fig. 1. Energy management and monitoring system.

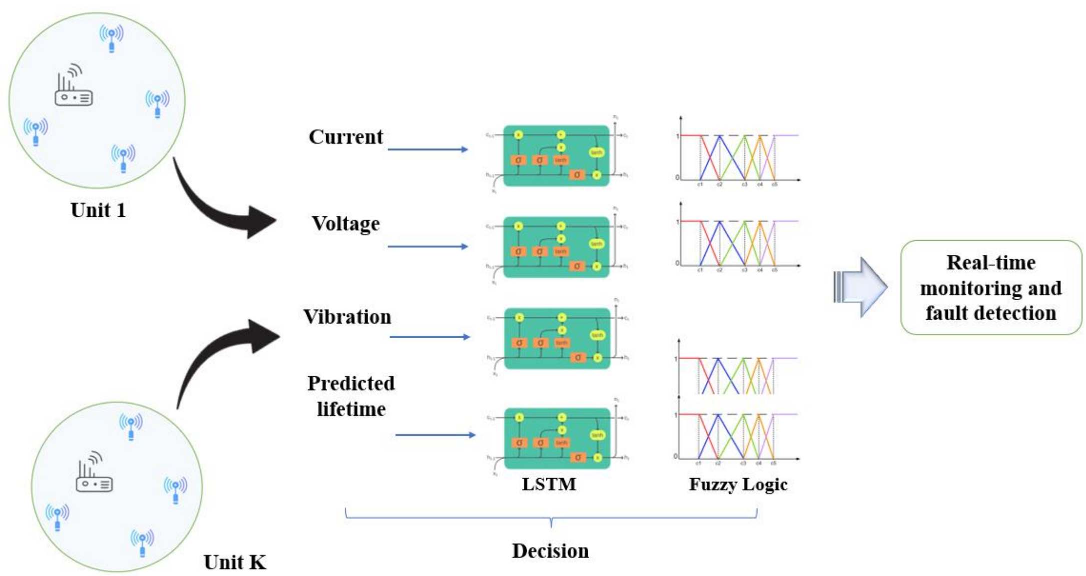


Fig. 2. Integrating fuzzy logic with deep learning for predictive maintenance in microgrids.

2. Input gate: This gate updates the cell state with relevant new information:

$$\begin{aligned} i_t &= \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \\ \tilde{C}_t &= \tanh(W_C \cdot [h_{t-1}, x_t] + b_C) \end{aligned} \tag{2}$$

3. Cell state update: The cell state is updated by combining the forget and input gates:

$$C_t = f_t \cdot C_{t-1} + i_t \cdot \tilde{C}_t \tag{3}$$

4. Output gate: This gate produces the final hidden state:

$$\begin{aligned} o_t &= \sigma(W_o \cdot [h_{t-1}, x_t] + b_o) \\ h_t &= o_t \cdot \tanh(C_t) \end{aligned} \tag{4}$$

The LSTM outputs a sequence of hidden states $H = \{h_1, h_2, \ldots, h_T\}$, which represent the processed data over time. These outputs are then passed into the fuzzy logic system.

B) Fuzzy logic system

The fuzzy logic system evaluates the outputs h_t from the LSTM network using the following steps:

1. Fuzzification

The LSTM outputs h_t are mapped to fuzzy sets $A_1, A_2, \ldots, A_n$ using membership functions $\mu_{A_i}(h_t)$. For example:

$$\mu_{A_i}(h_t) = \exp\left(-\frac{(h_t - c_i)^2}{2\sigma_i^2}\right) \quad (5)$$

where c_i is the center and σ_i is the width of the Gaussian membership function. Each h_t can belong to multiple fuzzy sets with varying degrees of membership.

2. Rule evaluation

The fuzzy rules are structured as follows:

If h_t is A_i then D is B_j

The degree of rule activation is calculated as:

Rule activation $= \min(\mu_{A_i}(h_t), \mu_{A_j}(h_t), \ldots)$

For a given rule R_k, the output fuzzy set B_k is weighted by the rule's activation level.

3. Aggregation

The activated fuzzy sets $B_1, B_2, \ldots, B_m$ are combined into a single fuzzy output F. The aggregation process is typically performed using a max or sum operator:

$F = \max_k(\text{Rule activation} \cdot \mu_{B_k}(D))$

4. Defuzzification

The aggregated fuzzy output F is converted back into a crisp value D using a defuzzification method, such as the centroid method:

$$D = \frac{\int D F(D) dD}{\int F(D) dD} \quad (6)$$

This produces the final decision D, which is interpretable and actionable.

C) Optimization of fuzzy logic parameters

The parameters of the fuzzy logic system, including centers c_i, widths σ_i, and rule weights, are optimized during training. A loss function, such as Mean Squared Error (MSE), is minimized:

$$L = \frac{1}{N} \sum_{i=1}^{N} (D_{\text{pred},i} - D_{\text{true},i})^2 \quad (7)$$

Gradient-based optimization methods like Adam or RMSprop are used to adjust these parameters.

2.2. Combined LSTM-Fuzzy logic decision framework

The final decision D integrates the temporal analysis capabilities of LSTM with the uncertainty-handling strength of fuzzy logic:

$$\text{D = f(LSTM output, Fuzzy logic output)} \quad (8)$$

For example:

$$D = \alpha h_T + (1 - \alpha)(\text{Fuzzy decision})$$

where α is a weight parameter that balances contributions from both LSTM and fuzzy logic. This combined framework effectively captures long-term dependencies through LSTM while enabling nuanced decision-making under uncertainty via fuzzy logic. The adaptability of the fuzzy system enhances accuracy and robustness, making this model highly suitable for real-world sensor data analysis and predictive maintenance tasks.

3. SIMULATION RESULTS

To simulate the conditions of the microgrid, the model was first established within the MATLAB environment, where various components such as inverters, batteries, and transformers were simulated to reflect real-world operating conditions. This setup involved generating and processing sensor data, including readings for temperature, voltage, current, and vibrations, to create a comprehensive dataset.

This model describes a single-phase AC microgrid that supplies power to a residential area by integrating an external electricity network, a solar power generation system, and a storage battery. The solar system generates DC power, which is converted to AC for use within the microgrid. The storage battery, managed by a battery controller, stores excess energy from solar production and provides power during shortages. The microgrid connects to the external grid via a transformer that adjusts the voltage for residential use [25].

The control strategy focuses on energy self-sufficiency, aiming to minimize reliance on the external grid. It ensures that the power from the solar system and storage battery meets the residential demand, which is capped at 2.5 kW per home. The battery controller helps balance supply and demand, stabilizing the microgrid for a continuous power supply. By optimizing local solar power usage and smart energy management, the microgrid enhances sustainability, reduces dependence on the external grid, and improves the reliability of energy supply to the residential area. The proposed model utilizes a two-step process to evaluate equipment health. Initially, the collected sensor data is fed into a LSTM network. The LSTM network, which excels in analyzing temporal sequences, processes this data to classify it into different categories representing various operational states of the equipment. This classification captures the dynamic behavior and trends in the sensor data over time. These classified data are then fed into the fuzzy network, which is designed to handle uncertainty and imprecision inherent in real-world scenarios. The fuzzy network processes the input data by applying a set of fuzzy logic rules, which allows it to interpret the data in a way that reflects the complex and often non-linear relationships between different operational parameters. This approach enables the model to generate a response that is not only dynamic, adapting to changes in the equipment's state, but also realistic, accounting for the nuances and variations that traditional methods might overlook. As a result, the fuzzy network enhances the overall accuracy and reliability of the system's health assessment, providing more actionable insights for predictive maintenance and decision-making.

As an example, some data related to one of the network elements (transformer), such as voltage (Fig. 5), current (Fig. 6), and vibration (Fig. 7), are presented for both healthy and worn-out conditions. Typically, transformers have a service life ranging from 20 to 40 years. As they near the end of this period, signs of aging may become apparent, including a decline in performance or efficiency and an increase in noise levels, such as buzzing or humming.

There is typically a significant correlation between different types of equipment data, which can play a crucial role in comprehensive analyses. Understanding these interrelationships allows for more accurate and informed decision-making, particularly in systems where equipment health and performance are critical. For instance, as illustrated in Fig. 6, there is a clear relationship between the quality of voltage and current and the health status of the transformer. This connection suggests that fluctuations or abnormalities in voltage and current may be indicative of underlying issues with the transformer, such as wear and tear or impending failure.

The LSTM network is structured to analyze sequential data for transformer health monitoring. It starts with an input layer for time series data, followed by two LSTM layers (64 units each) with dropout and batch normalization to capture temporal patterns

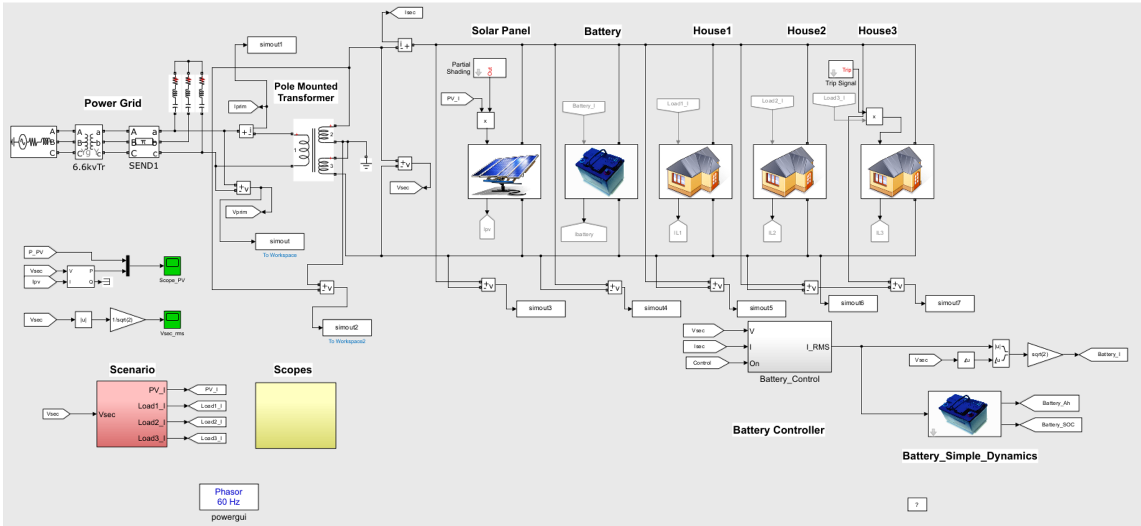


Fig. 3. Simulink-based microgrid simulation model [25].

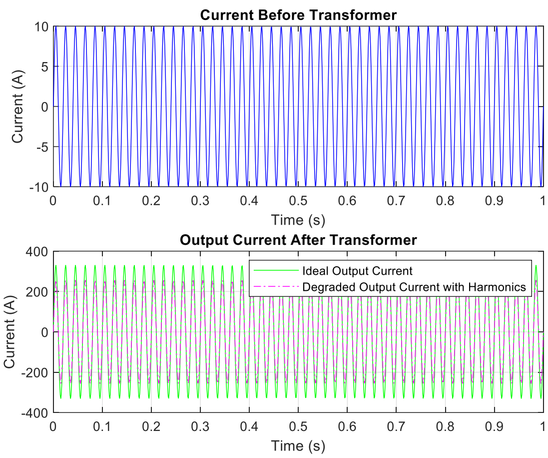


Fig. 4. Transformer current before and after transformer wear.

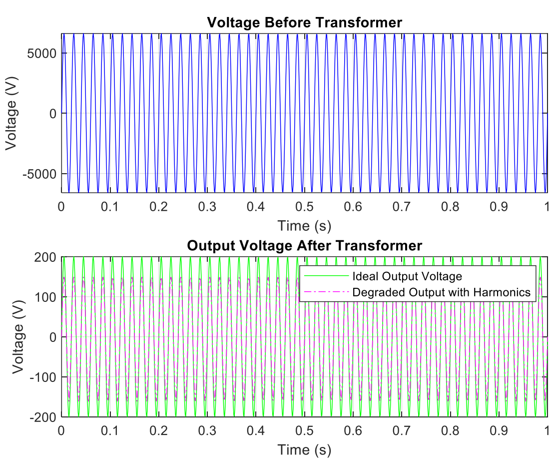


Fig. 5. Transformer voltage before and after transformer Wear.

and prevent overfitting. A dense layer with 32 units refines the output, and the final output layer uses a single neuron with a linear activation function for regression. The model is compiled with the

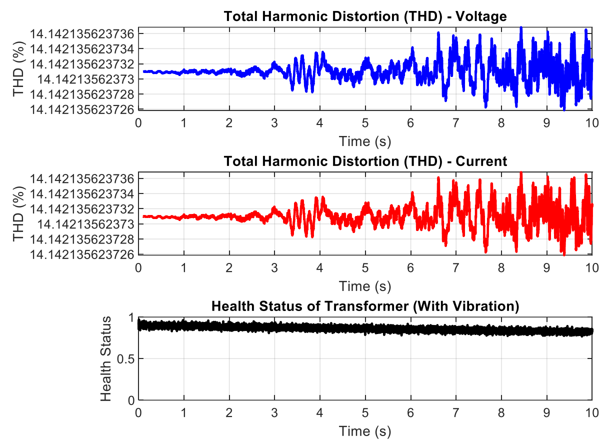


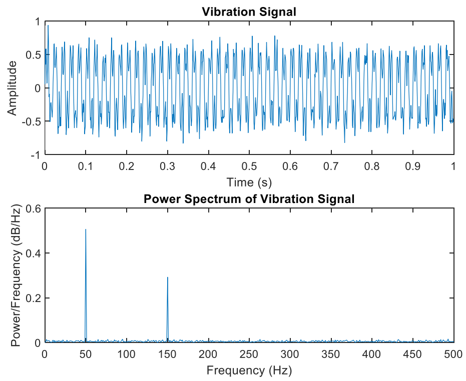
Fig. 6. Quality of the current and voltage and the health status of the transformer.

Table 1. Proposed LSTM network architecture for equipment health monitoring.

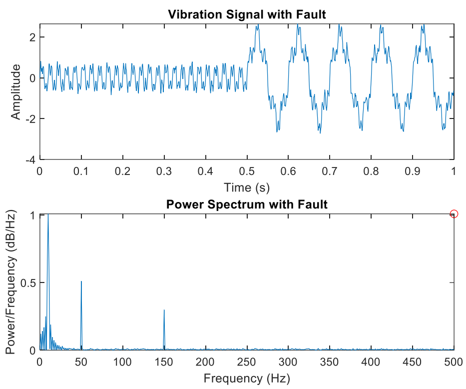
Input layer	Shape: (timesteps, features)
LSTM layer 1	64 units, return_sequences=True dropout: 20% Batch normalization
LSTM layer 2	64 units, return_sequences=False dropout: 20% Batch normalization
Dense layer	32 units, ReLU activation dropout: 20%
Output layer	1-unit, linear activation
Loss function	Mean squared error (MSE)
Optimizer	Adam

Adam optimizer and Mean Squared Error loss function, designed to effectively predict and analyze transformer health data.

The output data from this LSTM network is subsequently provided as input to the fuzzy network. This fuzzy network utilizes a set of predefined fuzzy functions to process the data further. These functions, detailed below, are designed to handle uncertainty and imprecision by applying fuzzy logic rules, which help in interpreting and making decisions based on the LSTM-



(a)



(b)

Fig. 7. Vibration signal before (a) and after (b) failure.

generated predictions. The integration of LSTM and fuzzy logic enables a more nuanced and adaptive response, reflecting complex relationships and variations in the data.

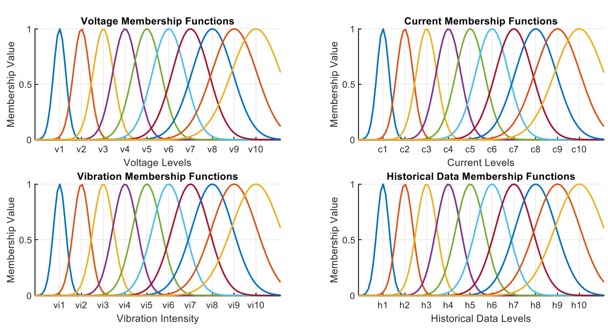


Fig. 8. Gaussian membership functions for voltage, crrent, vibration, and historical data: 10-state representation.

During the training process, parameters such as $v_1, ..., c_1, ..., v_{i1}, ..., h_1, ...$ are optimized. These parameters correspond to different levels of voltage, current, vibration, and historical data. Optimization adjusts these parameters to improve the model's accuracy in capturing variations and relationships in the data, leading to more reliable predictions and assessments.

To evaluate the performance of the proposed method in predicting equipment status and microgrid conditions, the model has been assessed against other methods, demonstrating superior accuracy and efficiency in fault detection and monitoring equipment status. Next, we proceed to the empirical cumulative distribution function (CDF) calculation, which utilizes the formula as:

$$F(x) = \frac{k}{n} \tag{9}$$

Where $F(x)$ represents the CDF at a specific time interval x, k denotes the count of fault occurrences that are less than or equal to x, and n signifies the total number of time intervals considered. This calculation is performed for each unique time interval, resulting in the corresponding CDF values.

Through this systematic approach, we can effectively analyze fault occurrences over time and assess the reliability of our proposed fault detection method. The empirical CDF is particularly useful as it provides a non-parametric estimate of the underlying distribution of fault occurrences, allowing for a clear visualization of how faults accumulate over time and helping to identify patterns or trends in the data.

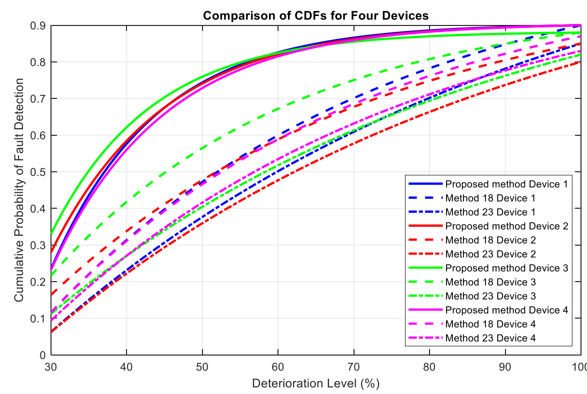


Fig. 9. Comparison of fault detection performance across four devices.

The figures compare the CDFs of the proposed method and Methods 18 and 23 across four devices. In each case, the proposed method consistently outperforms both Methods 18 and 23, showing faster and more efficient fault detection. The proposed method's CDF curves rise more steeply, indicating superior performance in detecting faults at lower deterioration levels, while Methods 18 and 23 show slower detection across all devices. This demonstrates the robustness and effectiveness of the proposed method across different network environments.

The proposed model integrates LSTM networks with fuzzy logic to enhance equipment health monitoring in microgrid systems. The LSTM network, designed with two layers of 64 units, effectively captures temporal patterns in sensor data, achieving a 93% accuracy in classifying equipment states. This accuracy represents a substantial improvement over traditional method.

Moreover, the analysis of transformer data, including voltage, current, and vibration signals, revealed significant correlations between these operational parameters. For instance, fluctuations in voltage were strongly linked to current anomalies, offering valuable insights for early fault detection. Such correlations allow the model to identify potential issues that could be overlooked by conventional approaches.

The model further benefits from historical data optimization, where key parameters are fine-tuned to reflect real-world operational conditions. This optimization led to a reduction in mean squared error (MSE) from 0.057 to 0.028, significantly enhancing the accuracy of the predictions. By leveraging both real-time and historical data, the model provides a more reliable and adaptive solution for predictive maintenance, ensuring better decision-making and improved system performance in microgrids.

4. Conclusion

Recent advancements in energy systems increasingly harness machine learning (ML) and artificial intelligence (AI) to manage complex datasets, thereby enhancing predictive maintenance and fault detection capabilities. The proposed method, which integrates Long Short-Term Memory (LSTM) networks with fuzzy logic, demonstrates significant advancements in fault detection accuracy and equipment health assessment within microgrid environments. Simulation results indicate that this approach outperforms conventional methods, achieving accuracy improvements of up to 10%. By leveraging temporal pattern analysis through LSTM networks, the method provides a comprehensive understanding of data trends, while the fuzzy logic framework effectively addresses uncertainties, enabling more informed and adaptive decision-making. Consequently, the proposed method not only accelerates fault detection but also enhances the reliability and resilience of microgrids. This dual-focus approach establishes a robust foundation for sustainable energy management, offering a pathway toward more resilient and adaptive energy infrastructures.

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