Adaptive Microgrid Architecture to Manage System Resiliency

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***Abstract*— In light of the growing risks posed by high-impact, low-frequency events (such as those driven by climate change and other emerging hazards) utilities are increasingly deploying Distributed Energy Resources (DER), both utility- and customer-owned, to enhance grid reliability. These assets play a vital role in addressing system constraints during peak demand (thermal and voltage), mitigating power outage impacts, and improving overall resilience by supporting the formation of microgrids when distribution grid integrity is compromised. Yet, microgrid deployment presents its own technical challenges, particularly in coordinating the DERs involved. Critical functions such as grid separation (islanding), black start procedures, operational control, and eventual grid reconnection, must be executed with precision to ensure system stability. Poor coordination can exacerbate existing grid disturbances, extend recovery timeframes, and ultimately undermine the very resilience the microgrid is intended to deliver. To address these challenges, this paper proposes a microgrid architecture anchored by three resilience-enhancing pillars: (1) robust protection and power quality, (2) high-speed, reliable communication infrastructure, and (3) Machine Learning (ML) driven control and management. Each pillar is introduced through its operational goals and technical contributions, followed by a test case illustrating the integrated architecture in action.**

Keywords—Adaptive control; machine learning; microgrid; robust control; power system resilience.

I. INTRODUCTION

The conversion of energy into electricity remains a cornerstone of societal advancement. As underscored by the Rockefeller Foundation [1], electricity is now a more pivotal driver of economic growth and global competitiveness than ever before. Even in developing regions, robust, secure, and reliable power systems are essential to economic stability and social progress.

This widespread dependence on electricity has spurred innovation and improved quality of life, but it also exposes the urgency of updating aging infrastructure. A modernized grid is key to ensuring resilient and consistent power delivery to both everyday consumers and critical facilities.

Since the earliest stages of electrification, the safety and reliability of power systems have been foundational concerns, particularly within transmission networks, given their central role in system performance [2], [3], [4]. Within distribution systems, however, safety, strategic planning, and system availability are equally vital, enabling the efficient transfer of power from high-voltage transmission to end users.

To evaluate the reliability of electric power systems, regulators and utilities employ service quality indicators; quantitative metrics designed to measure system performance [2]. In distribution networks, reliability assessments typically draw on infrastructure and equipment data to estimate outage restoration times. While such outages are generally short and frequent, they are accounted for in power system design. However, their cumulative impact over the course of a year can degrade service quality metrics, potentially triggering financial penalties to offset disruptions experienced by customers.

Beyond these routine disturbances, power delivery can be compromised by rare but severe events capable of causing extensive damage. The system's ability to recover from such high-impact failures defines its resilience [5], [6]. Though a universally accepted technical definition is still lacking, experts broadly agree that resilience is associated with low-probability, high-consequence disruptions [7].

The U.S. Department of Energy (DOE) has noted the lack of universally accepted metrics for assessing grid resilience. As a result, federal policy does not prescribe specific resilience standards for electric systems [8], [9]. Instead, resilience (defined by the grid's ability to adjust to evolving conditions and recover rapidly from disruptions) is treated as an integral aspect of the broader reliability framework.

Multiple factors affect the resilience of distribution systems, ranging from natural disasters to human-induced risks, such as cyber-attacks, labor shortages, and other societal dynamics. When resilience is diminished, the repercussions often extend beyond infrastructure damage, posing risks to vulnerable communities and broader societal functions.

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In response, utilities are increasingly integrating Distributed Energy Resources (DER), whether utility-owned or customer-owned, to improve grid reliability. These resources help mitigate system violations during periods of high demand (thermal and voltage), reduce the impact of power outages, and bolster resilience by enabling the formation of microgrids when the integrity of the distribution grid is disrupted [10].

However, forming a microgrid introduces its own set of challenges, primarily due to the need for precise coordination of the DER involved. Key activities (including islanding from the distribution grid, black start procedures, operational control, and reconnection) must be carefully managed to ensure stability. Poor coordination during these stages can exacerbate grid issues, prolong restoration efforts, and turn a potential solution for reliability and resilience into a source of additional disruption.

This paper proposes a microgrid architecture grounded in three key pillars of resilience: (1) robust protection and power quality, (2) fast and reliable communication infrastructure, and (3) Machine Learning (ML) based management for intelligent microgrid control. Each pillar is briefly examined through its objectives, culminating in a test case to demonstrate the proposed approach in practice. Section II describes the resilient microgrid architecture, Section III highlights a case study while Section IV concludes the paper and highlights future work.

II. Resilient Microgrid Architecture

As outlined earlier, the three foundational pillars of resilient microgrid architecture serve as a framework for the effective coordination of DER. These pillars encompass key technical recommendations designed to address the following operational challenges and performance objectives (illustrated in Fig. *1*):

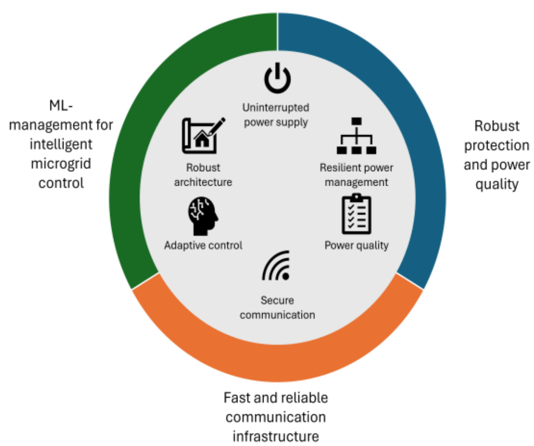

Fig. 1. Performance objectives of the resilient microgrid architecture.

- Uninterrupted Power Supply: Maintain service to controllable loads despite intermittent generation.
- Resilient Power Management: Leverage energy storage and dynamic load control to mitigate generation variability.
- Current Imbalance Minimization: Apply targeted techniques to preserve power quality across phases.
- Secure Communication: Ensure the integrity, reliability, and responsiveness of control signal transmission.
- Adaptive Control: Incorporate predictive control, anomaly detection, and optimization strategies to enhance operational intelligence.
- Robust System Architecture: Define the microgrid's structural design and its supporting communication network.

These performance objectives are described as follows.

A. *Uninterrupted power supply*

This goal of the resilient microgrid architecture is composed by the DER deployed within the microgrid. It includes:

- Intermittent DER such as solar Photovoltaic (PV), wind turbines.
- Energy storage systems, such as battery banks or buffer intermittent generation.

These energy resources, whether utility-owned or customer-owned, must be coordinated during microgrid formation to account for their availability and operational roles. This includes identifying devices that provide a grounding reference, such as Grid Forming Inverters (GFM), as well as supporting generation sources configured to follow the reference, such as Grid Following Inverters (GFL) [11], [12], [13].

The available DER capacity within the microgrid influences its charge and discharge cycles, as well as the operational usage rate while grid connected. This coordination supports preparation for potential islanding events. Additionally, DER capacity determines the microgrid's autonomy (defined by the number of hours it can supply energy independently) and governs the usage rate sustainable during island mode.

B. *Resilient power management*

In addition to DER, intelligent load-controlling devices play a key role in managing energy within a microgrid. Examples include smart thermostats, switches, and heat strips, controllable loads that the microgrid controller can leverage to reduce demand and extend the duration of available energy resources [14], [15]. See an illustration in Figure 2.

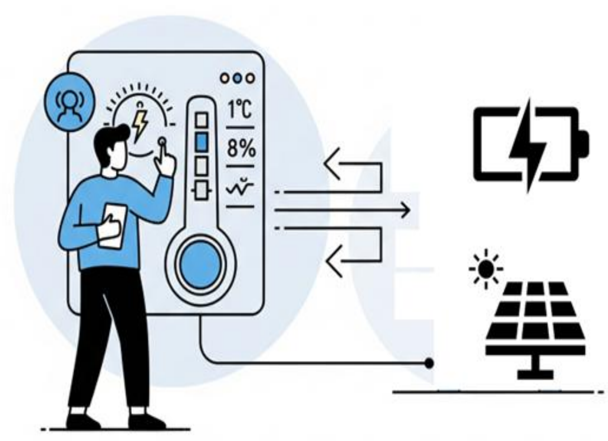

Fig. 2. Demand side management from within a microgrid.

This is especially relevant for energy storage systems, where discharge rates depend directly on the load profile. Coordinated adjustments (such as slightly lowering thermostat setpoints) can help batteries deliver additional service hours during periods without local generation, all while minimizing customer discomfort.

Traditionally, demand-side management has been used to help utilities mitigate system violations (thermal and voltage) while connected to the grid, often enabling deferral of large infrastructure investments. Within the context of microgrids, controllable loads offer an additional advantage: they transform demand into a dynamic energy management tool, enabling finer optimization of energy use and supporting resilient island-mode operation.

Power intermittency, stemming from the variability of available generation types, is a key consideration in microgrid power management. To maintain uninterrupted supply and improve system resilience, the following strategies can be implemented:

- Energy Storage Sizing: Leverage historical generation and load data to appropriate size Energy Storage Systems (ESS), ensuring coverage of worst-case generation deficits.
- Load Prioritization: Categorize controllable loads into tiers (critical, semi-critical, and non-critical) and implement load shedding for non-critical demands during supply shortfalls.
- Demand Response (DR): Dynamically adjust controllable loads to align with real-time generation availability.
- Together, these measures support optimized energy utilization within the microgrid, helping ensure reliable performance and extended autonomy during islanded operation.

Equation (1) serves as a reference point for assessing the microgrid's operational status by evaluating the current load relative to the available DER.

$$Pgen + Pdis(t) - Pch(t) = Pload(t) - Pshed(t) \quad (1)$$

Where:

Pgen(t): Power from renewable sources.
Pdis(t), Pch(t): Discharging and charging power of ESS.
Pload(t): Total load demand.
Pshed(t): Sheddable load (non-critical loads).

The ESS State of Charge (SOC) is updated as indicated in (2).

$$min \sum_{t=1}^{T} Pshed(t) \quad (2)$$

This is subject to the constraint of the ESS state of charge, SoC:

$$SoCmin \le SoC(t - 1) \le SoCmax \quad (3)$$

The objective of this equation is to minimize load shedding by maximizing the utilization of renewable generation.

C. *Current imbalance minimization*

Managing current imbalance is a critical operational objective within microgrids. It supports maintaining voltage levels within acceptable ranges, prevents conductor overload, and minimizes zero-sequence current; factors that, if left unaddressed, can contribute to system faults and compromised reliability [16], [17].

In a three-phase system, current imbalance can lead to voltage imbalance and equipment damage. Current imbalance is defined as the deviation from balanced three-phase currents. This impact can be calculated using the Current Imbalance Impact (CII) [18] shown at (3).

$$CII = \frac{|I_{max} - I_{avg}| + |I_{min} - I_{avg}|}{I_{avg}} * 100\% \quad (4)$$

Where Imax, Imin, Iavg are the maximum, minimum, and average of the three-phase currents.

A robust control strategy is essential for maintaining phase balance and minimizing disruptions within microgrid operations. This strategy begins with actionable interventions, such as applying phase swapping for single-phase loads where technically feasible and dynamically adjusting the operation of controllable loads across phases to correct imbalance. These approaches provide the groundwork for a more intelligent and responsive microgrid framework.

Building on this, the control strategy is formalized through an optimization problem aimed at minimizing CII. The optimization targets load-level power adjustments on each phase, governed by system-level constraints that ensure total power demand is met, either fully or within allowable shedding margins, and that device-specific constraints, such as minimum on/off durations, are respected.

By harmonizing device-level control with system-wide optimization, this framework supports both operational reliability and efficiency. It enables microgrids to handle variable demand profiles and DER with greater agility, paving the way for more resilient and adaptive energy ecosystems.

D. *Secure Communication*

Microgrid operation relies on uninterrupted, low-latency data exchange among controllers, sensors, DERs, and loads. Secure communication is crucial to ensure control commands, measurements, and system updates (as shown in Figure 3) are delivered accurately and promptly enabling essential functions such as voltage regulation, frequency control, and seamless islanding transitions,.

During island operation, microgrids must function independently, without assistance from the main grid. To maintain system integrity and extend autonomy, secure communication is essential. It enables seamless coordination among distributed assets such as energy storage systems, grid-forming inverters, and controllable loads.

Critical functionalities like demand response, load prioritization, and predictive dispatch rely on the accuracy and timeliness of real-time data. In the absence of secure communication, optimization algorithms may receive corrupted or delayed inputs, potentially leading to inefficiencies or operational faults. Far more than a background utility, secure communication serves as the microgrid's nervous system, empowering intelligent control, defending against emerging threats, and ensuring that distributed resources operate as an integrated, resilient whole [19].

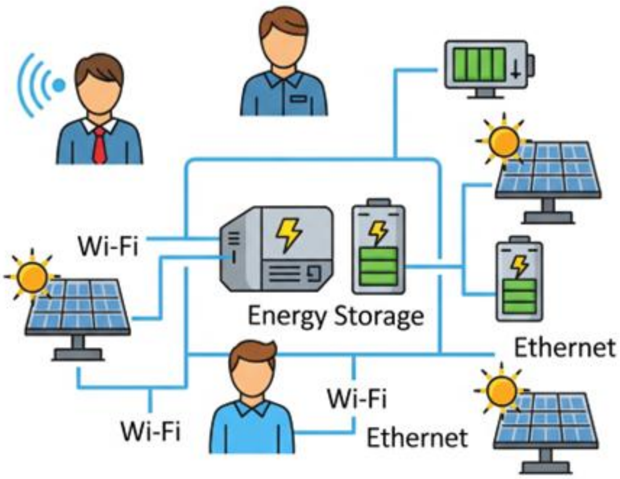

Fig. 3. Communication as the microgrid nervous system.

Recent advancements in Internet of Things (IoT) technologies have enabled the integration of heterogeneous devices and control strategies within microgrid architectures. To achieve the full functionality of the IoT, intelligent protocols/algorithms are needed for Device to Device (D2D) communications in the IoT [20]. In this work, a foundational communication framework to support interoperability, scalability, and security across diverse technologies is proposed.

The framework outlines a set of minimum requirements for communication infrastructure, including: confidentiality and data integrity, enforced through industry-standard encryption algorithms such as Advanced Encryption Standard (AES) -256 and secure transport protocols (e.g., (Datagram Transport Layer Security) [DTLS], (Transport Layer Security) [TLS]); device authentication, achieved via digital certificates or pre-shared keys; and low-latency communication, facilitated by Quality of Service (QoS) prioritization for control messages and edge computing for distributed decision-making. To enhance resilience against cyber threats, the architecture incorporates Intrusion Detection Systems (IDS) and network redundancy mechanisms.

Additionally, the proposed solution leverages a multilayered IoT communication stack, comprising: the application layer, employing lightweight messaging protocols, such as Message Queuing Telemetry Transport (MQTT) or Constrained Application Protocol (CoAP); the network layer, utilizing Internet Protocol version 6 (IPv6) with IPv6 over Low-Power Wireless Personal Area Networks (6LoWPAN) to enable efficient header compression and address allocation; and the link layer, based on low-power communication standards such as IEEE 802.15.4 or Low-Rank Adaptation (LoRa) to support constrained and distributed environments. Collectively, these components establish a secure, responsive, and extensible communication backbone suited for next generation microgrid systems [21], [22], [23], [24], [25], [26].

E. *Adaptive control and Robust architecture*

Microgrids function in highly dynamic environments where variables such as solar irradiance, wind conditions, load profiles, and grid connectivity can change rapidly. To sustain optimal system performance, adaptive control mechanisms adjust control parameters in real time, eliminating the need for predefined system models.

This approach enhances voltage and frequency regulation, particularly during critical transitions between grid-tied and islanded operation. A key example is adaptive droop control, which achieves more balanced current sharing and improved bus voltage stability compared to static control schemes [19].

Unlike conventional controllers that depend on accurate, fixed system representations, adaptive control accommodates incomplete or fluctuating system data, making it especially effective in settings with plug-and-play DERs or continuously evolving network topologies.

This work suggests that a suite of Machine Learning (ML) techniques can be designed to enhance microgrid intelligence across forecasting, control, protection, and cybersecurity domains.

Generation and Load Forecasting leverages Long Short-Term Memory (LSTM) networks to predict renewable energy generation and load demand. The models use inputs such as weather data, historical generation and consumption patterns, and temporal factors (e.g., time of day) to improve forecasting accuracy and enable more informed operational decisions.

Optimal Power Dispatch is approached through Reinforcement Learning (RL), where a trained agent optimizes Energy Storage System (ESS) charging and discharging, along with load control actions, to minimize costs and load shedding. The agent observes system states, including State of Charge (SOC), current generation, load, and time; and executes actions involving ESS power and load control signals. The reward function penalizes a combination of shedding cost, power imbalance, and ESS degradation, driving the agent toward efficient and resilient dispatch strategies.

To ensure timely fault mitigation, a Fast Protection System is also suggested to enhance response speed and reduce system vulnerability to electrical disturbances or equipment failures.

For phase balancing, clustering algorithms such as k-means are used to group loads with similar demand patterns and strategically assign them across phases to improve balance. Reinforcement Learning can also be deployed to enable real-time phase switching decisions, allowing adaptive control based on evolving operational conditions.

Finally, Anomaly Detection in Communication can be addressed using unsupervised learning methods like autoencoders or isolation forests. These algorithms identify abnormal traffic patterns that may indicate cyber-attacks or system faults, enhancing the microgrid's security posture and operational reliability.

III. CASE STUDY AND ANALYSIS

This section presents a simple test case based on the IEEE 8500 node test system where a microgrid is formed. In this microgrid, there are 50 residential customers (2.5 kW nominal each, power factor 0.95 – summer load assumed) plus an commercial customer (50 kVA, power factor 0.9). In this microgrid, the residential customers have rooftop solar panels installed. Their installations vary between 1.5 (60% of customers) and 3 kW (40% customers), allowing customers to supply their own demand and some of them being able to deliver a few kW to the grid.

The commercial customer is supported by its own installation of rooftop solar (100 kW) and a battery energy storage systems with a capacity of 2 MWh with an interfacing inverter of 250 kVA. The system schematic is shown in Figure 4.

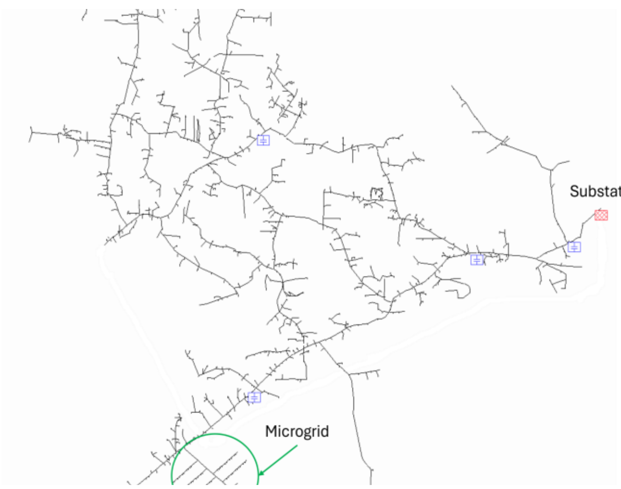

Fig. 4. IEEE 8500 nodes test system including microgrid.

After an outage event, the microgrid separates from the grid through the recloser installed at the edge of the microgrid. Once this occurs, the adaptive control determines the SoC of the Battery Energy Storage System (BESS) installed at the commercial customer. Simultaneously, it disconnects all the solar PV delivering power to the microgrid.

Once the microgrid is OFF, the adaptive algorithm based on the SoC uses the BESS as GFM for referencing the microgrid. Once the BESS inverter is connected in GFM configuration the black start operation begins, as shown in Figure 5. The voltage increase at the BESS point of connection, as shown in Figure 5.

During the initial 60 milliseconds of operation, photovoltaic (PV) systems remain intentionally disconnected, allowing system voltage to stabilize within acceptable limits. This delay is essential for enabling Grid Following (GFL) devices to synchronize with the GFM inverters, thereby preventing faults or voltage oscillations that could compromise microgrid stability.

The current profile at the BESS is illustrated in Figure 6, highlighting a reduction in delivered current as GFL devices (solar PV systems) begin to contribute power to the microgrid. This interaction supports the overall demand and effectively extends the operational capacity of the BESS. The coordination between GFM and GFL components is managed by the adaptive control system, ensuring seamless integration and balanced power sharing.

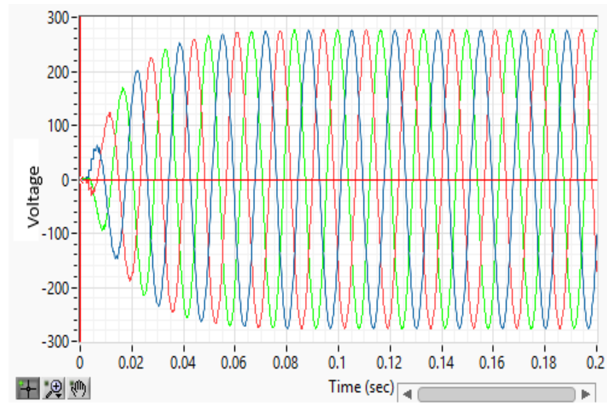

Fig. 5. Voltage during black start led by BESS.

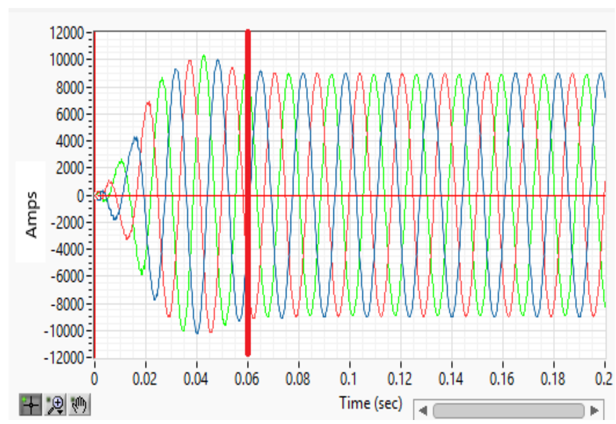

Fig. 6. BESS current during the power restoration.

IV. CONCLUSION AND FUTURE WORK

This paper presented a microgrid architecture anchored by three resilience-enhancing pillars: (1) robust protection and power quality, (2) high-speed, reliable communication infrastructure, and (3) Machine Learning (ML)-driven control and management. Each pillar was introduced through its operational goals and technical contributions. A simulated test case illustrating the benefits of the proposed framework was briefly presented, highlighting the energy interactions occurring during the microgrid islanding and later black start.

The Future work will entail quantitative results on D2D Quality of Supply (QoS), using formal optimization models to ensure chance-constrained guarantees in the network. Other goals, such as current imbalance, secure communications will be discussed in further publications.

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