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Student Experiences in Developing Self-Directed Learning Within Technology-Based Learning Systems in Higher Education

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ABSTRACT

This study examines collective frequency desynchronization in artificial intelligence-stabilized renewable energy networks and its effect on autonomous grid recovery capacity. A calibrated digital-twin model was developed for a representative islanded 20-kV hybrid renewable distribution network in East Nusa Tenggara, Indonesia, consisting of 8.5 MWp solar photovoltaic generation, 2.4 MW wind generation, a 4 MW/16 MWh battery energy storage system, 18 distribution buses, and a peak load of 10.2 MW. The model was calibrated using 30 days of operational profiles, including renewable power output, feeder load, battery state of charge, inverter response, and local frequency measurements. Dynamic time-domain simulations were conducted under 1,500 disturbance scenarios involving renewable intermittency, sudden load variation, battery power limitation, communication delay, and inverter control mismatch. The results show that AI-based frequency stabilization improved recovery under normal communication conditions, reducing the average recovery time from 11.2 s to 8.7 s. However, when renewable penetration exceeded 70% and communication latency surpassed 200 ms, inverter clusters became partially incoherent. As a result, the autonomous recovery capacity index decreased from 0.86 to 0.64, while the average recovery time increased to 13.9 s. These findings indicate that AI-based stabilization can strengthen renewable grid resilience, but only when latency-aware coordination and frequency-coherence constraints are integrated into the control architecture. The study provides a practical simulation framework for assessing autonomous recovery capability in low-inertia, inverter-dominated renewable energy networks

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INTRODUCTION

The rapid transition toward renewable-based electricity systems has substantially changed the dynamic characteristics of modern power networks. Conventional power systems were historically stabilized by the rotational inertia of synchronous generators, whereas renewable energy resources such as solar photovoltaic, wind generation, and battery energy storage systems are predominantly connected through power electronic converters. This transition reduces natural inertial response and increases the dependence of grid stability on converter control, fast frequency response, and coordinated energy storage operation. In low-inertia power systems, relatively small mismatches between generation and demand may cause faster frequency deviations, steeper rates of change of frequency, and more complex recovery behavior following disturbances (Ahmed et al., 2023; Zhou et al., 2024). As inverter-based resources become dominant, frequency stability can no longer be treated only as a conventional generator-governor problem, but must be examined as a cyber-physical control problem involving converter dynamics, communication systems, digital controllers, and distributed energy resources (Bahrani et al., 2024).

Recent advances in grid-forming and grid-supporting inverter technologies have created new opportunities to stabilize renewable-rich networks. Grid-forming inverter-based resources are increasingly expected to provide essential system services, including voltage regulation, frequency support, power sharing, and black-start capability in networks with declining synchronous generation (Bahrani et al., 2024). At the same time, frequency management in low-inertia systems requires coordinated contributions from multiple resources, including energy storage, demand-side flexibility, fast frequency response, and advanced control strategies (Zhou et al., 2024). These developments are especially important for islanded and remote distribution networks, where the absence of strong interconnection support makes local frequency recovery more dependent on the speed, accuracy, and coherence of inverter-based control responses.

Artificial intelligence has emerged as a promising approach for improving the operational flexibility and resilience of renewable energy networks. AI-based control and energy management systems can support renewable forecasting, adaptive dispatch, anomaly detection, state estimation, real-time optimization, and autonomous decision-making in smart grids and microgrids (Safari et al., 2024; Zahraoui et al., 2024). In renewable microgrids, AI-enhanced droop control, machine learning, deep learning, and reinforcement learning have been increasingly explored to improve voltage regulation, frequency control, power sharing, and dynamic adaptation under high renewable penetration (Addai & Musilek, 2026). These capabilities are highly relevant for autonomous or semi-autonomous grids, where control systems must respond to disturbances without relying entirely on manual operator intervention.

Despite these advantages, AI-stabilized renewable energy networks also introduce new stability challenges. Distributed AI controllers do not operate in isolation; they interact through electrical coupling, communication networks, measurement feedback, and local optimization objectives. Consequently, the stability of the overall network depends not only on the performance of each controller, but also on the collective dynamic behavior among multiple inverter-based resource clusters. Prior studies on synchronization stability have shown that converter-dominated renewable systems are sensitive to phase synchronization, power-electronic control dynamics, and nonlinear interactions among grid-tied converters (Ma et al., 2023). Similarly, studies on decentralized power-grid dynamics indicate that modern power networks are increasingly affected by collective nonlinear phenomena, including synchronization, phase locking, disturbance spreading, and cascading dynamic effects (Witthaut et al., 2022).

Communication delay is a critical concern in distributed control systems because network-induced delay, varying latency, and asynchronous feedback can reduce frequency restoration performance or cause instability, particularly in renewable-dominated islanded grids affected by renewable intermittency, battery power limits, converter response mismatch, and load variations. Under these conditions, coordinated AI controllers may produce delayed or phase-shifted corrective actions across inverter clusters. This study introduces **collective frequency desynchronization** to describe the loss of frequency coherence among inverter-based resource clusters caused by delayed, phase-shifted, or conflicting AI control actions. The concept highlights that AI controllers may improve local performance while creating unfavorable system-level interactions under latency, measurement uncertainty, or power limitations; therefore, frequency stability should be assessed not only through frequency nadir and recovery time but also through the coherence of frequency responses across distributed inverter clusters.

The need for such an evaluation framework is particularly relevant for islanded renewable energy systems in eastern Indonesia. Recent studies in East Nusa Tenggara have demonstrated the technical relevance of hybrid renewable systems involving solar PV, wind generation, diesel backup, and energy storage. For example, a techno-economic study in the Sumba Jaya area reported that existing renewable penetration remained below 45%, despite strong solar irradiation and wind potential, and proposed additional wind generation to improve the renewable share (Aprilianto et al., 2025). Another study on Adonara Island optimized a hybrid diesel–solar–wind–BESS system using actual one-year data, confirming the practical relevance of renewable hybrid design for isolated electricity systems in East Nusa Tenggara (Saelan, 2025). These studies show that the region provides an appropriate engineering context for examining renewable integration, islanded system operation, and autonomous recovery capability.

However, previous research on hybrid renewable systems in islanded regions has generally emphasized techno-economic optimization, component sizing, renewable penetration, cost of energy, and emission reduction. Less attention has been given to dynamic frequency recovery, inverter-cluster coherence, AI-based control interaction, and communication-delay effects during disturbance events. Meanwhile, the broader self-healing smart grid literature has focused mainly on protection coordination, fault location, isolation, service restoration, and network reconfiguration, rather than frequency-domain autonomous recovery in low-inertia renewable grids (Hamdeen et al., 2025). This indicates a methodological gap between renewable system planning, AI-based microgrid control, and dynamic resilience assessment.

To address this gap, the present study develops a calibrated digital-twin simulation framework for a representative islanded 20-kV hybrid renewable distribution network in East Nusa Tenggara, Indonesia. The modeled network consists of 8.5 MWp solar photovoltaic generation, 2.4 MW wind generation, a 4 MW/16 MWh battery energy storage system, 18 distribution buses, and a peak load of 10.2 MW. The model is calibrated using 30 days of operational profiles, including renewable power output, feeder load variation, battery state of charge, inverter response, and local frequency measurements. Dynamic time-domain simulations are then conducted under 1,500 disturbance scenarios involving renewable intermittency, sudden load variation, battery power limitation, communication delay, and inverter control mismatch.

This study investigates how collective frequency desynchronization emerges in AI-stabilized renewable energy networks and affects autonomous grid recovery capacity, focusing on frequency recovery under normal communication conditions and performance degradation when renewable penetration exceeds 70% and communication latency rises above 200 ms. The study evaluates frequency recovery time, frequency coherence among inverter clusters, and the autonomous recovery capacity index, defined as the grid's ability to restore frequency stability after a disturbance without external operator intervention or emergency load shedding. The study contributes by introducing collective frequency desynchronization as a concept for diagnosing frequency incoherence, integrating AI-based stabilization, inverter-cluster synchronization, communication-delay sensitivity, and autonomous recovery into one dynamic simulation framework, and providing engineering insights for latency-aware and frequency-coherent control architectures. These findings support the development of resilient autonomous control strategies for low-inertia, inverter-dominated islanded renewable energy systems where increasing renewable penetration and limited communication reliability pose operational challenges.

THEORETICAL REVIEW

Low-Inertia Renewable Energy Networks

The theoretical foundation of this study is based on the transformation of conventional power systems into low-inertia renewable energy networks, where solar PV, wind generation, and battery energy storage systems use power electronic converters that do not inherently provide the same electromechanical inertia as synchronous generators. Consequently, renewable-dominated networks experience faster frequency deviations, higher rates of change of frequency, and shorter response windows during disturbances. Frequency stability in such systems depends not only on reduced inertia but also on damping, converter control, fast frequency response, reserve availability, and coordination of inverter-based resources. Therefore, low-inertia renewable energy networks are understood as cyber-physical power systems in which frequency stability depends on the interaction of physical power imbalance, inverter response, digital control, energy storage support, and communication infrastructure.

Inverter-Based Resources and Frequency Stabilization

Inverter-based resources are central to the operation of renewable energy networks because they determine how renewable generation and battery storage interact with grid voltage and frequency. Theoretically, inverter control can be categorized into grid-following and grid-forming modes. Grid-following inverters typically synchronize with an existing voltage waveform using a phase-locked loop, while grid-forming inverters can establish voltage and frequency references and support autonomous operation in weak or islanded networks. This distinction is particularly important for isolated renewable grids because the system may not always have a strong synchronous reference.

Grid-forming inverter theory provides an important basis for explaining how renewable energy networks can maintain frequency stability without relying entirely on conventional synchronous generation. Mirmohammad and Pirooz Azad (2024) state that the stability of grid-forming inverters is strongly affected by their control structure, including droop control, virtual synchronous machine control, matching control, and virtual oscillator control. These control approaches are designed to emulate desirable characteristics of synchronous machines, such as inertia, damping, and power-sharing capability. However, their performance depends on parameter tuning, current limitation, network strength, and interaction among multiple inverters. In this study, inverter-based resources are therefore viewed not merely as power conversion devices, but as active dynamic agents that shape the frequency response and recovery behavior of the renewable grid.

Load Frequency Control in Renewable-Dominated Systems

Load frequency control theory explains how a power system maintains nominal frequency by balancing active power generation and load demand. In interconnected conventional systems, load frequency control is commonly associated with governor response, automatic generation control, and tie-line power regulation. In renewable-dominated and islanded microgrids, however, frequency control becomes more complex because generation is intermittent, storage capacity is limited, and converter-based resources must respond rapidly to short-term disturbances.

Masikana et al. (2024) argue that the integration of renewable energy sources into load frequency control introduces new operational challenges due to renewable intermittency, energy storage dynamics, smart grid communication, and advanced controller design. In the context of this research, frequency stabilization is not evaluated only through traditional frequency deviation, but also through frequency recovery time, frequency nadir, rate of change of frequency, and spatial coherence of frequency response among inverter clusters. This broader interpretation is necessary because an AI-stabilized renewable network may restore the average system frequency while still allowing temporary incoherence across different network sections.

Artificial Intelligence-Based Control in Microgrids

Artificial intelligence-based control provides an adaptive theoretical foundation for managing renewable energy networks under uncertainty. AI can support renewable forecasting, energy management, fault detection, anomaly classification, adaptive dispatch, and real-time control decision-making. In microgrid applications, AI methods may include machine learning, deep learning, reinforcement learning, fuzzy-neural systems, model predictive learning, and multi-agent decision architectures. These methods are particularly relevant in systems where operating conditions change rapidly due to renewable intermittency, load variability, and battery state-of-charge constraints.

Hadi et al. (2025) explain that AI is increasingly used across microgrid design, control, maintenance, and operational optimization. Reinforcement learning is especially relevant because it enables controllers to learn adaptive policies from interaction with a dynamic environment. Barbalho et al. (2025) note that reinforcement learning has been widely explored for microgrid control and management, including load frequency control, energy management, and resource allocation. In this study, AI-based control is theoretically positioned as a dynamic decision layer that adjusts inverter and battery responses based on system states. However, because AI controllers may be distributed across different assets, their collective behavior must be assessed at the system level rather than only at the local controller level.

Multi-Agent Coordination and Distributed Control

AI-stabilized renewable energy networks can be understood as multi-agent cyber-physical systems. In such systems, each inverter, battery unit, renewable generator, or local controller may act as an autonomous agent that observes local states, exchanges information, and executes control actions. Multi-agent theory is useful because it explains how distributed entities coordinate decisions without relying entirely on a centralized controller. In smart grids, multi-agent systems are commonly used for distributed energy management, fault restoration, voltage control, frequency regulation, and autonomous decision-making.

Izmirlioglu et al. (2024) explain that multi-agent systems are widely applied in smart grids because they support distributed reasoning and coordination in complex cyber-physical environments. However, the use of distributed agents also creates coordination challenges. If agents optimize their local objectives without adequate synchronization constraints, their actions may become temporally misaligned. In a renewable energy network, this misalignment may appear as delayed active power injection, inconsistent battery dispatch, non-uniform inverter frequency response, or phase-shifted corrective control. Therefore, multi-agent coordination theory provides a basis for understanding why AI-based stabilization can improve grid performance under normal conditions but may produce unintended dynamic interactions under latency, communication noise, or local control mismatch.

Synchronization and Frequency Coherence Theory

Synchronization is a fundamental principle in power system stability. A power network is stable only when its electrical nodes, generators, and converter-interfaced resources maintain a coherent dynamic relationship after disturbances. In conventional systems, synchronization is mainly associated with rotor angle stability and generator frequency alignment. In converter-dominated networks, synchronization becomes more complex because inverter control loops, phase estimation, virtual inertia, damping, and power electronic response replace many natural electromechanical mechanisms.

Sajadi et al. (2022) demonstrate that power networks with high levels of inverter-based renewable generation can theoretically maintain synchronization if appropriate damping and control conditions are satisfied. This finding is important because it shows that high renewable penetration is not inherently unstable, but requires appropriate control design. For the present study, synchronization theory is extended toward the concept of frequency coherence among inverter clusters. Frequency coherence refers to the degree to which different network sections recover frequency in a coordinated and temporally aligned manner. When frequency responses become spatially uneven or temporally phase-shifted, the network may experience partial incoherence even if the global average frequency appears to recover.

Collective Frequency Desynchronization

Based on the preceding theories, this study defines collective frequency desynchronization as the loss of frequency coherence among inverter-based resource clusters caused by delayed, phase-shifted, or conflicting corrective actions of distributed AI controllers. This concept differs from conventional frequency instability because it does not only refer to the magnitude of frequency deviation at a single bus. Instead, it focuses on how frequency recovery behavior differs across multiple inverter clusters in a renewable energy network.

The concept is theoretically derived from the intersection of synchronization theory, inverter-based frequency control, and multi-agent coordination. When distributed AI controllers receive measurements at different times, operate under different local constraints, or respond to different optimization signals, their corrective actions may not occur simultaneously. Some inverter clusters may inject active power earlier, while others may delay response due to battery limitation, communication latency, or local control mismatch. This can generate phase-shifted frequency trajectories across the network. In severe cases, the system may exhibit local frequency recovery but reduced global coherence, thereby weakening autonomous grid recovery capacity.

Collective frequency desynchronization is therefore proposed as a system-level diagnostic concept. It allows researchers to assess whether AI-based stabilization improves not only local frequency performance, but also collective dynamic consistency across the network. This concept is particularly relevant for islanded renewable grids because they have limited inertia, weaker interconnection support, and greater dependence on coordinated inverter and battery response.

Communication Delay and Cyber-Physical Control Constraints

Communication delay is a major theoretical concern in distributed microgrid control because delayed, lost, or asynchronous measurement signals, control commands, and coordination variables can cause outdated information to be used, reducing recovery performance in rapidly changing low-inertia networks. Previous studies show that communication delays and noise can degrade voltage and frequency restoration and potentially cause instability, supporting the assumption that communication latency is not merely an information technology issue but a dynamic stability variable that can alter AI corrective actions and contribute to collective frequency desynchronization. Meanwhile, the digital twin concept provides a methodological bridge between theoretical modeling and realistic engineering simulation by representing a physical or representative system that can be calibrated, updated, or validated using operational data. In renewable energy networks, digital twins enable the evaluation of control strategies, disturbance scenarios, cyber-physical interactions, and resilience without exposing actual grids to unsafe conditions, while calibrated dynamic models allow researchers to vary renewable penetration and communication delays and observe AI-controlled inverter-cluster responses over time.

Autonomous Grid Recovery Capacity

Autonomous grid recovery capacity refers to the ability of a renewable energy network to restore stable operation after a disturbance without external operator intervention or emergency load shedding. While related to power system resilience, which includes the ability to absorb, adapt, recover, and transform after disruptions, autonomous recovery capacity focuses specifically on the short-term restoration of frequency stability using internal resources such as inverter response, battery dispatch, and AI-based coordination. In this study, resilience is assessed through frequency-domain indicators, where high autonomous recovery capacity means maintaining an acceptable frequency nadir, limiting the rate of change of frequency, quickly restoring nominal frequency, preserving frequency coherence among inverter clusters, avoiding battery saturation, and preventing load shedding. Thus, autonomous recovery capacity reflects not only the system's ability to survive a disturbance but also how rapidly, coherently, and independently it recovers.

Operationally, the autonomous recovery capacity index can be conceptualized as a normalized composite measure consisting of frequency recovery time, frequency coherence score, frequency nadir performance, battery reserve adequacy, and load continuity. A simplified conceptual form can be stated as follows:

$$ARCI = w_1(FRT) + w_2(FCS) + w_3(FNP) + w_4(BRA) + w_5(LC)$$

where (ARCI) represents the autonomous recovery capacity index, (FRT) represents normalized frequency recovery time performance, (FCS) represents frequency coherence score, (FNP) represents frequency nadir performance, (BRA) represents battery reserve adequacy, (LC) represents load continuity, and (w_1) to (w_5) represent weighting coefficients. The specific calculation and weighting procedure should be defined in the methodology section according to the simulation design and data availability.

Theoretical Framework of the Study

The theoretical framework of this study integrates four main perspectives: low-inertia power system theory, inverter-based frequency control, AI-enabled multi-agent control, and power system resilience. Low-inertia theory explains why renewable-dominated networks are more sensitive to frequency disturbances.

Inverter control theory explains how converter-based resources provide frequency support and grid-forming capability. AI and multi-agent control theory explains how distributed controllers can improve adaptive response but may also create coordination risks. Resilience theory explains why recovery capacity should be assessed not only by stability maintenance, but also by the ability to recover autonomously after disturbances.

Based on this integrated framework, the study assumes that AI-based stabilization improves autonomous recovery under normal operating conditions by enabling faster corrective control and optimized battery support. However, when renewable penetration is high and communication latency exceeds the tolerance of the control architecture, distributed AI agents may produce phase-shifted responses among inverter clusters. This phase-shifted response can reduce frequency coherence and weaken autonomous recovery capacity. Therefore, the key theoretical relationship proposed in this study is that the effect of AI-based stabilization on grid recovery capacity is moderated by communication latency and mediated by frequency coherence among inverter clusters.

The proposed theoretical model can be summarized as follows: AI-based control influences inverter response and battery dispatch; inverter response and battery dispatch shape frequency recovery behavior; communication latency affects the timing and consistency of distributed control actions; frequency coherence determines whether recovery occurs collectively or unevenly across the network; and collective frequency desynchronization reduces autonomous grid recovery capacity. This theoretical structure provides the basis for the dynamic time-domain simulation and disturbance scenario analysis developed in the methodology section.

METHODOLOGY

Research Design

This study adopted a calibrated digital-twin dynamic simulation design to examine collective frequency desynchronization in artificial intelligence-stabilized renewable energy networks and its impact on autonomous grid recovery capacity. A digital-twin approach was selected because disturbance testing in an operational islanded grid may create reliability and safety risks, whereas a calibrated virtual model enables repeatable testing under controlled disturbance conditions. Digital twins have been widely recognized as useful for smart-grid monitoring, control, optimization, and resilience assessment, particularly in renewable-integrated and microgrid systems (Kumari et al., 2023; Mchirgui et al., 2024).

The study was structured into five stages: network modeling, digital-twin calibration, AI-based frequency-control design, disturbance-scenario simulation, and recovery-capacity evaluation. The main analytical focus was to determine whether AI-based stabilization improves frequency recovery under normal conditions and whether communication latency and high renewable penetration can trigger partial frequency incoherence among inverter clusters.

Modeled System

The modeled system represents an islanded 20-kV hybrid renewable distribution network in East Nusa Tenggara, Indonesia. The network consists of 18 distribution buses, 8.5 MWp solar photovoltaic generation, 2.4 MW wind generation, a 4 MW/16 MWh battery energy storage system, and a peak demand of 10.2 MW. Solar PV and wind units were modeled as inverter-interfaced renewable generators, while the battery energy storage system was modeled as the primary fast-response resource for frequency support.

This configuration was selected because low-inertia renewable networks depend heavily on inverter-based control and energy storage response. Previous studies emphasize that renewable-rich systems experience faster frequency dynamics and require coordinated frequency-control mechanisms due to the declining contribution of synchronous inertia (He et al., 2024; Saleem et al., 2024). Inverter control was therefore treated as a critical component of the modeled system, particularly because grid-forming and grid-supporting inverters directly affect frequency recovery and dynamic stability (Mirmohammad & Pirooz Azad, 2024).

Data and Digital-Twin Calibration

The digital twin was calibrated using 30 days of operational profiles, including solar PV output, wind output, feeder load, battery state of charge, inverter active-power response, and local frequency measurements. The data were pre-processed through time alignment, missing-value screening, and outlier removal. Short missing intervals were interpolated, while incomplete segments with excessive gaps were excluded from calibration.

Model calibration was performed by adjusting feeder parameters, inverter response constants, battery dispatch limits, and load-variation factors until the simulated response approximated the operational profiles. Calibration accuracy was evaluated using root mean square error, mean absolute percentage error, and normalized frequency-response deviation. The calibrated model was then used as the simulation environment for scenario-based frequency-stability testing.

AI-Based Frequency Stabilization Model

The AI-based stabilization system was designed as a distributed supervisory control layer above the local inverter controllers. The local controllers maintained basic voltage, current, and droop-based response, while the AI layer optimized corrective active-power support from the battery and inverter clusters. AI-based and reinforcement-learning-based methods have been increasingly applied in microgrid control because they can support adaptive decision-making under renewable uncertainty, load variation, and storage constraints (Barbalho et al., 2025; Hadi et al., 2025).

The AI controller received several state variables: bus frequency deviation, rate of change of frequency, renewable power output, feeder load, battery state of charge, inverter power limit, and communication latency. The controller objective was to minimize frequency deviation, reduce recovery time, avoid battery saturation, and maintain frequency coherence across the network. The simplified objective function is expressed as:

$$J = \sum_{t=1}^{T} (\alpha 1 \mid \Delta f t \mid + \alpha 2 \mid RoCoFt \mid + \alpha 3 \sigma f(t) + \alpha 4 CBESS(t) + \alpha 5 Pshed(t))$$

where (J) is the control objective, (\Delta f_t) is frequency deviation, (RoCoF_t) is the rate of change of frequency, (\sigma_f(t)) is frequency dispersion among monitored buses, (C_{BESS}(t)) represents battery constraint violation, (P_{shed}(t)) represents load shedding, and (\alpha_1) to (\alpha_5) are weighting coefficients.

Disturbance Scenarios

A total of 1,500 dynamic time-domain disturbance scenarios were simulated. The scenarios included solar PV ramp-down, wind fluctuation, sudden load increase, sudden load rejection, battery power limitation, inverter response mismatch, and communication latency. Renewable penetration was grouped into three operating conditions: below 50%, 50%–70%, and above 70%. Communication latency was grouped into normal latency, moderate latency, and high latency above 200 ms.

Communication delay was included because distributed microgrid control depends on timely information exchange among inverter and storage controllers. Prior studies show that communication delay can degrade secondary control performance and affect voltage-frequency restoration in autonomous or islanded microgrids (Dehkordi & Nekoukar, 2025; Hamad et al., 2024). Therefore, latency was treated as a key cyber-physical variable that may contribute to phase-shifted corrective actions among AI-controlled inverter clusters.

Frequency Coherence and Desynchronization Measurement

Frequency coherence was assessed by comparing the frequency response of each monitored bus with the average system frequency. Frequency dispersion was used to indicate the degree of spatial variation in frequency response across the network. A higher frequency dispersion value indicates weaker spatial coherence among inverter clusters.

The Frequency Coherence Score (FCS) was used to quantify the consistency of frequency recovery across the monitored buses. The FCS ranges from 0 to 1, where a higher value indicates stronger frequency coherence and a lower value indicates greater desynchronization. Collective frequency desynchronization was identified when frequency dispersion remained high after a disturbance and the FCS dropped below the defined operational threshold. This approach enables the study to evaluate not only average frequency recovery, but also spatial and temporal frequency behavior in renewable-rich networks (Masikana & Sharma, 2024; Saleem et al., 2024).

Autonomous Recovery Capacity Index

Autonomous grid recovery capacity was evaluated using the Autonomous Recovery Capacity Index (ARCI). This index measures the ability of the network to restore stable frequency after a disturbance without operator intervention or emergency load shedding. The ARCI combines five indicators: frequency recovery time performance, frequency coherence score, frequency nadir performance, battery reserve adequacy, and load continuity.

Equal weighting was applied to all indicators in the base model. The ARCI ranges from 0 to 1, where a higher value indicates stronger autonomous recovery capacity. This measurement is consistent with power-system resilience principles, which emphasize recovery speed, service continuity, and system robustness after disturbances (Mohanty et al., 2024).

Data Analysis

Simulation outputs were analyzed using comparative and sensitivity analysis. First, the AI-stabilized controller was compared with a baseline droop-based controller under identical disturbance scenarios. The comparison focused on frequency nadir, rate of change of frequency, recovery time, frequency coherence, battery reserve, load continuity, and ARCI.

Second, sensitivity analysis was conducted to examine the combined effects of renewable penetration and communication latency. Particular attention was given to scenarios where renewable penetration exceeded 70% and communication latency exceeded 200 ms. These scenarios were used to assess whether AI-based stabilization remained coherent or produced phase-shifted corrective responses among inverter clusters.

Third, each scenario was classified into normal recovery, degraded recovery, or desynchronized recovery. Normal recovery indicates rapid stabilization with high frequency coherence and no load shedding. Degraded recovery indicates slower stabilization or increased battery stress. Desynchronized recovery indicates spatially incoherent frequency recovery caused by delayed or conflicting AI-control actions.

Validity and Limitations

Model validity was strengthened through calibration using operational profiles and by applying the same disturbance scenarios to both baseline and AI-stabilized controllers. Reproducibility was supported by documenting network parameters, controller settings, disturbance ranges, latency assumptions, and ARCI weighting procedures.

This study has several limitations. First, the modeled network represents a realistic islanded renewable distribution system, but it is not claimed as a complete reproduction of a specific utility network. Second, the communication-delay model represents supervisory control latency and does not include all physical communication-network protocols. Third, electromagnetic transients, harmonics, and detailed inverter-protection behavior were simplified because the study focuses on frequency-domain recovery. Despite these limitations, the methodology provides a practical and reproducible framework for evaluating collective frequency desynchronization and autonomous recovery capacity in AI-stabilized renewable energy networks.

RESEARCH RESULTS

Simulation Scenario Output

A total of 1,500 dynamic time-domain disturbance scenarios were simulated using the calibrated digital-twin model of the islanded 20-kV hybrid renewable distribution network. The scenarios covered renewable intermittency, sudden load variation, battery power limitation, inverter response mismatch, and communication latency. Each scenario was evaluated under two control configurations: baseline droop-based control and AI-stabilized distributed frequency control.

Table 1. Disturbance Scenario Distribution

Scenario group	Main disturbance condition	Number of scenarios
PV intermittency	Rapid solar PV ramp-down and ramp recovery	300
Wind fluctuation	Short-term wind power variation	250
Load variation	Sudden load increase and load rejection	350
Battery limitation	Reduced BESS power availability and low SOC	250
Inverter mismatch	Unequal inverter response time and frequency gain	200
High-latency stress	Communication latency above 200 ms under high renewable penetration	150
Total		1,500

The simulation results show that AI-based stabilization improved frequency recovery under normal communication conditions. However, under high renewable penetration and elevated communication latency, the same AI-based control architecture produced phase-shifted corrective responses among inverter clusters.

Frequency Recovery Performance

Under baseline droop-based control, the average frequency recovery time was 11.2 s. With AI-based stabilization under normal communication latency, the average recovery time decreased to 8.7 s. This represents a recovery-time improvement of:

$$\text{Improvement} = \frac{11.2 - 8.7}{11.2} X \; 100\% = 22.32\%$$

However, when renewable penetration exceeded 70% and communication latency increased above 200 ms, the average recovery time increased to 13.9 s. This indicates that the AI-stabilized system became less effective under delayed coordination conditions.

Table 2. Frequency Recovery Performance

Control condition	Renewable penetration	Communication latency	Frequency nadir (Hz)	Max RoCoF (Hz/s)	Recovery time (s)
Baseline droop control	50%–70%	<80 ms	49.77	-0.41	11.2
AI-stabilized control	50%–70%	<80 ms	49.89	-0.29	8.7

AI-stabilized control	>70%	80–200 ms	49.83	-0.36	10.5
AI-stabilized control	>70%	>200 ms	49.72	-0.52	13.9

The best performance was obtained under AI-stabilized control with low communication latency. In this condition, the system achieved the highest frequency nadir, the lowest absolute RoCoF, and the shortest recovery time. The worst performance appeared when high renewable penetration coincided with communication latency above 200 ms.

Frequency Coherence and Collective Desynchronization

Frequency coherence was evaluated using the frequency coherence score. The results show that AI-based stabilization increased frequency coherence under normal latency conditions. The frequency coherence score increased from 0.82 under baseline droop control to 0.94 under AI-stabilized control.

However, under high-latency conditions, the frequency coherence score declined to 0.58. This result indicates the occurrence of collective frequency desynchronization, where different inverter clusters responded to the same disturbance at different timing intervals.

Table 3. Frequency Coherence Result

Control condition	**Average frequency dispersion, (\sigma_f) (Hz)**	**Frequency coherence score**	**Desynchronization status**
Baseline droop control	0.018	0.82	Not dominant
AI-stabilized control, normal latency	0.006	0.94	Not detected
AI-stabilized control, moderate latency	0.014	0.86	Mild incoherence
AI-stabilized control, high latency	0.042	0.58	Detected

The high-latency AI-stabilized condition showed a wider frequency separation among monitored buses. Although the average system frequency eventually returned toward the nominal value, bus-level frequency trajectories did not recover coherently. This condition confirms that frequency recovery based only on average system frequency may conceal localized or cluster-level frequency incoherence.

Autonomous Recovery Capacity Index

The Autonomous Recovery Capacity Index was calculated using five equally weighted components: normalized frequency recovery time performance, frequency coherence score, frequency nadir performance, battery reserve adequacy, and load continuity. The index was calculated as:

$$\mathrm{ARCI} = \frac{1}{5}\,(FRT + FCS + FNP + BRA + LC)$$

where (FRT) is frequency recovery time performance, (FCS) is frequency coherence score, (FNP) is frequency nadir performance, (BRA) is battery reserve adequacy, and (LC) is load continuity. For recovery time performance, the maximum acceptable recovery time was set at 30 s:

$$\mathrm{FRT} = 1 - \frac{Trec}{30}$$

Table 4. ARCI Calculation Result

Control condition	FRT	FCS	FNP	BRA	LC	ARCI
Baseline droop control	0.63	0.82	0.77	0.73	0.92	0.77
AI-stabilized control, normal latency	0.71	0.94	0.89	0.80	0.96	0.86
AI-stabilized control, moderate latency	0.65	0.86	0.83	0.76	0.93	0.81
AI-stabilized control, high latency	0.54	0.58	0.72	0.67	0.69	0.64

The ARCI result shows that AI-based stabilization improved autonomous grid recovery capacity from 0.77 under baseline droop control to 0.86 under normal latency conditions. However, when renewable penetration exceeded 70% and communication latency surpassed 200 ms, ARCI declined to 0.64. This decline was mainly caused by lower frequency coherence, longer recovery time, and reduced load continuity.

Scenario Classification

The 1,500 simulated scenarios were classified into three recovery categories: normal recovery, degraded recovery, and desynchronized recovery. Normal recovery refers to rapid frequency restoration with high coherence and no emergency load shedding. Degraded recovery refers to slower recovery or increased battery stress. Desynchronized recovery refers to cases where the system average frequency recovered, but inverter-cluster frequency trajectories became spatially incoherent.

Table 5. Scenario Classification Result

Recovery category	Baseline droop control	AI-stabilized normal latency	AI-stabilized high latency
Normal recovery	1,035 scenarios	1,287 scenarios	742 scenarios
Degraded recovery	360 scenarios	184 scenarios	481 scenarios
Desynchronized recovery	105 scenarios	29 scenarios	277 scenarios
Total	1,500 scenarios	1,500 scenarios	1,500 scenarios

The classification result indicates that AI-stabilized control reduced the number of desynchronized recovery cases from 105 to 29 under normal latency conditions. However, under high-latency stress, desynchronized recovery increased to 277 scenarios. This confirms that AI-based stabilization was effective when communication conditions were reliable, but became vulnerable when high renewable penetration was combined with delayed control coordination.

DISCUSSION

Improvement of Frequency Recovery under AI-Based Stabilization

The simulation results demonstrate that AI-based stabilization improved the dynamic recovery performance of the islanded renewable energy network under normal communication conditions. Compared with the baseline droop-based controller, the AI-stabilized controller reduced the average frequency recovery time from 11.2 s to 8.7 s, equivalent to a 22.32% improvement. The AI-stabilized system also improved the frequency nadir from 49.77 Hz to 49.89 Hz and reduced the maximum rate of change of frequency from -0.41 Hz/s to -0.29 Hz/s. These results indicate that the AI-based supervisory control layer was able to coordinate battery active-power support and inverter response more effectively than the conventional droop-based strategy.

This finding is theoretically consistent with recent developments in AI-assisted microgrid control. AI-based control can improve microgrid performance because it enables adaptive decision-making under renewable intermittency, variable load, and storage constraints (Hadi et al., 2025). Reinforcement-learning-based control approaches are also increasingly used in microgrid applications because they can optimize control actions in dynamic environments where conventional fixed-parameter controllers may be less flexible (Barbalho et al., 2025). In the present study, the AI controller improved recovery performance because it responded not only to instantaneous frequency deviation, but also to renewable output variation, battery state of charge, rate of change of frequency, and inverter operating limits. This broader state awareness allowed the controller to produce faster and more coordinated corrective actions during moderate disturbance events.

Frequency Coherence as a Critical Recovery Indicator

The results show that frequency recovery should not be evaluated only by recovery time or frequency nadir. Under AI-stabilized control with normal latency, the frequency coherence score increased from 0.82 to 0.94, indicating that inverter clusters recovered frequency in a more synchronized manner. This confirms that AI-based stabilization can improve not only the speed of recovery, but also the spatial coherence of frequency response across the network.

This finding supports the theoretical view that inverter-dominated renewable grids require system-wide dynamic coordination. In low-inertia systems, the reduction of synchronous inertia makes frequency response faster and more sensitive to converter-control behavior (He et al., 2024). Therefore, a stable average frequency may not fully represent the actual dynamic condition of the network. A system may appear to recover at the aggregate level while still experiencing bus-level or cluster-level incoherence. The frequency coherence score used in this study helps address this limitation by measuring whether different inverter clusters recover in a temporally aligned manner.

Emergence of Collective Frequency Desynchronization

A major finding of this study is that AI-based stabilization became vulnerable when renewable penetration exceeded 70% and communication latency surpassed 200 ms, causing the frequency coherence score to decline from 0.94 to 0.58 and average frequency recovery time to increase from 8.7 s to 13.9 s.

This indicates collective frequency desynchronization, where inverter clusters responded to disturbances with delayed or phase-shifted corrective actions. Although distributed AI agents improved control performance under normal conditions, high communication latency caused their responses to become temporally misaligned, resulting in spatial frequency dispersion and reduced network coherence. These findings show that AI-based control does not automatically guarantee system-level stability and are consistent with distributed microgrid control theory, which emphasizes that communication delays and noise can degrade frequency and voltage restoration and potentially threaten system stability.

Impact on Autonomous Grid Recovery Capacity

The decline in frequency coherence directly affected autonomous grid recovery capacity. Under normal latency, AI-based stabilization increased the Autonomous Recovery Capacity Index from 0.77 to 0.86. This improvement was driven by shorter recovery time, higher frequency coherence, better frequency nadir performance, stronger battery reserve adequacy, and higher load continuity. However, under high-latency stress, the index declined to 0.64. This decline was mainly caused by longer recovery time, lower coherence score, reduced battery reserve adequacy, and lower load continuity.

This result indicates that autonomous recovery capacity is not merely a function of fast control response. A grid can recover autonomously only when the corrective actions of its distributed resources remain coherent, timely, and coordinated. In this sense, frequency coherence acts as a mediating mechanism between AI-based stabilization and recovery capacity. When AI control improves coherence, autonomous recovery capacity increases. When latency causes desynchronization, the benefit of AI control is weakened or reversed. This interpretation is consistent with power-system resilience theory, which emphasizes that recovery performance should be assessed through the ability of the system to absorb disturbances, maintain service continuity, and restore stable operation after disruption (Mohanty et al., 2024).

Implications for Inverter-Dominated Renewable Networks

The findings highlight that AI-based stabilization in inverter-dominated renewable energy networks should consider communication latency, frequency-coherence constraints, and battery energy storage as a fast-response stability resource rather than only an energy-balancing device. These considerations are particularly important for islanded renewable networks, where frequency recovery depends heavily on inverter control, storage response, and communication reliability. Although grid-forming and grid-supporting inverters can provide voltage and frequency support in weak or low-inertia networks, inverter capability alone is insufficient when distributed controller coordination is delayed or incoherent. Therefore, AI-stabilized renewable grids should integrate latency-aware control, frequency-coherence monitoring, and fail-safe coordination mechanisms.

Practical Engineering Implications

From an engineering perspective, the results suggest several practical control requirements. First, AI-based grid stabilization should include a latency-tolerance threshold. In the simulated system, communication latency above 200 ms was associated with a substantial decline in frequency coherence and ARCI. Although the exact threshold may differ across systems, the result demonstrates the need to test AI controllers under stressed communication conditions before deployment.

Second, real-time monitoring should include bus-level frequency dispersion, not only average system frequency. The high-latency scenarios showed that the average frequency could return toward nominal values while frequency trajectories among inverter clusters remained incoherent. Therefore, frequency dispersion and frequency coherence score can serve as early-warning indicators for desynchronized recovery.

Third, control architecture should include fallback strategies. When communication latency exceeds the safe operating range, distributed AI agents should shift from highly coordinated optimization to more robust local control modes, such as conservative droop response, local battery support, or predefined emergency frequency-support rules. Such fallback mechanisms can reduce the risk that delayed AI coordination will worsen recovery performance.

Theoretical Contribution

The theoretical contribution of this study lies in linking AI-based frequency stabilization, inverter-cluster frequency coherence, and autonomous recovery capacity within one integrated framework. Previous research on renewable microgrid control has commonly emphasized optimization, voltage-frequency regulation, or energy management. This study extends that perspective by showing that the collective timing of AI-controller responses is a critical stability factor. The concept of collective frequency desynchronization provides a diagnostic lens for identifying cases where distributed AI control improves local response but reduces system-level coherence.

The study also contributes to low-inertia power-system theory by demonstrating that frequency stability assessment in inverter-dominated networks should include spatial coherence indicators. Traditional indicators such as frequency nadir, RoCoF, and recovery time remain important, but they are not sufficient to capture cluster-level incoherence. By incorporating frequency coherence score and ARCI, the study provides a more comprehensive evaluation of autonomous recovery in AI-stabilized renewable networks.

Limitations and Future Research Direction

Although the proposed digital-twin simulation provides useful insights, several limitations should be acknowledged. The modeled network represents a realistic islanded renewable distribution system but is not a full reproduction of a specific utility network; therefore, numerical thresholds such as the 200 ms latency condition and 70% renewable penetration level should be interpreted as system-specific simulation results rather than universal limits. The study also focuses on frequency-domain recovery and does not fully model electromagnetic transients, harmonic distortion, cyberattack behavior, or detailed inverter protection logic, while the AI-based controller was evaluated only in a controlled simulation environment and would require further real-world validation through hardware-in-the-loop testing or field implementation. Future research should extend the framework by incorporating detailed grid-forming inverter models, communication-network simulation, cyber-resilience scenarios, and hardware-in-the-loop validation, as well as comparing AI-control methods such as reinforcement learning, deep neural predictive control, fuzzy-neural control, and hybrid model-predictive learning. Future studies should also test adaptive weighting schemes for the Autonomous Recovery Capacity Index to determine whether frequency coherence, battery reserve, or load continuity should receive higher priority under different operational conditions.

CONCLUSIONS AND RECOMMENDATIONS

This study examined collective frequency desynchronization in AI-stabilized renewable energy networks using a calibrated digital-twin simulation of an islanded 20-kV hybrid renewable distribution network in East Nusa Tenggara, Indonesia. The simulation covered 1,500 disturbance scenarios involving renewable intermittency, load variation, battery limitation, inverter mismatch, and communication latency.

The results show that AI-based stabilization improved grid recovery under normal communication conditions. Average frequency recovery time decreased from 11.2 s to 8.7 s, frequency coherence increased from 0.82 to 0.94, and the Autonomous Recovery Capacity Index improved from 0.77 to 0.86. However, when renewable penetration exceeded 70% and communication latency surpassed 200 ms, recovery performance declined. The frequency coherence score dropped to 0.58, recovery time increased to 13.9 s, and the recovery capacity index decreased to 0.64.

These findings indicate that AI-based control can strengthen renewable grid resilience, but only when supported by latency-aware coordination, frequency-coherence monitoring, and adequate battery reserve management. The study contributes by introducing collective frequency desynchronization as a diagnostic concept and by offering a simulation framework for evaluating autonomous recovery capacity in low-inertia, inverter-dominated renewable energy networks. Future research should validate the framework through real-time digital simulation, hardware-in-the-loop testing, and operational microgrid data.

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