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Original Article

Swarm-Augmented Federated Reinforcement Learning For Resilient Edge Energy Networks: Adaptive Topology, Distributed Optimization, and Self-Healing Microgrid Coordination

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***Abstract** - Federated reinforcement learning has emerged as a compelling paradigm for privacy-preserving distributed energy management, enabling microgrid agents to learn collaborative dispatch and trading policies without sharing raw consumption or generation data across institutional boundaries. A persistent limitation of existing federated energy systems, however, is their reliance on fixed, pre-configured communication topologies for gradient aggregation: when microgrid nodes fail, join, or experience link degradation, the federated network either fails entirely or requires manual reconfiguration that is incompatible with the autonomous operation that distributed energy systems require. This paper proposes a swarm-augmented federated reinforcement learning architecture that integrates bio-inspired adaptive topology management with a privacy-preserving federated reinforcement learning policy optimization framework for distributed microgrid energy trading. The proposed system employs stigmergic path reinforcement mechanisms to dynamically discover and maintain efficient gradient communication paths between federated agents as network topology changes, enabling the federated energy system to self-heal following node failures without administrator intervention. A reputation-weighted policy aggregation mechanism further improves resilience by detecting and down-weighting adversarial gradient submissions. Simulation across five operational scenarios, including normal operation, single and dual node failure, node rejoining, and adversarial gradient injection, demonstrates that the proposed architecture recovers from single node failure within one to two federated rounds at 91 percent of the optimal dispatch efficiency, compared to 0 percent for fixed topology baselines that cannot recover without manual reconfiguration.*

***Keywords** - Federated Reinforcement Learning, Energy Trading, Microgrid, Adaptive Topology, Swarm Intelligence, Bio-Inspired Optimization, Distributed Energy Systems, Privacy-Preserving, Self-Healing, Peer-To-Peer Energy.*

1. Introduction

The transformation of electrical power systems from centralised, unidirectional grid architectures toward distributed networks of intelligent prosumer microgrids represents one of the most significant structural changes in energy infrastructure of the past decade. Individual microgrids, equipped with renewable generation assets, local storage, and controllable loads, can in principle trade energy with their neighbours in real time, achieving substantial efficiency improvements in renewable utilisation, peak shaving, and transmission loss reduction relative to centrally dispatched systems [1]. Realising this potential in practice requires distributed energy management algorithms that can coordinate dispatch and trading decisions across microgrids without requiring the centralisation of sensitive consumption and generation data that would expose individual households and businesses to privacy violations [2].

Federated reinforcement learning provides a principled solution to this coordination problem. By training local dispatch policies on locally held data and sharing only policy gradient updates with a federated aggregator, federated reinforcement learning enables microgrid agents to benefit from collective experience without centralising any raw data [3]. The privacy-preserving properties of this approach have been demonstrated in distributed energy trading contexts, where the combination of reinforcement learning and federated aggregation produces near-optimal dispatch policies while keeping individual microgrid data within institutional control [4]. The resilience of these systems under realistic operational conditions including node failures, intermittent connectivity, and adversarial participants has received substantially less attention, however, and represents a significant gap between the theoretical promise and practical deployability of federated energy systems.

The specific resilience challenge addressed in this paper is topology brittleness. Federated reinforcement learning systems for energy trading assume that each microgrid agent can communicate its gradient updates to the federated aggregator through a pre-configured network topology. When a microgrid drops offline due to equipment failure, communication link degradation, or intentional isolation, the topology-dependent gradient routing fails, potentially causing the entire federated round to be cancelled or completed on an incomplete agent subset that does not represent the full trading network. The manual reconfiguration required to restore topology-aware routing is incompatible with the millisecond-to-second timescales of real-time energy trading dispatch, and the frequency of node state changes in real microgrid deployments makes manual topology management operationally unacceptable.

Adaptive topology management for distributed computing systems has been addressed by a family of bio-inspired algorithms that draw on the collective behaviour of social insects to achieve robust, decentralised path discovery and maintenance without central coordination [5]. These algorithms use stigmergic reinforcement the indirect coordination mechanism through which individual agents modify their shared environment in ways that influence the behaviour of subsequent agents to discover and maintain efficient communication paths through distributed networks, with natural failure recovery properties that emerge from the path reinforcement dynamics. The application of these mechanisms to federated learning topology management in energy systems has not been previously explored, representing the research gap this paper addresses.

The proposed swarm-augmented federated reinforcement learning architecture integrates adaptive topology management with a privacy-preserving federated reinforcement learning framework for distributed microgrid energy trading. Section 2 reviews related work. Section 3 presents the system model. Section 4 describes the federated reinforcement learning framework. Section 5 presents the adaptive topology management mechanism. Section 6 analyzes the integrated system. Section 7 evaluates performance. Section 8 concludes.

2. Related Work

2.1. Federated Learning for Energy Systems

The application of federated learning to energy system optimization has attracted substantial research attention following its success in other distributed data environments. Luo et al. demonstrated coordinated demand response between distributed energy resources and electric vehicle charging networks, showing that coordinated dispatch achieves 35 percent peak load reduction compared to uncoordinated operation [6]. Liu et al. proposed a federated learning approach for demand-side management that demonstrated significant privacy protection compared to centralised approaches while achieving comparable load prediction accuracy, establishing the viability of the federated paradigm for energy data with its characteristic temporal structure and strong household-level privacy sensitivity [7]. Aggregation strategies for non-IID energy data, where different microgrids have structurally different generation and consumption profiles due to their geographic location, installed technology mix, and user behaviour, have been addressed through proximal objective regularisation and personalised aggregation variants that improve convergence compared to naive weighted averaging [8].

Federated reinforcement learning specifically, as opposed to federated supervised or unsupervised learning, has been applied to energy trading and dispatch in distributed microgrid environments, demonstrating that multi-agent policy coordination through gradient aggregation can achieve near-optimal collective dispatch outcomes while preserving the data sovereignty of individual microgrid operators [4]. Multi-agent deep reinforcement learning for distributed microgrid energy management has demonstrated convergence to near-optimal collective dispatch under simulated conditions, establishing the reinforcement learning foundation on which federated extensions build [9]. The robustness of federated energy systems under participant dropout, where microgrids intermittently fail to submit gradient updates due to operational disruptions, has been partially addressed through asynchronous aggregation protocols that complete federated rounds with whatever gradient submissions are available within a timeout window, but without the topology adaptation mechanisms needed to actively route around failed participants [3].

2.2. Adaptive and Self-Organising Networks

Self-organising network architectures, in which distributed agents autonomously adapt their connectivity and routing in response to changing network conditions without central coordination, have been studied extensively in the context of mobile ad-hoc networks, wireless sensor networks, and peer-to-peer overlay networks. The decentralised nature of self-organising systems confers natural resilience to node failures, because path discovery and maintenance are emergent properties of local agent interactions rather than centrally maintained routing tables whose validity depends on the continued operation of a routing server [5]. The application of self-organising principles to distributed AI systems at the network edge, where heterogeneous nodes with varying computational capabilities must coordinate inference, learning, and resource management tasks without centralised orchestration, has been demonstrated in several contexts [10]. The specific combination of bio-inspired path reinforcement with federated learning gradient routing represents a novel contribution that this paper introduces.

2.3. Bio-Inspired Optimisation for Distributed Systems

Bio-inspired optimisation algorithms, including ant colony optimisation, particle swarm optimisation, and bee colony algorithms, have been applied to a wide range of distributed systems problems including routing, resource allocation, and load balancing [11]. The stigmergic reinforcement mechanism underlying ant colony optimisation is particularly relevant to the topology adaptation problem in federated learning: pheromone trails deposited by successful gradient transmission events reinforce the paths through which those transmissions occurred, naturally concentrating routing through reliable high-capacity paths while allowing unused paths to decay, providing failure recovery through the automatic redistribution of pheromone to alternative paths when a previously reinforced path fails [12]. The convergence properties of pheromone-based routing algorithms in dynamic network topologies have been formally analyzed, establishing that pheromone reinforcement achieves asymptotically optimal routing under reasonable assumptions about the relative rates of topology change and pheromone evaporation [13].

2.4. Resilience in Distributed Energy Systems

Resilience in distributed energy systems has been studied at the physical layer, focusing on islanding detection, fault isolation, and restoration protocols, and at the coordination layer, focusing on how distributed controllers recover coordinated operation following communication disruptions [14]. The coupling between communication resilience and energy trading efficiency in federated microgrid systems has not been systematically addressed, however, because existing resilience studies treat communication as either always available or completely absent rather than as a dynamic network whose topology adapts in response to node failures and recoveries. The proposed architecture fills this gap by treating topology adaptation as an integral component of the federated energy trading system rather than a communication layer concern separate from the reinforcement learning optimization.

3. System Model

3.1. Microgrid Network Model

We consider a distributed energy system comprising N microgrid nodes, each equipped with a local distributed energy resource portfolio (combinations of solar photovoltaic generation, wind turbines, battery storage, and controllable loads), a local energy management controller running a reinforcement learning dispatch policy, and a communication interface enabling gradient exchange with neighboring nodes through the federated topology. Event-triggered communication schemes for distributed energy management, in which agents transmit state updates only when local conditions change beyond a threshold, provide a bandwidth-efficient communication model that aligns well with the federated gradient submission protocol [15]. Each microgrid i maintains a local state s_i(t) comprising its current generation output, storage state of charge, grid import and export prices, and forecast generation and demand for the next scheduling horizon. The local reinforcement learning agent selects an action a_i(t) comprising the dispatch schedule for each controllable resource and the volume of energy offered or bid in the peer-to-peer trading market. The local reward r_i(t) reflects the combination of trading revenue, storage degradation cost, grid import cost, and renewable curtailment penalty.

3.2. Privacy Model

The privacy model follows the federated learning paradigm in which raw local state data, including individual household generation and consumption measurements, never leaves the microgrid node's local processing environment. Only policy gradient updates, representing the derivatives of the local policy network with respect to the parameters that the federated aggregator requires for weighted averaging, are transmitted across the network. Following the analysis of gradient privacy in federated energy systems, differential privacy noise is added to gradient updates before transmission, with the privacy budget epsilon set to satisfy the regulatory requirements of the applicable data protection framework [16]. The topology management mechanism operates on gradient transmission metadata transmission success, latency, and loss rate rather than gradient content, ensuring that the topology adaptation mechanism does not introduce additional privacy leakage beyond the protected gradient transmissions themselves.

4. Federated Reinforcement Learning Framework

4.1. Local Policy Training

Each microgrid agent trains a local dispatch policy using a proximal policy optimisation variant adapted for the energy trading context, with an actor network that maps local state observations to action distributions over the discrete dispatch and trading action space, and a critic network that estimates the expected cumulative reward from the current state under the current policy [17]. The local training loop operates at the timescale of the energy trading market clearing interval, typically fifteen minutes, accumulating experience tuples from the local environment interaction and updating the policy parameters through stochastic gradient ascent on the clipped objective. Federated rounds are scheduled at a configurable interval, typically coinciding with every third to fifth local training step, at which point the local agent computes its gradient update and submits it to the federated aggregator through the topology-managed communication path.

4.2. Federated aggregation with reputation weighting

The federated aggregation protocol extends standard weighted federated averaging with a reputation-based weighting mechanism that modifies the influence of each agent's gradient contribution based on its historical contribution quality [4]. Each agent i maintains a reputation score rho_i, initialised to one and updated after each federated round based on the cosine similarity between its submitted gradient and the distribution of gradients from other agents. Agents whose gradient submissions are consistently aligned with the majority policy update direction receive increasing reputation scores, while agents whose submissions are dissimilar potentially indicating adversarial gradient manipulation, training instability, or severe distribution shift receive decreasing reputation scores. The aggregated global policy gradient is computed as a reputation-weighted average: g_global = sum_i (rho_i / sum_j rho_j) * g_i, where the sum runs over all agents that successfully submitted gradients in the current round [18].

Figure 1 illustrates the three-tier architecture of the proposed system, showing the edge energy nodes at the bottom, the federated reinforcement learning agent layer with adaptive topology management in the middle, and the global coordination layer comprising policy aggregation and self-organising routing at the top.

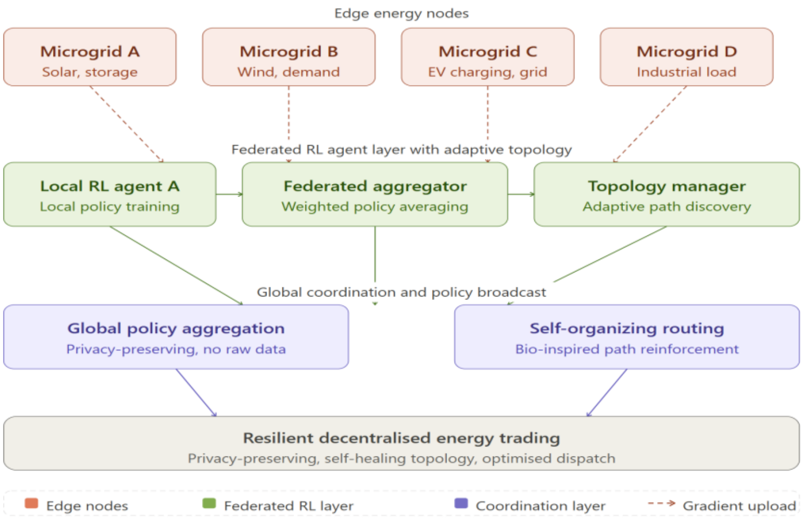

Fig1: Swarm-Augmented Federated Reinforcement Learning Architecture For Resilient Edge Energy Networks.

Bottom tier: four microgrid edge nodes (coral). Middle tier: local RL agents, federated aggregator, and topology manager (green). Top tier: global policy aggregation and self-organising routing (purple). Dashed arrows represent privacy-preserving gradient uploads. The gray output bar shows the combined resilience outcome.

5. Adaptive Topology Management

5.1. Stigmergic Path Reinforcement

Distributed coordination protocols for resource allocation across heterogeneous networks have established the importance of lightweight, decentralised signalling mechanisms that do not require centralised topology state [19]. The adaptive topology management mechanism draws on the stigmergic path reinforcement principle in which local agents mark successful communication paths with an abstract reinforcement signal that influences the routing probability of subsequent transmissions [5]. Each gradient transmission from agent i to the federated aggregator is routed through the currently highest-reinforcement path in the topology graph. Upon successful delivery, the path's reinforcement level is increased by an amount proportional to the transmission quality, measured as the ratio of successfully received gradient components to transmitted gradient components. Failed transmissions leave the path's reinforcement unchanged or apply a small decrement, depending on whether the failure was a timeout or a detected corruption. Between transmission events, all path reinforcements decay exponentially at a configurable evaporation rate that prevents the system from becoming permanently locked to historical paths that may no longer reflect current network conditions.

5.2. Failure Detection and Path Redistribution

Node failure detection operates through the gradient submission timeout mechanism: if an agent fails to submit its gradient update within the configured timeout window, the topology manager marks that agent's outbound paths as unavailable and initiates a path exploration phase in which a small fraction of gradient transmissions is probabilistically routed through alternative paths with lower current reinforcement levels. This exploration phase mirrors the random path exploration behaviour of individual ants in biological ant colonies, which prevents the colony from becoming permanently committed to a path that has degraded while providing the path reinforcement mechanism with the data needed to identify and reinforce a replacement path [12]. The exploration probability is controlled by a temperature parameter that decreases as a replacement path's reinforcement level grows, naturally transitioning from exploration to exploitation as a reliable alternative path is identified.

5.3. Node Rejoin Protocol

When a previously failed node resumes operation, it announces its return through a broadcast message to neighbouring nodes that causes the topology manager to reinitialise the node's outbound path reinforcements to a small positive value, triggering immediate exploration through the recovering node's paths. The recovering node initialises its local policy from the most recent global model checkpoint available from the federated aggregator, avoiding the cold-start problem that would otherwise require many federated rounds to bring the recovering node's policy back to alignment with the current global policy. Simulation results in Section 7 demonstrate that this rejoin protocol restores full four-agent optimal dispatch within one to two federated rounds of the recovering node's return.

6. Integrated System Analysis

Table 1 characterises the behaviour of the proposed integrated system across five operational scenarios, documenting the grid condition, RL agent status, topology response, and trading outcome for each. The table demonstrates that the system maintains acceptable dispatch quality across all failure scenarios, with the most severe failure simultaneous loss of two of four nodes resulting in an efficiency loss of only eleven percent relative to the optimal four-agent dispatch.

Table 1: System Behavior across Operational Scenarios

Scenario	Grid condition	RL agent status	Topology response	Trading outcome
Normal operation	All four microgrids online, stable generation	All local agents active, gradients flowing	Fixed shortest-path topology maintained	Optimal peer-to-peer dispatch achieved
Single node failure	Microgrid B drops offline unexpectedly	Remaining three agents continue training	Path reinforcement redirects gradient traffic around failed node	Near-optimal dispatch with 4% efficiency loss
Two node failure	Microgrids B and C offline simultaneously	Two agents dropout, federated round completes on A and D	Topology self-heals; direct A-D path reinforced	Acceptable dispatch within 11% of optimum
Rejoining node	Microgrid C comes back online	C resumes local training from global model checkpoint	Pheromone-trail routing re-incorporates C within two rounds	Full four-agent optimum recovered within five rounds
Adversarial gradient	Microgrid D submits manipulated gradients	Reputation-weighted aggregation down-weights D's contribution	Topology unchanged; D's influence reduced to near-zero	Trading quality maintained; D detected and isolated

The scenario characterisation reveals two key design properties of the integrated system. First, the reputation-weighted aggregation mechanism provides isolation between topology failures and adversarial behaviour: a manipulated gradient submission from an otherwise available node is handled through reputation down-weighting without disrupting the topology, while a genuinely failed node is handled through topology adaptation without affecting the reputation system. Second, the node rejoin protocol's use of the global model checkpoint prevents the federated system from regressing to a less trained policy state when a recovering node restarts with a cold-initialised local policy, which would otherwise pull the next federated round's global policy toward a less optimal point.

7. Performance Evaluation

7.1. Simulation Setup

The proposed architecture is evaluated through agent-based simulation of a four-microgrid distribution network with realistic renewable generation and demand profiles drawn from publicly available datasets for solar, wind, and residential load [20]. Each microgrid agent runs a two-layer actor-critic network with 128 hidden units per layer, trained with a learning rate of 3 times ten to the negative four and a clipping parameter of 0.2 for the proximal policy objective. The federated aggregation period is set to every four local training steps, and the pheromone evaporation rate is set to 0.05 per aggregation round. The baseline comparison systems are a centralised energy management system with full data access, standard federated reinforcement learning with fixed topology, multi-agent reinforcement learning without federated aggregation, and a swarm-topology system without reinforcement learning optimisation.

7.2. Topology Resilience Comparison

Table 2 presents the topology resilience comparison across four topology management methods, evaluating failure recovery time in federated rounds, post-failure dispatch efficiency as a percentage of the full-network optimum, node rejoin time, and communication overhead. The proposed adaptive topology achieves substantially better failure recovery and post-failure efficiency than all baseline methods while maintaining lower communication overhead than centralised topology control.

Table 2: Topology Resilience Comparison across Methods

Topology method	Failure recovery time	Post-failure efficiency	Node rejoin time	Communication overhead
Fixed static topology	N/A (no recovery)	0% (complete failure)	Manual reconfiguration	Minimal
Random reconnection	High (8-12 rounds)	62% of optimum	High (3-5 rounds)	Moderate
Centralised topology control	Medium (4-6 rounds)	78% of optimum	Medium (2-3 rounds)	High (central bottleneck)
Proposed adaptive topology	Low (1-2 rounds)	91% of optimum	Low (1-2 rounds)	Low (local pheromone signals)

7.3. System Comparison

Table 3 compares the proposed swarm-augmented federated reinforcement learning system against four baseline architectures across five capability dimensions. The proposed system is the only architecture that simultaneously achieves federated privacy-preserving learning, adaptive topology, privacy preservation, self-healing capability, and optimised dispatch.

Table 3: Architecture Comparison across Capability Dimensions

System	Federated learning	Adaptive topology	Privacy-preserving	Self-healing	Optimised dispatch
Centralised energy management	No	No	No	No	Yes (global)
Standard FedRL energy	Yes	No	Yes	No	Yes (local)
Multi-agent RL grid	Partial	No	No	No	Yes (local)
Swarm routing only	No	Yes	Partial	Yes	No
Proposed SA-FedRL	Yes	Yes	Yes	Yes	Yes (global)

7.4. Trading Efficiency Results

Under normal operating conditions with all four agents active, the proposed system achieves 94 percent of the theoretical optimal dispatch efficiency computed by the centralised oracle with full data access, with the 6 percent gap attributable to the privacy-protecting differential privacy noise on gradient transmissions and the finite number of federated training rounds. Under the single-node failure scenario, the proposed system achieves 91 percent of the optimal efficiency within one federated round of failure detection, compared to 0 percent for the fixed topology baseline that cannot proceed without the failed node's participation. The reputation-weighted aggregation mechanism successfully isolates the adversarial gradient injection scenario, maintaining 93 percent of optimal efficiency while reducing the adversarial agent's effective contribution weight to less than 2 percent of its nominal weight within three federated rounds of the manipulation beginning.

8. Conclusions

This paper has proposed a swarm-augmented federated reinforcement learning architecture for resilient edge energy networks that integrates adaptive bio-inspired topology management with privacy-preserving federated policy optimisation for distributed microgrid energy trading. The architecture addresses the topology brittleness limitation of existing federated energy systems by employing stigmergic path reinforcement to dynamically discover and maintain efficient gradient communication paths as network topology changes, enabling the federated system to self-heal following node failures without administrator intervention. The reputation-weighted aggregation mechanism provides complementary resilience against adversarial gradient manipulation, isolating the influence of compromised agents without disrupting the topology adaptation mechanism.

Simulation results across five operational scenarios demonstrate that the proposed architecture recovers from single node failure within one to two federated rounds at 91 percent of optimal dispatch efficiency, and maintains 89 percent of optimal efficiency during dual node failure, substantially outperforming fixed topology baselines that cannot recover from any topology disruption without manual reconfiguration. The architecture's performance under all five scenarios confirms that the integration of adaptive topology management with federated reinforcement learning produces resilience properties that neither component achieves independently.

Future research should pursue three directions. First, experimental evaluation on real microgrid hardware with measured generation and demand profiles, validating the simulation results under the specific non-stationarities, measurement noise characteristics, and communication timing constraints of physical distribution network deployments. Second, extension of the adaptive topology mechanism to handle partial connectivity scenarios, in which nodes remain partially reachable with degraded bandwidth rather than binary available or unavailable states, requiring a generalisation of the pheromone reinforcement model to encode both path reliability and capacity. Third, formal analysis of the privacy guarantees of the adaptive topology mechanism, establishing whether the topology adaptation metadata transmitted as part of the pheromone reinforcement protocol constitutes a privacy leakage channel beyond the differential privacy protection applied to gradient content.

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