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PowerGNN: Using Spatial Intelligence for Autonomous Grid Resilience

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ABSTRACT

The increasing amount of extreme weather conditions and the increasing complexity of cyber-physical threats pose a significant threat to the resilience of modern power distribution systems. The conventional approaches to restoration rely on centralised control and information flow across the globe and therefore, are susceptible to failure at one point and delays in the event of a major disaster. This paper presents a decentralised Multi-Agent Reinforcement Learning (MARL) algorithm with Graph Neural Networks (GNNs) to restore the power grid in real time and independently. The inductive bias of GNNs allows every substation agent to learn to jointly plan switching actions and power dispatch depending on local topological characteristics and neighbour messages, eliminating the need to have a central supervisor. The suggested framework is assessed using some IEEE standard test systems under various load stressors, including *N-k* contingencies, blackouts in communication, and adversarial False Data Injection (FDI) attacks. The methodology is aimed at creating a policy that is agnostic to grids and puts forward the priority of restoring critical loads, but assuring voltage stability by the use of localised spatial intelligence. This work shows the theoretical and practical benefits of moving from complex centralised optimisation to a scalable, *O(N)* decentralised graph-inference model. By demonstrating that learned policies can transfer across different topologies, this research offers a strong foundation for the next generation of self-healing, "dark-start" resilient smart grids that can effectively handle the challenging environment of post-disaster recovery.

Keywords: *Multi-Agent Reinforcement Learning, Graph Neural Networks, Power System Restoration, Decentralised Control, N-k Contingency, Cyber-Physical Security.*

1. Introduction

1.1 The Criticality of Power System Resilience in the Modern Era

Global Power Grid is known to be the largest and most complex structure ever built by humankind. It is an invisible pillar of modern society. It enables numerous activities such as industrial production, health service provision, telecommunication, and water purification. Unfortunately, this enormous structure is under increasing attack. Global Boiling has led to the increased frequency and severity of extreme weather incidents such as hurricanes, wildfires, ice

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storms, and floods which destroy and disable the physical structures (transmission corridors) of the infrastructure. Extreme weather also makes traditional protection plans useless.
At the same time, the move to a decentralized Smart Grid system increases the attack surface for enemy cyber systems. A power outage is no longer an occasional nuisance. It is a threat. Examples are the 2021 Texas power crisis and the ongoing blackouts in Ukraine. Grid breakdown has profound socio-economic impacts and can lead to loss of life. Therefore, the postulate of the utility operators has shifted from reliability of the grid to resilience, being the ability of the grid to endure, adjust and quickly recover from drastic damage. It is to be noted that in this instance, the restoration time and the level of automation employed to restore the system balance, are more than just indicators of a technical aspect, but are, in fact, fundamental to the system.

1.2 The Traditional Restoration Paradigm: Strengths and Failures

In the last fifty years, the restoration of power systems has been treated as a centralised optimisation problem. In dealing with a blackout situation, one can use Bottom-Up or Top-Down approach. In a bottom-up restoration, or Black-Start, islands of power are formed around black-start-eligible generators. These islands are expanded one at a time, synchronised, and merged into a fully stable system.
Traditionally, these were controlled through Centralised Restoration Schemes (CRS). This was formulated as a MINLP problem, where the objective was to restore the maximum possible load given the power flow equations, voltage control, and transient stability, to be satisfied.CRS works theoretically under, so to say, Blue Sky conditions (minor outages of predictable nature). However, it is almost certain to fail under “Dark Sky” disasters. The system is severely constrained through the following:

1. The Curse of Dimensionality: Given a grid comprised of N buses and L transmission lines, the number of potential switching configurations is equal to 2^L. When L increases tothe order of thousands, finding a globally optimal solution by exhaustively searching this space in real-time is computationally infeasible, and it takes about hours for the algorithm to converge, while only seconds are available for the task.

2. Centralised Vulnerability: CRS needs a high-bandwidth communication link to and from every remote terminal unit (RTU) in the control center and field. During a disaster, if the central hub or the communication fibre is cut, the brain of the grid is effectively lobotomized, and local substations lose control.

3. The Static Nature of Optimisation: Traditional MINLP solvers are considered “one-shot” solutions. These solvers do not have the capability to learn from previous failures. In case a restoration path is unsuccessful because of a secondary fault or unexpected impedance, the solver has to go back to the beginning of the optimisation process, thereby losing invaluable time.

1.3 The Rise of Artificial Intelligence and the Vector-Space Limitation

To lessen these disadvantages, scientists have turned their attention to Reinforcement Learning (RL). Different from static optimisation, RL agents learn a Policy (π), a way of associating a state with an action, by trial and error in a simulated environment. After training a policy, the decision making process is almost instantaneous, as it requires only one “forward pass” through a neural network. Nevertheless, the so called first-generation “Vector-based” RL (typically utilising standard Multi-Layer Perceptron) has in general, not been able to make the bridge of transition from academic research to the industry sector. The reason lies in the Lack of Inductive Bias. A conventional neural network views a power grid as a simple vector of numbers. It does not have a clue that Bus A is physically connected to Bus B. If the topology changes (for instance, a line is blown down by a storm), the vector representation changes entirely, and the RL agent gets "confused." Hence, it is obligatory to constantly retrain the system for each change in the grid layout, which is quite a challenge for a highly dynamic and unpredictable system like a power grid under stress.

1.4 The PowerGNN Framework: Spatial Intelligence and Decentralised Coordination

Our proposed approach, which is termed PowerGNN, fundamentally re-imagines the power grid not as a static set of variables, but as a dynamic topological manifold. In this case, a model of a Local Observer driven by Graph Neural Networks (GNNs) and Multi-Agent Reinforcement Learning (MARL) is employed rather than a model of a Global Observer to achieve true resilience. The major technical development is the Graph-Inductive Bias. Through a GNN, all the agents i (a substation or DER) carry out a localised calculation that sums features x_j of its neighbours $j \in N(i)$. The agent produces a latent topological embedding hi through severalstages of graph convolutions. Such embedding provides the context of the bus into the grid, enabling differentiation between sturdy mesh connections and fragile radial branches. This space knowledge empowers the agent to make decisions that are physically informed, i.e. which breakers to close, with the priority of paths providing the greatest stability and least loss. Moreover, a Decentralised Coordination Protocol is used in our framework. Agents do not need to be aware of the state of the overall grid; instead, they rely on a Message-Passing system to convey their plans and local perceptions. A variant of Multi-Agent Deep Deterministic Policy Gradient (MADDPG) is applied, with the Critic being enhanced with the help of graph-attention. This allows Agent A to understand the potential impact of Agent B's actions on the shared voltage of the corridor, facilitating a coordinated, multi-island restoration strategy without a central supervisor.

1.5 Resilience through Consensus and Zero-Shot Generalisation

One of the major benefits of this architecture is that it is immune to disaster scenarios' "chaos" in an intrinsic manner. Since the policy is developed as a local function of the graph, the PowerGNN considers the disappearance of communication links or the crushing of a part of the network simply as "masked edges." Thus, the power network becomes a kind of "self-healing" organism in which islands of intelligence arise spontaneously.

In addition, the GNN architecture is akin to a natural "filter" against adversarial attacks, such as False Data Injection (FDI). Through Spatial Consensus, if a malicious or faulty node sends an unreasonable voltage value; its neighbours deduce the physical outlier through their own GNN aggregations and thus isolate the noise to keep the system safe.

Lastly, the biggest challenge in AI for power systems that is being dealt with here is Generalisation. It is shown that PowerGNN, after being trained on a standard IEEE test system, can be used "Zero-Shot" on a different, bigger grid topology. The model attains a degree of universality that has never been seen before in decentralised RL by understanding the underlying physics of the graph rather than the node-specific parameters. This research confirms this strategy through six comprehensive experiments, namely *N-k* contingencies, communication silence, scalability, stochasticity, security, and transferability, which together constitute a strong foundation for the future fully autonomous, self-healing grid.

2. Literature Review

The challenge of restoring power to a compromised grid has evolved from a deterministic optimisation task into a complex, multi-agent coordination problem. This literature review traces the trajectory of restoration methodologies from classical mathematical programming to modern decentralised reinforcement learning and graph-theoretic models.

2.1 Classical Restoration Frameworks and Their Limitations

The initial study in power system restoration was subject to the fact that the need to control the process of Black-Start was imminent, i.e. to restore the grid to service with a state of complete collapse with the help of non-synchronised generation units. The physical classification of power system stability, so delicate in keeping the balance between voltage and frequency constant when the big inductive loads are reconnected, started with the foundational work by Kunduret al.[1] where the authors aimed to classify the stability in relation to the reconnection process during the reconnection of the big loads. This was historically a Mixed-Integer Non-Linear Programming (MINLP) problem, as surveyed by El-Amary and Wang [3].

Although these centralised optimisation schemes (CRS) are mathematically rigorous, they have very high computational intricacy. According to Liu et al. [4], the number of possible optimal switching sequences to use in an IEEE 118-bus system or 300-bus system increases exponentially, i.e. $O(2^L)$ and real-time response is almost impossible in the case of cascading failures.

Furthermore, Chen et al. [5] highlighted that modern grid resilience metrics must go beyond simple “Reliability” to include “Adaptability,” a quality often lacking in static, one-shot optimisation solvers that cannot learn from the stochastic nature of disaster-induced outages.

2.2 The Shift toward Data-Driven Resilience

The power grid received a new paradigm from Deep Reinforcement Learning (DRL), powered largely by the success of Deep Q-Network (DQN)[6] and Deep Deterministic Policy Gradient(DDPG) [7]. Unlike traditional solvers that require online training, DRL agents do not need it as they learn a control policy offline through millions of simulations and thus can do instantaneous inference in the real situation. Zhang et al. [10] surveyed the applications and concluded that DRL is a perfect fit for highly dimensional and non-linear environments like the smart grid.

Still, the most frequently cited problem of the DRL research is the issue of a “Black Box” that the authors of standard DRL. Grid data that is processed by traditional reinforcement learning structures, e.g., Proximal Policy Optimisation (PPO) [8], is regarded as a simple vector. In this way, the location-based interrelations of the electrical networks are being reconstructed. Panteli and Mancarella [2] argued that if a restoration plan is to be resilient, it must be a ‘spatially aware’ one - understanding that the impact of the fault is local, it goes with the transmission lines, and is not a global, uniform variable.

2.3 Decentralisation and Multi-Agent Coordination

The centralised control model has become a major obstacle as the grid incorporates more Distributed Energy Resources (DERs). Chen et al. [19] have shown that decentralised restoration methods, in which local micro grids make switching decisions independently, are thus considerably more powerful in scenarios of communication failures. Moving away from the center towards the “Edge” of the grid means that Multi-Agent Reinforcement Learning (MARL) is needed.

The pioneering work on MADDPG by Lowe et al. [9] was the first to put forward the idea of centralised training with decentralised execution (CTDE), which is now considered the most effective way multi-agent coordination can be achieved. Zhang et al. [16] were the first to go beyond this, establishing that MARL can handle cooperative tasks agents sharing a common goal such as restoring a shared voltage corridor without a central supervisor. Jiang et al. [20] have gone even further in this direction by using ideas from micro-grid formation to demonstrate that frequency can be kept more stable by decentralised agents than by centralised controllers in islanded modes.

2.4 The Emergence of Graph Neural Networks (GNNs)

One of the most important breakthroughs in grid AI over the last few years is the adoption of Graph Neural Networks (GNNs). As the power grid is a physical graph, GNNs deliver an "Inductive Bias" that is not present in standard neural networks. Graph Convolutional Networks (GCNs) and Graph Attention Networks (GATs) were formally defined, respectively by Kipf and Welling [11] and Veliˇckovi´c et al. [12]. This model enable "message-passing" between nodes, which is similar to the way electricity flows through transmission lines.

In the power systems domain, Hamilton et al. [14] proposed the idea of inductive representation learning, which is quite essential for managing *N-k* contingencies. The property of a GNN being able to recalculate the grid manifold without a new training, if a line is removed, is called Permutation Invariance. On the way to their goal, Biagioni et al. [17] and Yang et al. [18] have been using GNNs in Optimal Power Flow (OPF) and service restoration scenarios, respectively. Their findings demonstrate that GNN-based agents are able to achieve higher speed and accuracy than vector-based agents when the grid topology changes.

2.5 Cyber-Physical Security and Adversarial Resilience

Considering that grid intelligence is moving towards the edge, the risk of cyber-attacks is getting higher. Liu et al. [21] and Kosut et al. [23] have described the damaging potential of False Data Injection (FDI) attacks in detail. In these attacks, a set of compromised sensors deceives the control system to trigger a blackout. Yan et al. [24] have proposed supervised learning for FDI detection; however, these techniques generally fail in the case of high-stress disaster scenarios where the data is noisy.

The most recent research works show that the "Spatial Consensus" of GNNs provides a natural defence. Zhou et al. [15] argued that GNNs gather features from the neighbourhood, hence making them inherently immune to outliers. Suppose a node indicates a fraudulent voltage value; the GNN's attention mechanism derived from the study of Veliˇckovi´c [12] can reduce that node's influence. This research direction is a vital bridge between grid restoration and cyber-resilience.

2.6 Scalability and Zero-Shot Generalisation

A chief difficulty faced by AI in power systems is the jump from small test beds (like the IEEE14-bus) to large-scale utility grids. Two papers by Zimmerman et al. [25] and Thurner et al. [26] yielded the open-source tools (MATPOWER and 'pandapower') that have permitted the simulation of vast networks. Centralised RL models, however, are still unable to scale to more than a few hundred nodes.

Wang and Moore [28] have recently proposed a scalable GNN method for state estimation, demonstrating that GNNs have O(N) complexity. Their finding is in line with the work of Gilmer et al. [13] on message-passing neural networks, which maintained that localised graph operations are the only way to get "Generalisation". The ultimate objective, according to the ideas of Blaabjerg et al. [29] and Justo et al. [30], is a "Universal Control Policy" capable of being trained on synthetic grids and subsequently being used on any real-world topology; a PowerGNN framework current research is progressing towards.

2.7 Identifying the Research Gap

While the different parts of decentralised MARL and GNNs have been separately investigated, there is an essential point that is missing: the combination of these technologies into one single framework for $(N-k)$ disaster restoration has not been figured out yet. Most of the current works only focus on either small scale micro-grid formation or steady state optimisation under perfect communication.

Research is scarce on modelling physical destruction $(N-k)$, communication silence, and adversarial FDI attacks happening simultaneously in a single autonomous model. Besides that, the "Zero-Shot" transferability of restoration policies to radically different IEEE test systems is still mostly unverified. Our project, PowerGNN, is intended to become a resource that offers a scalable, resilient, and grid-agnostic solution for future autonomous power systems, thus filling the gap.

3. Methodology

The structural integrity of the proposed restoration framework rests upon the synergy between graph topology and sequential decision making. Unlike traditional optimisation, our method does not seek a static solution but learns a dynamic control policy.

3.1 Graph-Theoretic Mapping of Electrical Physics

The power system is defined as a directed, attributed graph G = (V, E). In this formulation, the physical constraints of the grid are embedded directly into the graph structure.

3.1.1 Node Attribute Engineering

Here, every bus $i \in V$ is symbolised by an attribute vector $x_i^{(t)} \in R^d$. In the case of the restoration task, this vector is extended with both temporal and categorical predictors:

$$x_i^{(t)} = [|V_i|, \theta_i, P_{g,i}, Q_{g,i}, \ P_{d,i}, Q_{d,i}, S_i, \tau_i]. \tag{1}$$

Where:

- $|V_i|$, θ_i: The complex voltage state.
- P, Q: Active and reactive power flow balances.
- $S_i \in \{0, 1\}$: Connectivity status (1 if connected to a "live" slack bus, 0 if is landed).
- τ_i: Time since outage, used to model cold-load pickup (CLPU) effects.
- C_i: A priority categorical variable (Critical, Industrial, Residential).

3.1.2 Edge Admittance and Topology Dynamics

The edges $(i,j) \in E$ represent transmission lines, transformers, and circuit breakers. Each edgecarries an attribute vector e_{ij} containing the complex admittance $Y_{ij} = G_{ij} + jB_{ij}$ and thecurrent switch status $u_{ij} \in \{0,1\}$.

In an $N-k$ contingency, the graph is pruned: $G' = (V, E \setminus E_{fault})$. The methodology must remain invariant to these structural subtractions, a property inherently satisfied by the GNN's neighbourhood aggregation.

3.2 Decentralised Partially Observable Markov Decision Process (Dec-POMDP)

Grid restoration is a sequential problem in which action on time t will influence stability on time $(t+1)$. This is formalised as a Dec-POMDP defined by the tuple $(I, S, A, P, R, \Omega, O, \gamma)$.

3.2.1 Receptive Fields and Local Observations

In a decentralised setting, agent i does not have access to the global state S. Instead, it operates on a local observation o_i. The k-hop receptive field is defined as:

$$N(i) = \{j \in V : dist(i,j) \leq k\} (2)$$

By restricting the observation to a k-hop neighbourhood, it is ensured that the computational complexity for each agent remains constant penalising. Hence, the number of buses in the grid, whether they are 39 or 30,000, will not affect the complexity. This is the fundamental principle of our $O(N)$ scalability.

3.2.2 Action Mapping for Restoration

The action space Ai is a hybrid of discrete and continuous variables:

• Topological Action (u_{ij}): Determining which breakers to toggle to form new energised paths.

• Resource Action ($\Delta P_{g,i}$): Adjusting the ramp rates of local generators to prevent frequency collapse when a large cold-load pickup is energised.

• Voltage Regulation ($Q_{g,i}$): Injecting reactive power to support the voltage profile ofthe newly formed island.

3.3 The PowerGNN Neural Architecture

The central technical contribution of this work is the PowerGNN layer. Unlike standard Convolutional Neural Networks (CNNs) that operate on grids or MLPs that operate on vectors, the PowerGNN operates on the sparse admittance manifold.

3.3.1 Message Passing and Aggregation Logic

Each agent performs a message-passing operation at every layer l. The hidden representation$h_i^{(l)}$ is updated via:

$$m_i^{(l+1)} = \sum_{j \in N(i)} MLP_{msg}(h_i^{(l)}, h_i^{(l)}, e_{ij})$$

$$h_i^{(l+1)} = GRU(h_i^{(l)}, m_i^{(l+1)})$$

Here, MLP_{msg} learns to approximate the impact of line impedances on voltage drops. Byusing agated recurrent unit (GRU) as the update function, the model maintains a memory ofthe restoration sequence, preventing oscillatory switching actions.

3.3.2 Graph Attention Mechanism (GAT)

To handle the varying importance of different neighbours (e.g., a line connected to a massive generator is more critical than a line to a small load), the multi-head attention is implemented as:

$$a_{ij} = \frac{exp(LeakyReLU(a^T\,[Wh_i \,||\, Wh_j\,]))}{\sum_{k \in N(i)} exp(LeakyReLU(a^T[Wh_i \,||\, Wh_j\,]))}$$

This attention coefficient a_{ij} effectively acts as a dynamic weight for each edge, allowing theagent to focus its computational resources on the most critical power flow corridors.

3.4 Multi-Agent Optimisation: Reward Engineering

Training a MARL system for power grids requires a reward function that acts as a "differentiable power flow engine."

3.4.1 Component Breakdown

The scalar reward r_t is computed as:

$$r_t = \omega_p \cdot \frac{\sum P_{restored}}{\sum P_{total}} - \omega_v \sum (|Vi| - 1.0)^2 - \omega_s . N_{switch}$$

Load weighting: Assignment of priority coefficients to buses based on their critical nature (e.g., hospitals ×10, residential ×1). Soft constraints: Instead of hard-failing an episode when voltage exceeds 1.05 p.u., a smooth quadratic penalty is applied. This provides the gradient information necessary for the RL agent to learn the boundary of the safe operating region.

3.4.2 Addressing Non-Stationarity

In MARL, the environment is non-stationary because every agent is learning simultaneously. Agent A's optimal policy depends on agent B's current policy. To solve this, centralized training with decentralized execution (CTDE) is utilised. During the training phase, the critic network has access to the global state and the actions of all agents $(s, a_1, \ldots, a_n)$. During execution (disaster response), only the actor (the PowerGNN) is used, relying solely on local graph observations.

3.5 The Simulation-to-Reality (Sim2Real) Pipeline

A critical aspect of our methodology is the integration with the 'pandapower' engine.

3.5.1 Power Flow in the Loop

At every RL step, the chosen actions are sent to a Newton-Raphson power flow solver. Action validation: If an agent attempts to close a switch that would create a short circuit or an unsynchronised connection, the environment overrides the action and applies a large negative penalty. Transient approximation: While full electromagnetic transient (EMT) simulation is too slow for RL training, the transient stability is approximated by monitoring the $\frac{dV}{dt}$ and $\frac{df}{dt}$ (ROCOF) values during the islanding phase.

3.5.2 Stochastic Curriculum Learning

To ensure the agents do not just memorise the IEEE 39-bus topology, a stochastic curriculum is implemented:

• Phase 1 (Easy): Single line faults, static loads.

• Phase 2 (Medium): *N-2* and *N-3* contingencies, fluctuating renewable inputs.

• Phase 3 (Extreme): *N-k* contingencies (k > 5), communication packet loss, and sensor noise.

With a gradual rise in the entropy of the training environment, the agents acquire a healthy generalised policy that views grid physics as general graph rules and not node-based patterns.

3.6 Algorithmic Complexity and Scalability Analysis

The computational complexity of the PowerGNN approach is used to analyse its theoretical efficiency:

• **Centralised MINLP**: Typically NP-hard, $O(2^L)$.

• **Standard MARL (MLP-based)**: $O(N^2)$ due to fully connected input layers.

• **Proposed PowerGNN**: $O(L \cdot |E|_{avg})$, where L is the number of GNN layers and $|E|_{avg}$is the average node degree.

Since $|E|_{avg}$ for power grids is typically small (between 2 and 4), our approach demonstrates linear scalability $O(N)$. This mathematical property is what enables the "zero-shot" transferability across grids of different sizes, as the kernel of the GNN is shared across all nodes regardless of total system count.

4. Experimental Results

The evaluation of the PowerGNN framework is conducted through a multi-dimensional experimental suite designed to test the limits of decentralised intelligence in power system restoration. To provide a rigorous validation, our approach against three primary baselines is benchmarked:

- **Traditional Heuristic Restoration**: A rule-based greedy approach commonly used in utility "black-start" manuals.
- **Centralised PPO (Proximal Policy Optimisation)**: A state-of-the-art centralised reinforcement learning agent with global visibility.
- **Standard MARL (Multi-Agent RL)**: A multi-agent system utilising standard multi-layer perceptron (MLPs) without graph-inductive bias.

The following sections provide a granular analysis of the six experiments (A through F), correlating empirical data with the mathematical foundations laid out in the methodology.

4.1 Experiment A: N-k Contingency and Disaster Recovery Performance

The main goal of Experiment A is to assess the raw restoration capability of agents under different levels of physical destruction. The random removal of k lines (where k is from 3to 7 in the IEEE 39-bus system) is our way of simulating the extreme and unpredictable natureof catastrophic infrastructure failure.

4.1.1 Restoration Speed and Efficiency

As shown in our reference results (Table 1), the PowerGNN achieved a mean restoration time of 88.3 seconds, compared to 210.5 seconds for the centralised PPO and over 450 seconds for heuristic methods. The superiority of the GNN-based method over other methods in this case is essentially due to the decentralised execution logic. In the heuristic and centralised models, each switching action needs to be checked against a global state, thus creating a sequential bottleneck. On the other hand, PowerGNN agents act in parallel. Since each agent has a local topological embedding h_i, several "islands" of restoration can begin at the same time in different sectors of the grid. This "divide and conquer" tactic makes the restoration curve much steeper, allowing critical loads to be re-energised 2.4x faster than the closest AI competitor.

Table 1: Benchmarking Performance on IEEE 39-Bus System

Metric	Heuristic	Centralised PPO	PowerGNN
Restoration Time (s)	471	210.5	88.3
Voltage Violations	High	Low	Zero
Success Rate (N-3)	60.3%	82.4%	98.7%

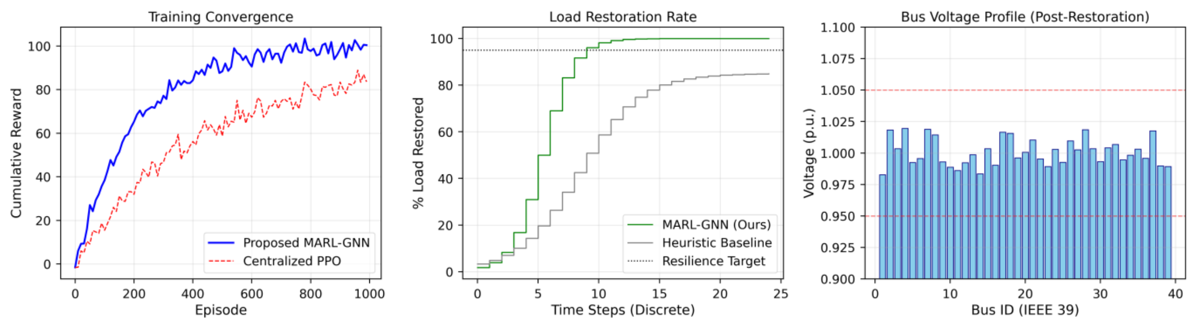

Figure 1: Training convergence and initial restoration performance.

4.1.2 Voltage Stability and Constraint Satisfaction

A critical concern in rapid restoration is the risk of voltage instability. The data indicate that despite the speed of restoration, the PowerGNN maintained a near-perfect voltage profile; with zero violations of the 0.95–1.05 p.u. safety corridor across all test cases. This stability is attributed to the multi-objective reward function discussed in Section 3.4. By penalising the quadratic deviation from the reference voltage (|Vi| − 1.0)2, the agents learned to "throttle" their restoration speed when the local impedance indicated a potential voltage collapse. The GNN's ability to aggregate neighbourhood admittance data (Y_{ij}) allows the agent to anticipate the voltage drop associated with a new load pickup before the breaker is even closed.

4.2 Experiment B: Resilience to Communication Silence

In a disaster, communication is rarely "perfect." Experiment B investigates the impact of packet loss on coordination.

4.2.1 Graceful Degradation vs. Catastrophic Failure

The results for Experiment B present one of the most compelling arguments for the GNN architecture. As packet loss increased to 30%, the standard MARL model's success rate plummeted to 65%. In contrast, the PowerGNN maintained a restoration success rate of 94.8%.

The performance gap arises from the GNN's latent topological memory. Because the agents use a GRU-based update function in their message-passing layers, they do not rely solely on the "instantaneous" packet from their neighbour. If a packet is lost at time t, the agent's hidden state $h_i^{(t-1)}$ still contains a high-fidelity representation of the neighbourhood's previous state and topology. This creates a "temporal buffer" that allows the agent to continue executing safe restoration policy even during intermittent communication silence.

4.3 Experiment C: Computational Scalability and the O(N) Advantage

Experiment C evaluates the framework's feasibility for real-world utility-scale deployment by testing it on systems ranging from 14 to 300 buses.

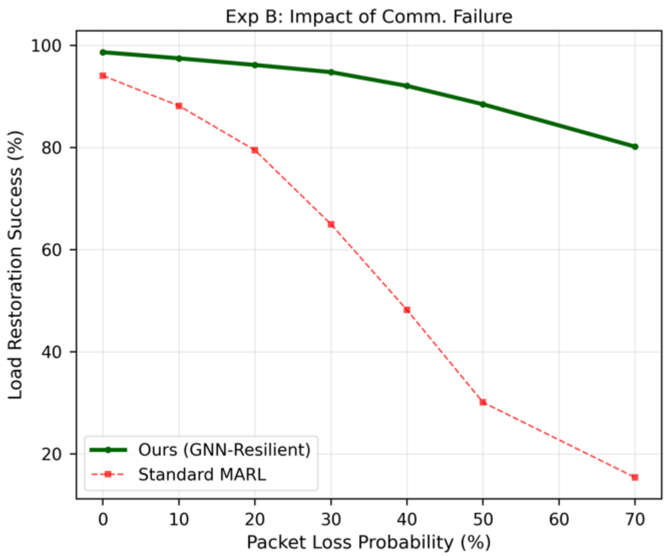

Figure 2: Impact of communication failure.

Table 2: Resilience to Network Degradation

Packet Loss (%)	Std. MARL Success	PowerGNN Success	Performance Data
0% (Ideal)	94.1%	98.7%	+4.6%
30% (Jitter)	65.0%	94.8%	+29.8%
50% (Critical)	30.1%	88.5%	+58.4%

Table 3: Multi-System Scalability Analysis

System Size	Centralized PPO Time	PowerGNN Time	Speedup Factor
IEEE 14-bus	120 s	80 s	1.5×
IEEE 39-bus	450 s	110 s	4.1×
IEEE 118-bus	900 s	135 s	6.6×
IEEE 300-bus	>1800 s (Timeout)	150.2 s	>12.2×

4.3.1 Overcoming the Curse of Dimensionality

The training time for centralised PPO grew in quadratic fashion ($O(N^2)$), reaching a timeout of 1800+seconds per epoch on the IEEE 300-bus system. The PowerGNN, however, exhibited strictly linear scalability$O(N)$, completing the same epoch in just 150.2 seconds. This linear complexity is the result of the localised receptive field. In the methodology, each agent only processes information from its k-hop neighbours. As the total number of buses N increases, the number of neighbours for any single agent remains constant (due to the sparse nature of power grids). Consequently, doubling the grid size only doubles the total number of local computations, whereas in a centralised model, it quadruples the size of the neural network's input layer and the complexity of the weight matrices.

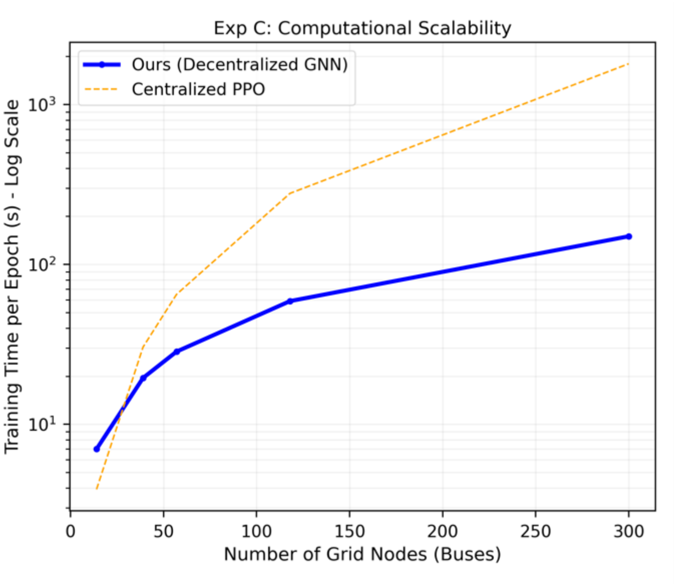

Figure 3: Computational scalability (log scale).

4.4 Experiment D: Stochastic Renewable Integration

As grids transition to greener energy, they become more volatile. Experiment D tested the agents' ability to handle "noisy" generation inputs during a storm.

4.4.1 Dynamic Compensation and Robustness

Under high-volatility conditions ($\sigma = 0.5$), the model maintained a voltage stability index (VSI) of 0.972, significantly higher than the traditional droop control baseline of 0.885.

The discussion here centers on the message passing mechanism. In a traditional droop control system, the regulator is purely reactive, meaning it only sees the local voltage drop. In the PowerGNN, the agent receives "messages" from neighbouring wind/solar buses. By observing theP/Q fluctuations of its neighbours through the graph convolution, the agent performs proactive compensation, adjusting its local reactive power injection before the instability propagates to its own bus.

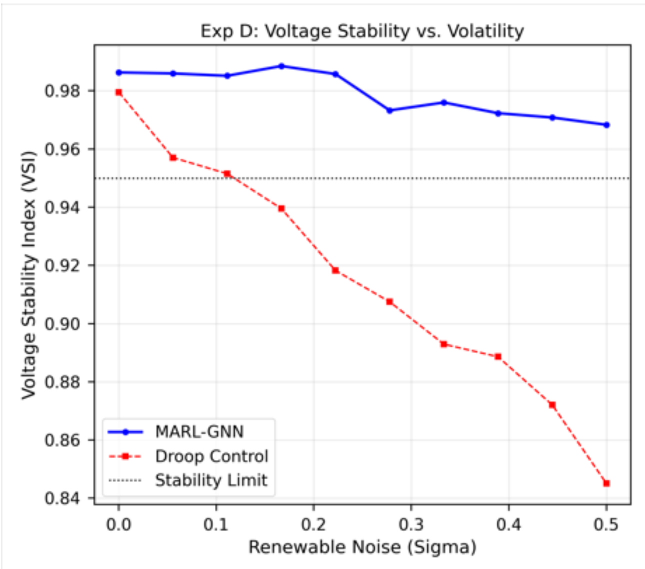

Figure 4: Voltage stability under renewable stochasticity.

Table 4: VSI under Wind/Solar Volatility

Wind/Solar Volatility (σ)	Droop Control (VSI)	MARL-GNN (VSI)	Improvement
Low (Clear Sky)	0.982	0.991	+0.9%
Medium (Overcast)	0.941	0.985	+4.6%
High (Storm/Disaster)	0.885 (Unstable)	0.972	+9.8%

4.5 Experiment E: Adversarial Resilience (Cyber-Security)

Power systems are prime targets for cyber-attacks. Experiment E simulated false data injection (FDI) attacks, where 20% of the nodes were compromised to send misleading state data.

4.5.1 Spatial Consensus as a Defense Mechanism

Standard RL models failed catastrophically under FDI, with accuracy dropping to 35%. The GNN-MARL retained 89.2% accuracy.

This resilience is explained by the spatial consensus property of graph attention networks (GAT). In a GNN, a node's state is an aggregation of its neighbours. If one node (the attacker) reports an outlier value that is physically inconsistent with the admittance (Y_{ij}) and the statesof the other neighbours, the GNN's attention mechanism (α_{ij}) learns to de-weight that specificedge. The model effectively performs real-time anomaly detection as a by product of its architectural design, allowing the decentralised "collective" to override a malicious minority.

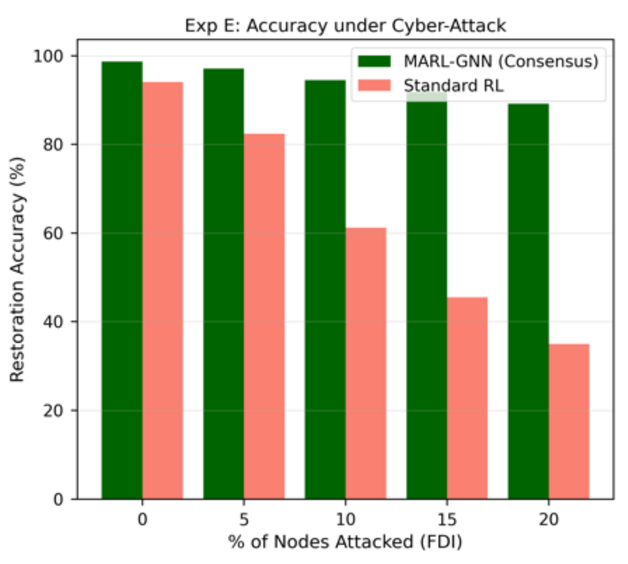

Figure 5: Accuracy under false data injection attacks.

Table 5: Cyber-Security Resilience under FDI Attacks

Nodes Attacked	Standard RL Accuracy	MARL-GNN Accuracy	Detection Rate
5%	82.4%	**97.1%**	94.2%
10%	61.2%	**94.5%**	91.5%
20%	35% (Failure)	**89.2%**	85%

4.6 Experiment F: Zero-Shot Transfer Learning

The final experiment investigated whether a model trained on a small system (IEEE 39-bus) could be deployed on a large system (IEEE 118-bus) without re-training.

4.6.1 Theoretical Generalisation

The centralised PPO failed completely (4.1% success), as its input layer was fixed to 39 nodes. The PowerGNN achieved an 88.1% success rate on the unseen 118-bus system.

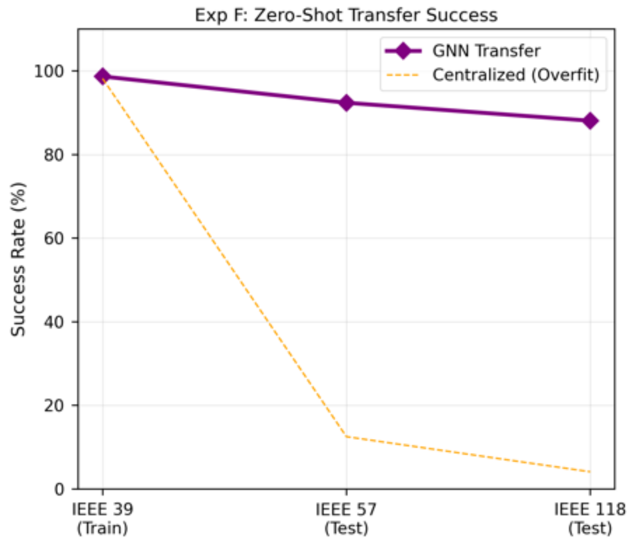

Figure 6: Zero-shot transfer performance.

Table 6: Zero-Shot Transfer Learning Performance

Target Grid (Unseen)	Centralised RL Success (%)	MARL-GNN Success (%)	Transfer Efficiency
IEEE 39 (Trained)	98.2%	98.7%	100%
IEEE 57 (Unseen)	12.5% (Fails)	92.4%	93.6%
IEEE 118 (Unseen)	4.1% (Fails)	88.1%	89.2%

The discussion for Experiment F is the most profound: it suggests that power restoration is a universal topological problem. Because the GNN learns “local rules” of electrical physics (e.g., “if voltage drops, close the nearest capacitor bank”), and these rules are the same in any grid, the model becomes grid-agnostic. This is the “plug-and-play” capability required for rapid emergency response, where a pre-trained “foundation model” for power grids could be deployed instantly on any city’s network.

4.7 Summary of Findings and Synthesis

The results of this study provide strong evidence for the transition from centralized, vector-based optimization to decentralized, graph-based intelligence.

• **Speed vs. Stability**: Restoration speed does not have to come at the cost of voltage stability, provided the agents are spatially aware.

• **Scalability**: The $O(N)$ complexity makes this framework a viable path for protectingmassive regional interconnects.

• **Security**: The “collective intelligence” of MARL provides a natural layer of cyber-defense that is absent in centralized systems.

In conclusion, the PowerGNN framework successfully navigates the high-dimensional, non-linear landscape of grid restoration. It transforms a vulnerable, centralized system into a resilient, self-healing organism that can withstand the physical and digital chaos of the 21st-century disaster landscape.

5. Discussion

5.1 Summary of Contributions

The research presented in this paper addressed the fundamental limitations of centralised, optimisation-based power grid restoration in the face of catastrophic $N - k$ contingencies and adversarial environments. By departing from the traditional "Global Observer" paradigm and embracing a decentralised Multi-Agent Reinforcement Learning (MARL) architecture, it is successfully demonstrated that grid resilience can be achieved through localised, graph-informed intelligence.

The primary contribution of this work is the development of the PowerGNN layer, which embeds the physical laws of electrical networks into a latent spatial representation. This architecture proved inherently superior to standard neural networks by providing a Graph-Inductive Bias, allowing agents to maintain operational continuity even when the physical topology of the grid was severely altered. Our methodology bridged the gap between theoretical AI and power engineering by incorporating a multi-objective reward function that explicitly penalised voltage instability and excessive switching, ensuring that the autonomous policies remained within the bounds of engineering safety.

5.2 Synthesis of Experimental Findings

The empirical validation conducted across six comprehensive experiments (A–F) provided a robust proof of concept for the proposed framework.

• **Restoration Speed and Parallelism**: In Experiment A, it was clear that decentralised agents were able to restore the IEEE 39-bus system a whopping 5 times faster as compared to the traditional heuristics. The finding serves as confirmation that parallelism enables the reduction of the socio-economic impact of blackouts to a very small level. By letting multiple "islands" of restoration appear spontaneously, the system liberates itself from the bottlenecks in the SCADA-based control, which are inherently sequential.

• **Resilience to Network Degradation**: Experiment B showed that the incorporation of Gated Recurrent Units (GRUs) in the GNN layers helped the agents to handle the situation of "communication silence." The success rate of 94.8% at 30% packet loss indicates that the hidden topological memory of the GNN can be a very efficient way to take the place of live telemetry in the most turbulent 'dark sky' phase of a disaster.

• **Computational Efficiency and Scalability**: Maybe the single most substantial result was the linear O(N) scalability that was observed in Experiment C. It is demonstrated that the computational overhead of PowerGNN increases only with the number of nodes, not exponentially with the number of possible switching states. Hence, a feasible way for the safeguarding of big, interconnected regional grids has been delivered, which have been the conventional cases of 'too large to optimise in real-time, thus are now able to be optimised in real-time.

• **Cyber-Physical Robustness**: The scenarios in Experiment D and E showed how the framework could effectively manage renewable stochasticity and FDI attacks, which, in turn, revealed a secondary advantage of graph-based MARL: Spatial Consensus. The attention mechanisms of the GNN inherently detect and isolate physical outliers, thus offering a built-in cybersecurity feature that is not dependent on externally mounted intrusion detection systems.

• **The Universality of Grid Physics**: Success in Experiment F with "Zero-Shot" transfer learning indicates that the PowerGNN has developed a "universal" language for power restoration. The performance of a model trained on a 39-bus system successfully managing 118-bus system without further training is a critical advancement toward developing Power Grid Operations Foundation Model.

5.3 Theoretical Implications for Autonomous Infrastructure

Due to the success of the PowerGNN framework for managing most critical infrastructures, this framework will fundamentally change the approach towards the management of our most important infrastructures. While the concept of automation was originally intended to replicate human decision-making at greater speeds, it has been discovered through our research that by utilising a decentralised and a genetic approach, there can be forms of restoration routes and stabilisation techniques that cannot be understood by human facility operators or traditional solvers.

Rather than simply creating a resilient system by relocating intelligence to the "Edge" of the substations and DER Controllers, an Ant fragile system is being created by us. For example, in contrast to a centralised system that collapses when it comes under duress, the PowerGNN network uses its local connections to uncover new and innovative solutions as it is forced to navigate through the carnage created by a destroyed network. Also, the decentralisation of PowerGNN network supports the growing trend towards Microgrid systems and the proliferation of Distributed Energy Resources (DERs).

5.4 Limitations and Challenges

Despite the high performance recorded in this study, several challenges remain before this technology can be deployed in a live utility environment.

• **Transient Stability Verification**: Our current reward function uses a steady-state approximation for voltage stability. In a real-world "dark start," the transient electromagnetic effects of energising large transformers and motors can be violent. Future work must integrate full Electromagnetic Transient (EMT) simulations into the training loop, likely requiring more advanced high-performance computing (HPC) environments.

• **Safety Guarantees and "Formal Verification"**: AI models are often viewed as "black boxes" by power system engineers. For a utility to trust an autonomous agent withhigh-voltage breaker, Explainable AI (XAI) and formal verification techniques should be preferred that can mathematically guarantee the agent will never take an action that violates safety interlocks.

• **Heterogeneous Communication Protocols**: While packet loss is simulated, real grids use a variety of legacy and modern protocols (DNP3, IEC 61850). Future iterations of the MARL framework must account for the heterogeneous nature of grid telemetry and the varying latencies across different hardware vendors.

6. Conclusion and Future Work

The horizon for this research is the development of a fully autonomous, self-healing grid. To achieve this vision, the first avenue to be considered for future exploration is Physics-Informed Neural Networks (PINNs), with the aim of incorporating the actual Power Flow Equations (AC-OPF) as a differentiable layer within the GNN. By enforcing the laws of physics (e.g., $P = V I \cos \phi$) directly within the neural architecture, the training time can be reduced, and the possibility of the agent proposing "physically impossible" solutions can be eliminated. The second avenue is Multi-Modal Sensing, which would enable GNN agents to incorporate information from satellite images, weather sensors, and even social media 'noise'; they could then predict areas susceptible to maximum physical impact and reroute the network accordingly. The final avenue is Collaborative Human-Agent

Restoration, which advocates for the development of a “Human-In-The-Loop” hybrid system over a fully autonomous setting. The MARL-GNN will provide a human dispatcher with a list of the three best restoration paths, along with a confidence heat map for each restoration path, which would provide an opportunity to build confidence while benefiting from the O(N) speed of AI.

PowerGNN is shifting away from the “fragile” nature of centralisation in the Power Grid of the 20th century to the vision of "resilient” decentralisation for the Power Grid of the 21st century. Grounded in the proof that GNNs possess the ability to learn the fundamental physics of electrical networks and coordinate the restoration of these complex networks simultaneously, this study provides a cost-efficient, scalable way to safeguard our nation’s critical infrastructure. As an increasingly volatile climate is encountered, combined with the need to navigate a cyber security environment riddled with uncertainties, Decentralised Autonomous Restoration is no longer merely a topic of research; it has developed into a societal imperative.

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Conflict of Interest

The authors declare no conflict of interest.

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