Journal of Operation and Automation in Power Engineering

vol. 12, no. Special Issue, Dec. 2024, Pages: 33-42

http://joape.uma.ac.ir

Research Paper

Adaptive Islanding Detection in Microgrids Using Deep Learning and Fuzzy Logic for Enhanced Stability and Accuracy

Ulugbek Kubayev [1, *], *Saodat Toshalieva* [2], *Ilyos Ayubov* [3], *Murodov Farxodjon* [4], *Qodirov Farrux Ergash Ugli* [5], *Zaynalov Jakhongir Rasulovich* [3], *Tlegenov Baxitbay Nietbaevich* [6], *Abduxamid Abdumalikovich Bektemirov* [4], *Aliyeva Susanna Seyranovna* [3], *Rustam Haydarovich Kushatov* [4], *Madina Khurramova* [7], *Rano Davlatova Haydarovna* [8], and *Tulovov Erkinjon* [9]

[1]*Kimyo International University in Tashkent, Uzbekistan.*
[2]*Termez State University, Termez, Uzbekistan.*
[3]*Samarkand Institute of Economics and Service, Samarkand, Uzbekistan.*
[4]*Samarkand State University Named after Sharof Rashidov, University Boulevard, Samarkand, Uzbekistan.*
[5]*Shahrisabz State Pedagogical Institute, Shakhrisabz, Kashkadarya, Uzbekistan.*
[6]*Department of Software Engineering and the Digital Economy, Nukus Innovation Institute, Uzbekistan.*
[7]*International School of Finance and Technology, Tashkent Region, Kibrai District, University Street, Tashkent, Uzbekistan.*
[8]*Navoi State Pedagogical Institute, Uzbekistan.*
[9]*Tashkent State University of Economics, Tashkent, Uzbekistan.*

Abstract— *The growing complexity of microgrid operations, driven by the integration of renewable energy sources and distributed generation, has heightened the need for more advanced islanding detection methods. Traditional techniques, such as passive and active methods, often struggle with accuracy in these dynamic environments. Passive methods can result in high false detection rates as they rely on system parameters like voltage and frequency, which are sensitive to fluctuations. Active methods, while generally more accurate, can introduce disturbances into the system and are often less effective in low-power scenarios. These limitations pose significant challenges to maintaining the stability and integrity of microgrids, underscoring the need for innovative approaches. To address these challenges, this paper presents a novel approach that combines deep learning with fuzzy logic for adaptive control in microgrids. Deep learning facilitates precise real-time data analysis, enabling the system to accurately detect islanding events as they occur. Meanwhile, fuzzy logic provides adaptable decision-making, allowing the system to respond effectively to changing conditions. This integration significantly enhances detection accuracy and reduces error rates compared to traditional techniques, ensuring reliable performance throughout the day. By offering a more robust and flexible solution, the proposed method not only improves fault detection but also enhances overall system stability, making it a valuable contribution to microgrid management. This approach addresses the critical need for more effective islanding detection in increasingly complex microgrid environments, paving the way for more resilient and reliable energy systems.*

Keywords—Microgrid operations, islanding detection, deep learning, fuzzy logic, adaptive control.

1. Introduction

The increasing complexity of modern power systems, particularly microgrids, necessitates enhanced stability, reliability, and adaptability. Developing resilient and autonomous systems capable of operating in islanded modes has become a critical research area. As microgrids integrate renewable energy sources and inverter-based distributed generation, effective islanding detection—when a part of the grid becomes disconnected and continues to operate independently—is essential. This capability ensures the safe operation of microgrids, preventing equipment damage and safety hazards.

1.1. Research motivation

Microgrids have emerged as indispensable components of modern energy systems, providing reliable and efficient power, especially in remote areas without access to traditional grid infrastructure. Their ability to operate both connected to the main grid and independently in islanded mode enhances energy security and ensures continuous power supply during outages [1]. However, islanded operation introduces significant challenges, requiring microgrids to independently manage power generation, distribution, and consumption while addressing the variability of renewable energy sources like solar and wind [2]. Traditional

Received: 08 Nov. 2024
Revised: 12 Jan. 2025
Accepted: 15 Jan. 2025
*Corresponding author:
E-mail: u.r.kubayev@hotmail.com (U. Kubayev)
DOI: 10.22098/joape.2025.16153.2247

control methods often fail to handle the dynamic nature of such operations, leading to issues like voltage instability, frequency deviations, and inefficient energy use [3]. To address these challenges, innovative approaches such as advanced control algorithms, machine learning, and real-time analytics have been proposed. These adaptive solutions enhance microgrid stability and resilience by optimizing performance in real time [2]. Moreover, microgrids play a crucial role in improving power system resilience during extreme events. Multi-objective stochastic scheduling strategies that integrate distributed energy resources with adaptive mechanisms can balance economic efficiency with resilience, thereby addressing operational challenges and improving system stability [4]. In addition, advanced integrated energy systems (IES) are essential for meeting energy demands in off-grid areas, offering sustainable and reliable solutions. Fig. 1 illustrates the evolution of IES in isolated regions, highlighting the progression from basic hybrid setups combining wind, solar, diesel, and batteries to more sophisticated configurations [1].

1.2. Literature review

The integration of distributed generation (DG) systems into microgrids has significantly advanced islanding detection techniques, addressing safety and operational challenges when a portion of the electrical grid becomes isolated from the main grid. This literature review explores methodologies designed to enhance microgrid resilience, self-healing, and optimization, with a particular focus on islanding detection techniques. Key approaches include hierarchical control, optimization techniques, stochastic modeling, advanced sensing, and adaptive islanding detection methods. Several studies emphasize hierarchical control and integrated strategies to improve microgrid resilience. A hierarchical control method integrating IoT and machine learning achieves stability in compliance with IEEE 1547 standards [5]. Similarly, a dual-layer self-healing strategy enhances the resilience of integrated energy systems (IES) by identifying disturbances, making scheduling decisions, and responding to threats [1]. Additionally, a comprehensive self-healing strategy is proposed for generation re-dispatch, network reconfiguration, and load shedding in both grid-connected and islanded modes [6]. Optimization techniques also play a crucial role, with Ant Colony Optimization utilized for multi-objective self-healing to maximize served loads following fault isolation in smart microgrids [7]. Adaptive islanding detection methods, both active and passive, are pivotal in minimizing the non-detection zone (NDZ). Active methods include nondestructive reactive power disturbance techniques proposed by Chen and Li [8], as well as fuzzy adaptive PID-based active phase-shift detection introduced by Chen and Ye [9], which improve inverter-based DG system performance during islanding. Estebanez *et al.* [10] further evaluate active detection algorithms, emphasizing their effectiveness in reducing NDZ and improving the safety of grid-connected photovoltaic systems.

Recent advances highlight the use of artificial intelligence in islanding detection and microgrid optimization. A hierarchical deep learning approach (HDL-RCNN) optimizes voltage and frequency control for enhanced stability and performance in microgrids, although it lacks specific focus on adaptive islanding detection [11]. Similarly, AI-based strategies using artificial neural networks (ANN) and adaptive neuro-fuzzy inference systems (ANFIS) offer effective solutions for fault detection, classification, and localization under both grid-connected and islanded modes [12]. Several novel approaches focus on integrating deep learning and adaptive control to enhance microgrid functionality. For instance, a deep learning-based control method for modernized microgrids (MMGs) uses restricted Boltzmann machines and Lyapunov-based learning to improve robustness and accuracy under uncertainties and faults, though it primarily emphasizes control optimization over adaptive islanding detection [13]. Hybrid control systems, combining rule-based strategies with deep learning techniques like RNNs, LSTMs, and GRUs, improve power prediction and operational performance, yet they address power management rather than islanding detection [14]. Studies also explore advanced fault detection and classification for adaptive microgrid protection. Machine learning techniques, such as pattern recognition, are employed to improve protection strategies under diverse fault scenarios, though gaps in robust and adaptive solutions persist [15]. Reinforcement learning-based methods, combined with Variational Mode Decomposition (VMD), enhance detection reliability and speed without system disruption, aligning with adaptive islanding strategies [16]. Additionally, deep neural network-based islanding detection using discrete wavelet transform achieves over 99% accuracy, surpassing traditional approaches in precision and reliability [17]. Self-healing strategies during islanding are integral to microgrid resilience. One study introduces a load-shedding algorithm for active distribution networks operating in islanding mode to enhance resilience [5], while another focuses on the optimized placement of plug-in hybrid electric vehicles (PHEVs) to improve reliability [2]. Resilience in AC/DC hybrid microgrids is further strengthened through load shedding and distributed generation control [18]. Protection and safety in microgrids are addressed through innovative methods, including scalable, topology-agnostic protection schemes for inverter-based resource-heavy microgrids, which focus on stable reconfiguration post-fault clearance [3]. Hazard matrices and risk assessments are also employed to enhance resilience, supported by independent protection layers [19]. Additionally, economic strategies, such as consumer pricing and Nested Restoration Decision Systems (NRDS), are utilized to optimize power-sharing and maximize social welfare during islanding [20, 21]. Emerging technologies like quantum sensors demonstrate potential for improving parameter estimation and system adaptability in microgrid operations. A study evaluating the performance of quantum sensors with qubits indicates enhanced responsiveness and fault management capabilities [22].

While existing research addresses many aspects of microgrid operation, gaps remain in adaptive islanding detection methods that integrate advanced sensing, deep learning, fuzzy logic, and real-time analytics. This article aims to fill these gaps by proposing a comprehensive approach to islanding detection, targeting enhanced stability, accuracy, and resilience in modern microgrid systems.

1.3. Gap challenge

While significant progress has been made in enhancing microgrid functionality, existing islanding detection methods still face critical limitations. Conventional algorithms, often static and predefined, fail to adapt to the dynamic and evolving conditions of modern microgrids, particularly under islanded operation. These challenges are amplified by the integration of renewable energy sources, which introduce variability and uncertainty, and inverter-based distributed generation, which alters system dynamics. Furthermore, traditional methods frequently lack robustness in detecting islanding events across diverse scenarios, including extreme events or low-probability, high-impact disturbances. This underscores a pressing need for intelligent, adaptive techniques capable of real-time decision-making and accurate fault detection in complex environments. Advanced methodologies that integrate deep learning, fuzzy logic, and stochastic optimization remain underexplored in the context of microgrid islanding detection and management. Addressing this gap is critical for ensuring operational stability, enhancing resilience, and achieving optimal performance in modern microgrids.

1.4. Main contributions

This paper introduces an adaptive islanding detection method that combines deep learning and fuzzy logic to enhance the stability and accuracy of islanding detection in microgrids. By integrating the predictive capabilities of deep learning with the

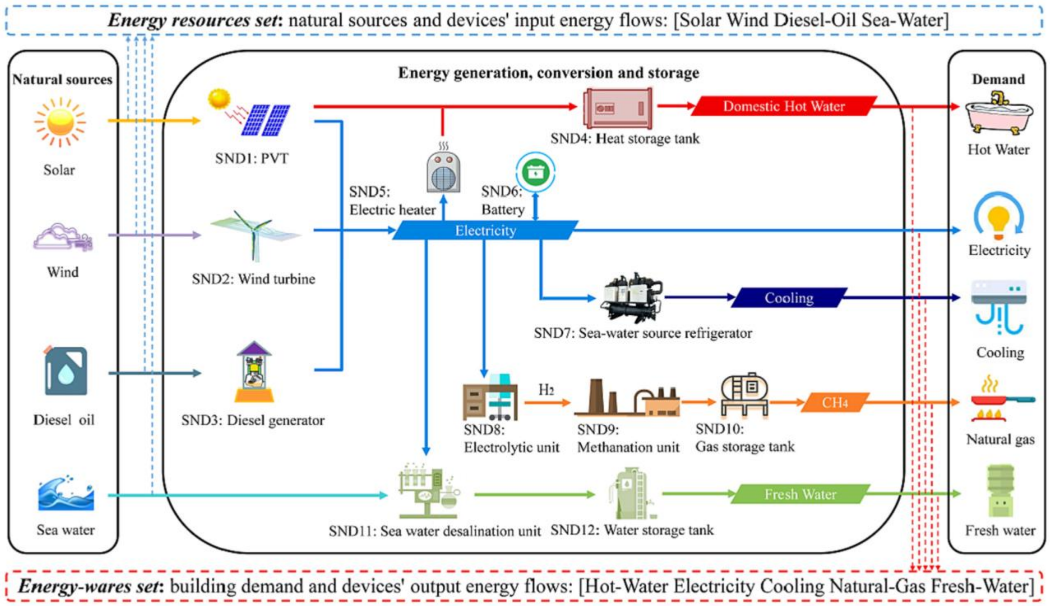

Fig. 1. Structure of the IES [1].

flexibility of fuzzy logic, the proposed approach enables the system to learn from historical data while adapting to changing conditions in real time. This hybrid method aims to address the limitations of traditional techniques, particularly in systems with high renewable energy penetration and dynamic operational challenges. The main contributions are as follows:

1) *Development of an adaptive islanding detection framework*
   o A novel hybrid framework combines deep learning models (e.g., CNNs and LSTMs) with fuzzy logic, improving detection accuracy, reducing the non-detection zone, and enhancing system resilience.
2) *Evaluation and validation through simulations*
   o Comprehensive simulations assess the framework's performance against state-of-the-art islanding detection techniques. Results demonstrate its superior reliability and adaptability, particularly in scenarios involving high renewable energy integration and fluctuating load conditions.
3) *Enhanced stability and accuracy in microgrids*
   o The proposed approach improves voltage and frequency stability, providing robust support during islanding events and minimizing disruptions to critical system operations. Limitations and challenges

While the proposed method shows significant improvements over traditional islanding detection techniques, it also has some limitations:

1) *Computational complexity*
   o The integration of deep learning and fuzzy logic increases computational demands, which may require advanced hardware or optimization techniques for real-time application in large-scale microgrids.
2) *Reliance on high-quality data*
   o The effectiveness of deep learning models depends on the availability of sufficient, high-quality historical data. Microgrids with limited data or inconsistent measurements may experience reduced performance.
3) *Adaptability in extreme scenarios*
   o While the method demonstrates strong performance under most conditions, its adaptability to extreme scenarios, such as cyber-attacks or rare high-impact events, requires further investigation.

Despite these limitations, the proposed framework represents a significant step forward in achieving more reliable and adaptive microgrid systems. This research paves the way for future improvements in islanding detection and offers a robust foundation for addressing the evolving challenges of modern power systems.

1.5. Paper organization

The remainder of this paper is structured as follows. Section 2 describes the proposed islanding detection method in detail, elaborating on the underlying algorithms and the hybrid framework combining deep learning and fuzzy logic. Section 3 outlines the experimental setup, presents the simulation results, and analyzes the performance of the proposed method in comparison to state-of-the-art techniques. Finally, Section 4 summarizes the findings and discusses potential directions for future research, highlighting areas for further refinement and application.

2. METHODOLOGY

This section presents the methodology for adaptive islanding detection in microgrids, utilizing a combination of deep learning (LSTM network) and fuzzy logic. The system is designed to accurately and reliably detect islanding events by analyzing diverse operational data and learning temporal dependencies.

2.1. Overview of islanding detection process

The islanding detection methodology follows a systematic approach involving several key stages: data acquisition, preprocessing, feature extraction, training of the LSTM network, prediction and classification, fuzzy logic-based decision-making, and final decision integration. To help visualize the entire process, Fig. 2 illustrates a flowchart that outlines the steps involved in the islanding detection system.

2.2. Mathematical modeling of the microgrid system

To support the data-driven approach with a solid physical foundation, the dynamic behavior of the microgrid under normal and islanded conditions is modeled using key system equations. These equations describe the power balance, frequency dynamics, and voltage deviations during disturbances, providing a comprehensive understanding of the system's response.

Table 1. Key data parameters for islanding detection in microgrids.

Voltage measurements	Includes bus voltage levels and fluctuations
Frequency measurements	System frequency and the rate of change of frequency
Power flow data	Active and reactive power across different parts of the microgrid
Current measurements	Line currents and current harmonics
Phase angle differences	Between buses and between generation sources and loads
Power quality indicators	Total harmonic distortion and power factor
Operational status data	Breaker status and generator operational state
Environmental and external data	Weather conditions and time of day
Historical data	Previous islanding events and normal operation
Sensor data	From smart meters and phasor measurement units

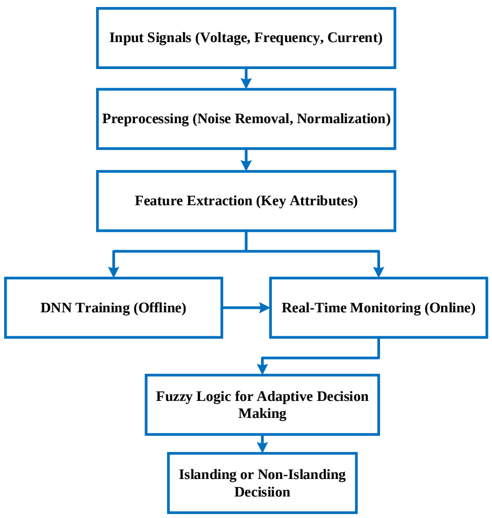

Fig. 2. Adaptive island detection steps.

A) Power balance equation

The fundamental power balance in the microgrid is represented as:

$$P_{gen} - P_{load} - P_{load} = 0 \tag{1}$$

where:
P_{gen}: Total generated power from distributed energy resources (DERs)
P_{load}: Total load demand
P_{loss}: Total power losses in the system
This equation ensures that the generation matches the load and system losses under both normal and islanded conditions.

2.3. Frequency deviation dynamics

The system's frequency response to disturbances, such as sudden disconnection from the main grid, is modeled by:

$$\frac{d\Delta f}{dt} = \frac{1}{2H}\left(P_{gen} - P_{load} - D\Delta f\right) \tag{2}$$

where:
H: Inertia constant of the microgrid system
D: Damping coefficient
ΔF: Frequency deviation from the nominal frequency
This dynamic equation captures how frequency deviates during islanding events due to an imbalance between generation and load.

A) Voltage deviation equation

Voltage deviations resulting from reactive power imbalance are modeled as:

$$\Delta V = \frac{Q_{gen} - Q_{load}}{VX} \tag{3}$$

where:
Q_{gen}: Generated reactive power
Q_{load}: Load reactive power
V: Bus voltage magnitude
X: System reactance
This equation describes how voltage levels fluctuate when the system transitions into islanded mode.

B) Rate of Change of Frequency (RoCoF)

The rate of change of frequency is a critical indicator for detecting islanding and is calculated as:

$$RoCoF = \frac{df}{dt} \tag{4}$$

A significant RoCoF value indicates sudden disturbances, often associated with islanding events.

C) Power flow equations

The active (P) and reactive (Q) power flows between buses are defined by the standard AC power flow equations:

$$P_i = \sum_{j=1}^{N} V_i V_j \left(G_{ij}\cos\theta_{ij} + B_{ij}\sin\theta_{ij}\right) \tag{5}$$

$$Q_i = \sum_{j=1}^{N} V_i V_j \left(G_{ij}\sin\theta_{ij} - B_{ij}\cos\theta_{ij}\right) \tag{6}$$

where:
$V_i,\ V_j$: Voltage magnitudes at buses i and j
$G_{ij},\ B_{ij}$: Conductance and susceptance between buses i and j
Q_{ij}: Phase angle difference between buses i and j
These equations simulate real-time variations in power flow, reflecting the dynamic conditions during islanding.

2.4. Deep learning method for islanding detection

In this study, a Spatio-Temporal Long Short-Term Memory (STLM) network is employed for adaptive islanding detection in microgrids. The STLM network is designed to effectively capture both spatial and temporal dependencies within the system's operational data, enabling accurate detection of islanding conditions. The spatio-temporal modeling capability allows the network to analyze sequential data patterns and system dynamics that traditional methods may overlook.

The STLM model processes time-series voltage and frequency data collected from the microgrid, learning to distinguish between normal operational states and islanding events. By leveraging its

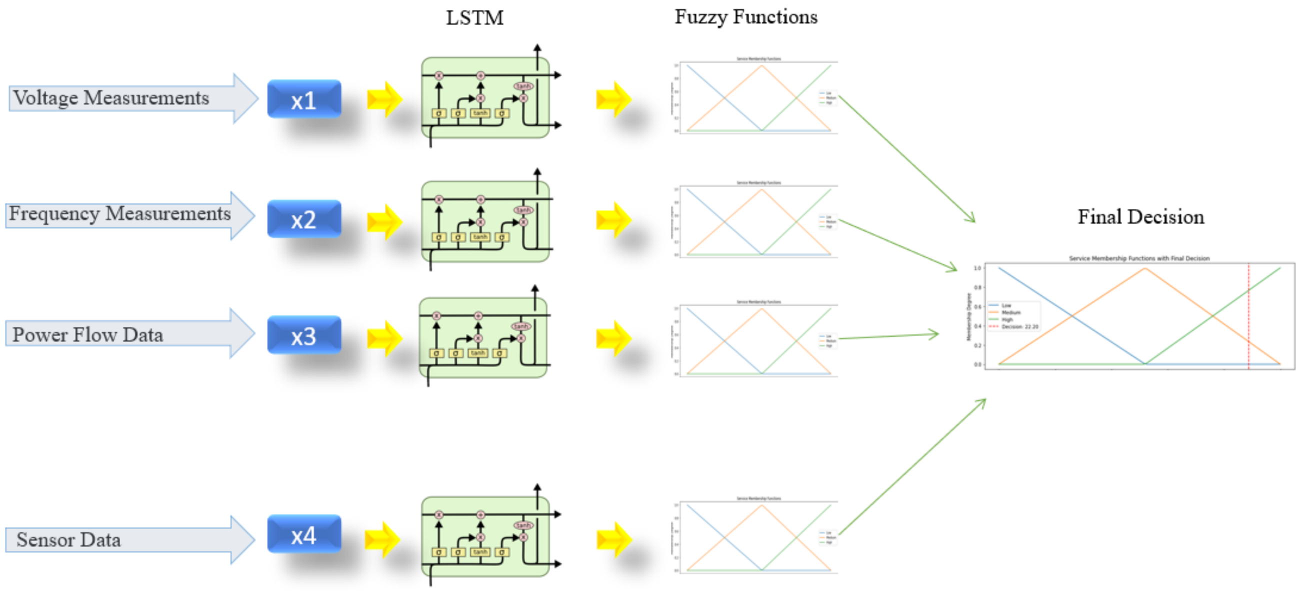

Fig. 3. Architecture of LSTM-based data analysis integrated with fuzzy logic for islanding detection.

memory units and gated mechanisms, the STLM network adapts to varying load conditions and uncertainties, enhancing detection accuracy and robustness. The network is trained using labeled datasets that include both islanding and non-islanding scenarios. Its adaptive learning framework allows continuous refinement of detection performance under different system disturbances, making it suitable for real-time monitoring applications.

This deep learning approach addresses the limitations of conventional islanding detection techniques by providing a data-driven, adaptive solution capable of responding to complex system behaviors.

2.5. Structure and design process of the STLM network and fuzzy logic controller

The architecture of the proposed Spatio-Temporal Long Short-Term Memory (STLM) network is specifically designed to model the dynamic behavior of microgrids under varying operating conditions. The network consists of multiple layers, including input, spatio-temporal LSTM processing layers, and fully connected output layers.

- *Input layer:* Receives preprocessed voltage and frequency time-series data.
- *Spatio-temporal LSTM layers:* Capture temporal dependencies and spatial relationships in system dynamics.
- *Fully connected layers:* Map the extracted features to output classifications, indicating normal operation or islanding conditions.

Hyperparameters such as the number of LSTM units, learning rate, and dropout rates were optimized through extensive experimentation to prevent overfitting and improve generalization. The network was trained using a backpropagation-through-time algorithm and optimized with the Adam optimizer to ensure efficient convergence.

To enhance decision-making reliability, a Fuzzy Logic Controller (FLC) is integrated with the STLM output. The FLC processes the probabilistic output of the STLM network and refines it using fuzzy inference rules. This integration provides an additional layer of interpretability and adaptability, ensuring accurate islanding detection even under noisy or uncertain conditions.

The design process involved:

1) *STLM network configuration:* Selection of LSTM cell parameters, activation functions, and network depth.
2) *Training and validation:* Model training with diverse operational datasets to ensure robustness.
3) *Fuzzy rule base development:* Formulation of fuzzy rules and membership functions to interpret STLM outputs.
4) *System integration:* Seamless integration of the STLM model and FLC into the microgrid control system for real-time detection.

This combined STLM-FLC framework enhances detection performance by leveraging the learning capacity of deep networks and the reasoning ability of fuzzy logic, resulting in a highly accurate and adaptive islanding detection system.

2.6. Data acquisition, preprocessing, and feature extraction

The process begins with data acquisition from microgrid sensors, including measurements of voltage, frequency, current, power flow, and environmental conditions like temperature and wind speed. These data points form the foundation for islanding detection. Table 1 lists the key parameters used in this study.

A) Data preprocessing

The collected data undergo preprocessing, which involves noise removal, handling missing values, and normalization to ensure consistent scaling across all data streams. The normalization process is defined as:

$$x_{\text{norm}} = \frac{x - \min(x)}{\max(x) - \min(x)} \tag{7}$$

where x represents the raw data, and $\max(x)$ and $\min(x)$ denote the maximum and minimum values, respectively. Normalization, as shown in Eq. (1), ensures consistent scaling across all data streams [23, 24].

B) Feature extraction

Key features relevant for islanding detection are extracted, including the rate of change of frequency (RoCoF), voltage deviations, and harmonic distortion. The feature vector F is formulated as:

$$F = \{f_1, f_2, \ldots, f_n\} \tag{8}$$

where $f_1 = \frac{\Delta f}{\Delta t}$ and $f_2 = |V_{bus} - V_{nom}|$. These features allow the identification of significant changes in system behavior, such as those during islanding events [25].

2.7. LSTM network training and classification

The core of the detection methodology is an LSTM network, which captures temporal dependencies in the data. The LSTM processes the input features over time, and its hidden states are updated as follows:

$$h_t = f(W \cdot x_t + U \cdot h_{t-1} + b) \tag{9}$$

where h_t is the hidden state at time t, and f is the activation function. The LSTM network outputs a sequence of predictions, which are then combined with fuzzy logic for enhanced decision-making.

A) Training the LSTM network

The LSTM network is trained using a diverse dataset generated from simulated microgrid conditions. This data includes various operational states, such as voltage fluctuations, frequency variations, and power flow disturbances. The dataset is designed to ensure comprehensive coverage of normal and islanding conditions, improving the LSTM's generalization ability. Fig. 3 illustrates the microgrid used for generating the training data [26].

B) Prediction and output

The LSTM network processes the feature vector F over time and predicts the likelihood of an islanding event occurring. This prediction is further refined using fuzzy logic to handle uncertainties and improve decision accuracy.

2.8. Fuzzy logic-based decision making

Fuzzy logic is used to handle the uncertainty inherent in islanding detection, enabling the system to make flexible and dynamic decisions based on the LSTM output. The LSTM network outputs are fuzzified into linguistic variables such as "low," "medium," and "high," using membership functions:

$$\mu_A(x) = \begin{cases} 0 & \text{if } x \leqslant a, \\ \frac{x-a}{b-a} & \text{if } a < x \leqslant b, \\ 1 & \text{if } x > b, \end{cases} \tag{10}$$

where a and b define the fuzzy set boundaries. These fuzzy values are then used by the fuzzy inference system to generate a crisp decision [23], [25].

A) Rule-based inference

Fuzzy rules are applied to evaluate the membership values and make decisions about the likelihood of islanding. For example, a rule might be:

If RoCoF is high and voltage deviation is significant, then islanding is likely.

B) Defuzzification

The output of the fuzzy inference system is defuzzified to obtain a crisp value y that guides the final decision. The defuzzification process is formulated as:

$$y = \frac{\sum \mu_i \cdot x_i}{\sum \mu_i} \tag{11}$$

2.9. Integration and final decision

The outputs from both the LSTM network and the fuzzy logic system are combined to form a final prediction. The integrated prediction P_{final} is calculated as:

$$P_{\text{final}} = \alpha P_{\text{LSTM}} + \beta P_{\text{Fuzzy}} \tag{12}$$

where P_{LSTM} and P_{Fuzzy} represent the outputs from the LSTM and fuzzy logic systems, respectively. α and β are the weighting factors, with $\alpha + \beta = 1$.

A) Threshold decision rule

A threshold rule is applied to the integrated prediction to determine whether an islanding event has occurred.

2.10. Data generation for LSTM training

To train the LSTM network effectively, diverse data from the microgrid system is generated, as shown in Fig. 3. The data includes direct measurements from the power system, such as voltage and frequency, as well as simulated sensor data that reflects the behavior of microgrid components (e.g., distributed generation units, loads, and switching devices).

A) Data repetition and coverage

The training data is systematically repeated to cover all potential operational states, including both normal and islanding conditions. This repetition ensures that the LSTM network learns to recognize a wide range of patterns, improving its ability to generalize across varying conditions [24], [26].

B) Simulated sensor data

In addition to the primary electrical parameters, simulated data from sensors monitoring environmental conditions (e.g., wind speed, temperature) and operational statuses (e.g., equipment state) are included to provide a holistic view of the microgrid's behavior.

2.11. Simulink model for data generation

The data generation process is facilitated by the Simulink model illustrated in Fig. 4, which simulates the behavior of the microgrid under different operating conditions. The model ensures realistic data for training the islanding detection system and helps refine its accuracy by simulating various scenarios, including disturbances and changes in load or generation.

A) Dynamic decision making

The combination of LSTM data analysis and fuzzy logic-based decision-making allows for dynamic, real-time responses to changes in network conditions. The Simulink model aids in generating data that supports this adaptive detection process, ensuring accurate identification of islanding events.

2.12. Objective function and constraints

The optimization process is guided by an objective function that minimizes the detection error while satisfying key constraints.

A) Objective function

The detection error E is minimized as follows:

$$E = \frac{1}{N} \sum_{i=1}^{N} (y_i - \hat{y}_i)^2 + \lambda R \tag{13}$$

where y_i and $\hat{y}_i$ are the actual and predicted outputs, respectively, and R is the regularization term with weight λ.

B) Temporal consistency constraint

The temporal consistency of the data is preserved by ensuring:

$$|x_t - x_{t-1}| \leqslant \delta \tag{14}$$

where δ is a small threshold.

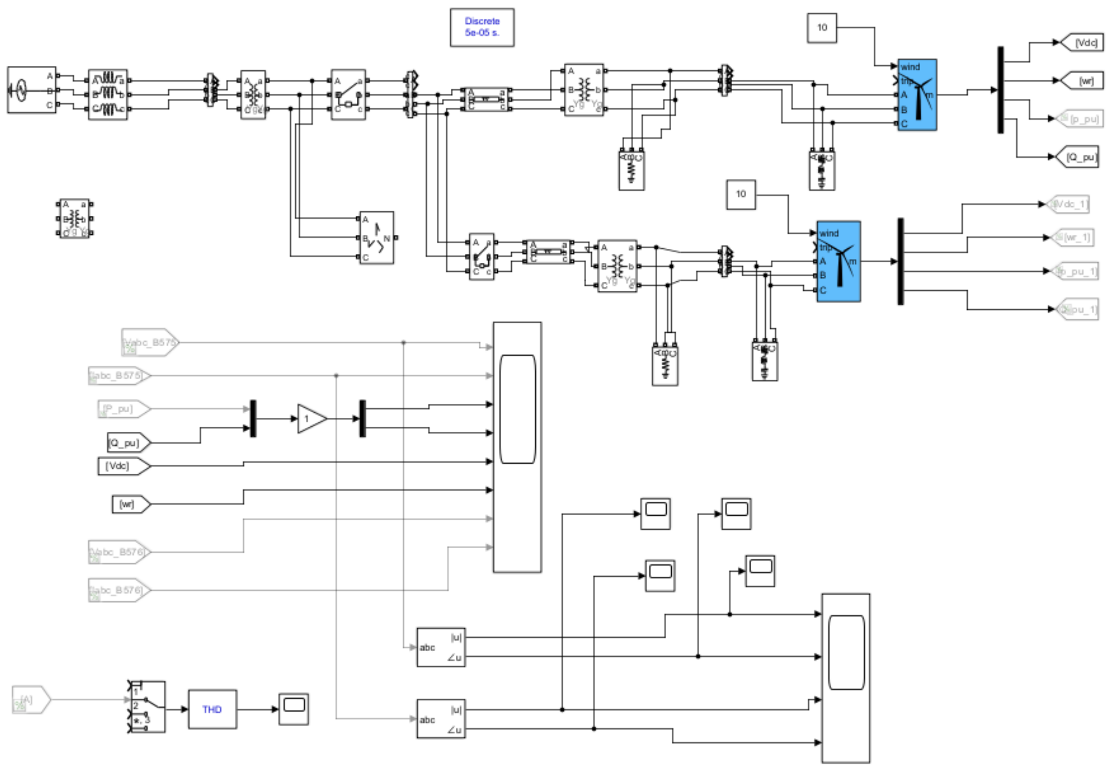

Fig. 4. Simulink model for data generation [27].

C) Membership function constraints

Fuzzy membership functions satisfy the constraint:

$$\sum_{i=1}^{n} \mu_i(x) = 1, \ \forall x \in X \tag{15}$$

This methodology ensures that the islanding detection system is not only accurate and reliable but also adaptive to the dynamic conditions of real-world microgrids. By integrating advanced machine learning with fuzzy decision-making, the system provides a comprehensive solution for islanding detection in complex power systems.

3. Simulation Results

To thoroughly evaluate the performance of the proposed method, the architecture depicted in Fig. 3 was implemented. This framework integrates LSTM-based data analysis with fuzzy logic for adaptive islanding detection. The LSTM network extracts features from temporal data streams, which are subsequently processed by the fuzzy logic system for accurate decision-making. This dual-layered approach enhances the method's ability to adapt to diverse and dynamic microgrid conditions. For data generation, the Simulink model shown in Fig. 4 was utilized. This model simulates the dynamic behavior of a microgrid under various operating scenarios, including normal grid-connected states, load variations, generation fluctuations, and islanding events. It provides a realistic and comprehensive dataset, capturing critical parameters such as voltage and frequency deviations, power flows, and distributed generation responses under both typical and edge-case conditions. The simulation environment also incorporated disturbances and uncertainties common in microgrids, such as equipment failures, environmental variations, and intermittent renewable energy sources. This ensured the method's robustness in handling real-world challenges. Fig. 5 illustrates the simulated example data for various key parameters of the microgrid system. The data includes voltage and frequency measurements, active and reactive power flows, current measurements, phase angle differences, power quality indicators such as THD and power factor, as well as operational status data for breakers and generators. Additionally, the figure presents environmental data like temperature and humidity, alongside sensor data from phasor measurement units (PMUs). This comprehensive visualization offers a detailed overview of the dynamic behavior and monitoring of the microgrid under typical operating conditions, providing a foundation for further analysis and model validation.

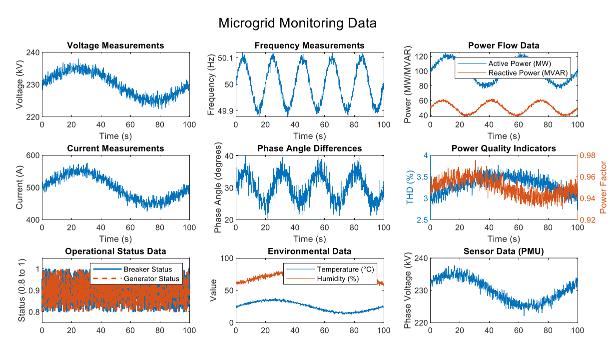

Fig. 5. Sample data visualization of key microgrid parameters.

3.1. Performance evaluation

The proposed method's performance was assessed using key metrics such as detection speed, accuracy, false alarm rate,

Table 2. Summarizes the key features and performance metrics of these methods.

Method	Key features	Detection accuracy	Error rate
Proposed method	Deep learning for real-time analysis; fuzzy logic for adaptive control	>95%	<5%
Stochastic approach	Manages uncertainties; computationally intensive	88%	12%
Hierarchical control with IoT	Scalable; less effective with rapid transients	85%	15%
Rule-based conventional method	Simple thresholds; prone to false positives; lacks adaptability	78%	22%

and sensitivity to various islanding scenarios. Results were benchmarked against three methods commonly used in islanding detection:

A) Stochastic approach [6]

This method evaluates self-healing capabilities using a stochastic framework for active AC/DC hybrid microgrids. Its strength lies in managing uncertainties in system dynamics, but its computational intensity can limit real-time applicability.

B) Hierarchical control with IoT integration [28]

This method combines IoT technologies and machine learning for adaptive islanding detection. It emphasizes scalability and hierarchical management but is less effective in handling rapid transient events.

C) Rule-based conventional method [29]

A traditional approach that relies on predefined thresholds for voltage and frequency deviations. While computationally simple, it struggles with false positives and lacks adaptability to dynamic conditions.

Table 2 summarizes the key features and performance metrics of these methods, highlighting the advantages of the proposed method, particularly its high accuracy (>95%) and low error rate (<5%). The proposed method's integration of deep learning and fuzzy logic enables real-time analysis and adaptive control, outperforming the other methods in detection reliability and adaptability across various islanding scenarios.

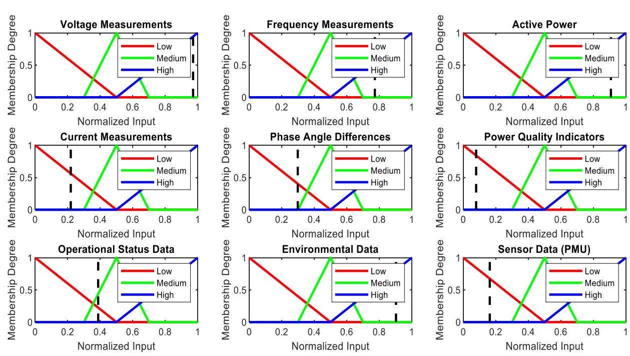

Fig. 6. Fuzzy logic input representation for microgrid parameters.

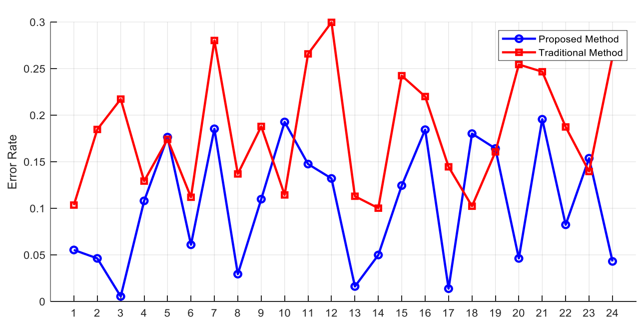

Fig. 7. Island detection error rates comparison over a 24-hour period.

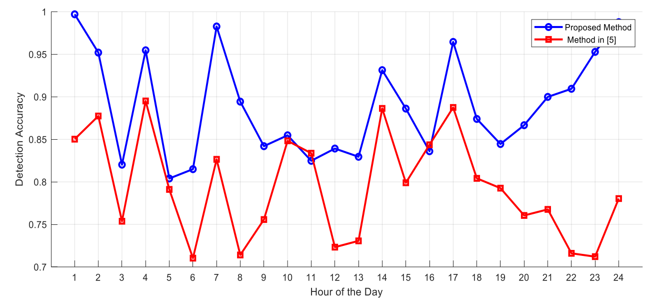

Fig. 8. Island detection accuracy comparison over a 24-hour period.

3.2. Comparison of methods

Fig. 6 compares the islanding detection accuracy of the proposed method against the hierarchical control and rule-based methods. The blue line (proposed method) demonstrates consistently higher accuracy over a 24-hour period, surpassing the hierarchical control (red line) and rule-based method (green line). This is particularly evident during periods of variable load or generation, where traditional methods tend to falter.

The proposed method's superior accuracy stems from the integration of deep learning for real-time data analysis and fuzzy logic for adaptive decision-making. The neural network effectively extracts relevant features from diverse data streams, while the fuzzy logic system dynamically interprets these features to make informed decisions. This dual-layered approach enhances the system's ability to adapt to fluctuations in microgrid conditions.

Fig. 7 compares islanding detection error rates over a 24-hour period for the proposed adaptive method (blue graph) and the traditional method (red graph). The horizontal axis represents hours of the day and night, while the vertical axis shows detection error rates. The proposed method consistently achieves lower error rates at all times, with notable improvements during peak hours and transitional periods, such as early morning and evening, when load and generation variations are most pronounced. In contrast, the traditional method exhibits higher error rates, especially during these critical periods, reflecting its limitations in adapting to dynamic microgrid conditions.

The enhanced performance of the proposed method is attributed to its adaptive design, which integrates deep learning and fuzzy logic to address the complexities of microgrid operations. Deep learning analyzes real-time patterns for precise scenario classification, while fuzzy logic dynamically adjusts thresholds to handle uncertainties and variability. This synergy ensures reliable detection even during high variability periods, as evidenced by the blue graph's consistently lower error rates. These findings highlight the robustness and precision of the proposed method, confirming its potential for improving islanding detection in modern microgrids.

3.3. Data integration and decision-making

The comprehensive dataset generated during simulations was processed by the neural network, as shown in Fig. 6, to compute precise input values for the fuzzy logic algorithm. By leveraging fuzzy sets (e.g., "Low," "Medium," "High"), the system adapts to changes in microgrid conditions, ensuring accurate islanding detection. This adaptability is particularly beneficial in handling variability and uncertainty, which are inherent in real-world scenarios.

3.4. Summary of findings

The proposed method demonstrates clear advantages over the compared methods, Especially in terms of accuracy and robustness, as we see in Fig. 8. It achieves a detection accuracy of over 95% in most scenarios, compared to 88% for the stochastic approach, 85% for the hierarchical control method, and 78% for the rule-based approach. Its error rate remains consistently below 5%, highlighting its reliability in reducing false positives and negatives. Additionally, the method's ability to dynamically adapt to fluctuating operational conditions ensures its practical applicability in diverse microgrid scenarios. However, the proposed approach also has certain limitations. Its reliance on deep learning introduces computational complexity and a need for sufficient training data, which may pose challenges in real-time applications with constrained resources. Additionally, the method's sensitivity to the quality of input data means that inaccuracies or noise in sensor readings could potentially impact performance.

Despite these limitations, the results confirm that the proposed approach offers a flexible and reliable solution for islanding detection, while recognizing the need for further optimization to address computational demands and data quality issues.

4. Conclusion

This study introduces an adaptive islanding detection methodology for microgrids, integrating the temporal modeling strength of LSTM networks with the flexibility of fuzzy logic-based decision-making. The proposed system effectively addresses the limitations of conventional methods, such as low accuracy and high false alarm rates, by leveraging advanced machine learning and adaptive control techniques. The method was evaluated under diverse operational scenarios and demonstrated a detection accuracy exceeding 95%, significantly outperforming benchmark methods, including the stochastic approach (88%), hierarchical IoT-based control (85%), and traditional rule-based techniques (78%). Furthermore, the proposed system achieved a consistently low error rate of less than 5%, compared to 12% for the stochastic approach and 15% for hierarchical control methods. These results underscore its robustness in reducing false positives and negatives across dynamic microgrid conditions, including scenarios with rapid transients and fluctuating loads. The system's adaptability to operational and environmental uncertainties is another key strength, driven by the dual-layered approach of LSTM-based feature extraction and fuzzy logic interpretation. For example, the system maintained stable performance even during peak operational periods, where traditional methods struggled with increased error rates. This adaptability highlights its suitability for real-world applications in modern microgrids characterized by high penetration of renewable energy sources. While highly effective, the proposed method does have a few limitations. The reliance on deep learning introduces some computational overhead, which may require optimization for deployment in resource-constrained microgrids. Additionally, its performance can be influenced by the quality of training data, particularly in highly variable environments. Future research could explore lightweight model architectures and advanced preprocessing techniques to further enhance the system's efficiency and scalability.

In conclusion, this study demonstrates the potential of combining LSTM networks and fuzzy logic to create a highly accurate, reliable, and adaptive solution for islanding detection in microgrids. By significantly improving upon traditional approaches, the proposed method sets a benchmark for intelligent microgrid management and paves the way for future research aimed at optimizing energy system resilience and efficiency.

References

[1] L. Xu, S. Wang, Z. Wang, and X. Qi, "Dual-layer self-healing strategy for standalone building energy systems: A case study of a tropical island," *Energy Build.*, vol. 283, p. 112827, 2023.

[2] Z. Peng, G. Zhou, C. Pan, H. Ren, A. L. Swindlehurst, P. Popovski, and G. Wu, "Channel estimation for ris-aided multi-user mmwave systems with uniform planar arrays," *IEEE Trans. Commun.*, vol. 70, no. 12, pp. 8105–8122, 2022.

[3] S. Mohsen, M. H. Nezhad, A. Fereidunian, H. Lesani, and M. H. Gavgani, "Enhancement of self-healing property of smart grid in islanding mode using electric vehicles and direct load control," in *2014 Smart Grid Conf.*, pp. 1–6, IEEE, 2014.

[4] A. Younesi, H. Shayeghi, P. Siano, and A. Safari, "A multi-objective resilience-economic stochastic scheduling method for microgrid," *Int. J. Electr. Power Energy Syst.*, vol. 131, p. 106974, 2021.

[5] K. Khalili, I. Pourkeivani, and M. Abedi, "Micro-grids resilience enhancement using self-healing capability," in *2019 Int. Power Syst. Conf.*, pp. 750–756, IEEE, 2019.

[6] S. Moradi, G. Zizzo, S. Favuzza, and F. Massaro, "A stochastic approach for self-healing capability evaluation in active islanded ac/dc hybrid microgrids," *Sustainable Energy Grids Networks*, vol. 33, p. 100982, 2023.

[7] Y. Koraz and A. Gabbar, "Risk analysis and self-healing approach for resilient interconnect micro energy grids," *Sustainable Cities Soc.*, vol. 32, pp. 638–653, 2017.

[8] X. Chen and Y. Li, "A nondestructive islanding detection method based on adaptive and periodic disturbance on reactive power output of inverter-based distributed generation," *J. Appl. Math.*, vol. 2014, no. 1, p. 132348, 2014.

[9] H. Chen and J. Ye, "An improved active phase-shift islanding detection method based on fuzzy adaptive pid algorithm," *Int. J. Power Energy Syst.*, vol. 43, no. 10, 2023.

[10] E. J. Estébanez, V. M. Moreno, A. Pigazo, M. Liserre, and A. Dell'Aquila, "Performance evaluation of active islanding-detection algorithms in distributed-generation photovoltaic systems: Two inverters case," *IEEE Trans. Ind. Electron.*, vol. 58, no. 4, pp. 1185–1193, 2010.

[11] N. Khosravi, M. Dowlatabadi, and K. Sabzevari, "A hierarchical deep learning approach to optimizing voltage and frequency control in networked microgrid systems," *Appl. Energy*, vol. 377, p. 124313, 2025.

[12] R. Kumari and B. K. Naick, "Enhancing protection in ac microgrids: An adaptive approach with ann and anfis models," *Comput. Electr. Eng.*, vol. 115, p. 109103, 2024.

[13] O. Akbulut, M. Cavus, M. Cengiz, A. Allahham, D. Giaouris, and M. Forshaw, "Hybrid intelligent control system for adaptive microgrid optimization: Integration of rule-based control and deep learning techniques," *Energies*, vol. 17, no. 10, p. 2260, 2024.

[14] S.-R. Yan, W. Guo, A. Mohammadzadeh, and S. Rathinasamy, "Optimal deep learning control for modernized microgrids," *Appl. Intell.*, vol. 53, no. 12, pp. 15638–15655, 2023.

[15] M. Zaben, M. Y. Worku, M. A. Hassan, and M. A. Abido, "Machine learning methods for fault diagnosis in ac microgrids: A systematic review," *IEEE Access*, 2024.

[16] A. Jaiswal, S. Chandra, A. Priyadarshi, S. Sachan, and S. Deb, "Reinforcement learning based islanding detection technique in distributed generation," *Energy Rep.*, vol. 9, pp. 6006–6019, 2023.

[17] R. Aazami, M. Shoaei, A. Moradkhani, M. Shirkhani, A. ELrashidi, and K. M. AboRas, "Deep neural networks based method to islanding detection for multi-sources microgrid," *Energy Rep.*, vol. 11, pp. 2971–2982, 2024.

[18] W. Ali, A. Ulasyar, M. U. Mehmood, A. Khattak, K. Imran, H. S. Zad, and S. Nisar, "Hierarchical control of microgrid using iot and machine learning based islanding detection," *IEEE Access*, vol. 9, pp. 103019–103031, 2021.

[19] W. Sun, S. Ma, I. Alvarez-Fernandez, R. Roofegari nejad, and A. Golshani, "Optimal self-healing strategy for microgrid islanding," *IET Smart Grid*, vol. 1, no. 4, pp. 143–150, 2018.

[20] S. Talari, M. R. Haghifam, and A. Akhavein, "Optimization of the microgrid scheduling with considering contingencies in an uncertainty environment," 2013.

[21] Z. Wang and J. Wang, "Self-healing resilient distribution systems based on sectionalization into microgrids," *IEEE Trans. Power Syst.*, vol. 30, no. 6, pp. 3139–3149, 2015.

[22] M. N. Ambia, K. Meng, W. Xiao, and Z. Y. Dong, "Nested formation approach for networked microgrid self-healing in islanded mode," *IEEE Trans. Power Delivery*, vol. 36, no. 1, pp. 452–464, 2020.

[23] N. Afsari, S. SeyedShenava, and H. Shayeghi, "A milp model incorporated with the risk management tool for self-healing oriented service restoration," *J. Oper. Autom. Power Eng.*, vol. 12, no. 1, pp. 1–13, 2024.

[24] N. Kumar, S. Dahiya, and K. Singh Parmar, "Multi-objective economic emission dispatch optimization strategy considering battery energy storage system in islanded microgrid," *J. Oper. Autom. Power Eng.*, vol. 12, no. 4, pp. 296–311, 2024.

[25] I. Sepehrirad, R. Ebrahimi, E. Alibeiki, and S. Ranjbar, "Thevenin impedance concept for fast detection of microgrid islanding scenarios in the presence of small synchronous generators," *J. Oper. Autom. Power Eng.*, vol. 12, no. 2, pp. 91–106, 2024.

[26] O. A. Allan and W. G. Morsi, "A new passive islanding detection approach using wavelets and deep learning for grid-connected photovoltaic systems," *Electr. Power Syst. Res.*, vol. 199, p. 107437, 2021.

[27] binod ghimire, "Islanding detection in distributed generation." https://www.mathworks.com/matlabcentral/fileexchange/62672-islanding-detection-in-distributed-generation. Accessed: 2025-01-19.

[28] K. Khalili, I. Pourkeivani, and M. Abedi, "Micro-grids resilience enhancement using self-healing capability," in *2019 Int. Power Syst. Conf.*, pp. 750–756, IEEE, 2019.

[29] N. Malwar, S. Kadwane, and R. Somalwar, "Review on study of active islanding detection technique in distributed generation for microgrids," in *AIP Conf. Proc.*, vol. 3188, AIP Publishing, 2024.